

MEMETIC META-HEURISTIC OPTIMIZATION FOR ECONOMIC LOAD DISPATCH IN BESS BASED ANCILLARY SERVICES

Thesis Submitted For the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

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DEDICATION

This thesis is dedicated to

My Parents (Mr. Tilak Raj Sehgal & Late Mrs Chanchal Kumari Sehgal) and parents-in-laws (Mrs Usha Mehta & Late Mr. A.C. Mehta) for their inspiration, motivation and blessings.

To my Husband (Mr. Saurabh Solly Mehta), daughter (Leisha Mehta), and son (Vevaam Mehta) for their encouragement, support, sacrifice and endless love.

To my supervisors (Dr. Vikram Kumar Kamboj and Dr. Aman Ganesh) for their continuous guidance, support and motivation.

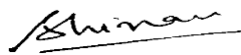
To my brother, sister, relatives and friends for their encouragement to finish this study.

And lastly, I dedicate this thesis to Almighty God for guidance, power, strength and blessings.

DECLARATION

I declare that the work which is being presented in the thesis, entitled “**Memetic Meta-Heuristic Optimization for Economic Load Dispatch in BESS Based Ancillary Services**” 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 carried out during the period January 2019 to February 2022 under the supervision of Dr. Aman Ganesh (Professor, School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, India) and Dr. Vikram Kumar Kamboj (Professor, School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, India).

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 “**Memetic Meta-Heuristic Optimization for Economic Load Dispatch in BESS Based Ancillary Services**” submitted by **Shivani Sehgal** 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 her 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

With the advancement of technology and modernization, there is a greater need for electric power to meet the demand of various industrial, residential, agricultural, and commercial applications. According to a recent survey, global energy consumption has grown by nearly 20%. With the continuously increasing demand for electrical energy, it becomes important to produce surplus power to satisfy consumer demand at the most economical cost. Nowadays, the electric power system is considered to be the most complex industrialized system of this civilized era and performs a foremost role in the proper functioning of modern societies. Therefore, the generation and the dispatch of electric power must be achieved reliably and efficiently. The planning, processing, and controlling of the electric power system (generation, transmission and distribution) is a key challenge to electrical engineers all over the world. The main objective in the operation, control and planning of power system generation is to distribute the load/power requirement at the most optimum cost while meeting all the constraints in the system.

Reducing the environmental impact of power generation from thermal power plants is also an important issue in regard to global warming. With the increase in the number of thermal power plants, the amount of emissions in the atmosphere is also increasing and is a major cause of environmental pollution. Electrical energy is mostly produced from conventional sources like coal, oil, and natural gas along with nuclear and hydro sources. Globally the major part of electricity is produced in fossil-based thermal power plants and due to the unceasing increase in the energy demand, fuel consumption is also amassed and hence decreasing the limited and irreplaceable existing fuel resources. The latest trend to emphasize the use of renewable energy, in addition to traditional energy sources, plays a significant part in meeting total power demand and decreasing environmental issues.

Economic load dispatch (ELD) is among the significant optimization problem in the operation of electric power systems with an aim to meet the required power with minimum operating/fuel cost under various system and operating constraints and thus

recommending the efficient schedule/dispatch of power from the generating units. Traditionally, the ELD was concerned only with conventional thermal sources but nowadays due to inadequate fossil resources and environmental concerns alternate methods of energy generation have gained popularity over the conventional thermal generation methods. Alternative energy-generating technologies such as solar and wind have gained appeal as a viable alternative to traditional thermal power generation

The traditional power grid dissipates a significant amount of electricity generated and makes the system inefficient. Many of these inefficiencies may be removed by using energy storage systems (ESSs). Battery Energy Storage Systems (BESSs) use precisely built batteries to store electric charge. Based on the electrochemical process BESSs is a subcategory of ESSs. The ESSs are referred to as the ability of a system to store energy using thermal, electromechanical, or electrochemical processes. In order to balance energy output and consumption, the systems complement intermittent energy sources based on tidal, wind and solar power. All energy storage technologies, in essence, harvest and store energy for future use.

Electric vehicles (EVs) are promoted in the motor vehicle market unanimously and will prove to be a promising approach to reduce pollution in a short time, but also cause a new challenge to the electric energy industry in regard to proper planning, operation and control of power system. The reduced dependence on fossil-based fuels and electrifying the vehicle industry help to suppress greenhouse gases and pollutants. Electric vehicle charging stations are being provided to properly access the use of EVs by plugging the vehicle into the power system and directly charging its batteries. The increase in the number of electric vehicles will cause considerable uncertainties in the operational behavior of the power system. This further increases the load demand due to the haphazard charging of vehicles. So the continuous expansion in demand for energy has stimulated researchers to contemplate renewable energy sources (RESs) along with the BESSs. The energy available from standalone vehicles may be employed as BESSs for ancillary services, allowing for optimal utilization of the generated energy during the charging and discharging processes. The integrated system based on renewable sources,

electric vehicles (PEV/BESSs) is accessible in limited land resources and balances the total energy produced and consumed with energy storage and optimum load dispatch.

With the constant growth in demand for electric energy and the scarcity of energy supplies, the electric power business is regarded to be the most challenging and complicated, thus needing the optimal/economic dispatch of power generation. The ultimate goal of the optimal/economic load dispatch problem associated with overall power production and utilization in an electric system is to attain the system total power requirement at the most reduced operational cost by scheduling the power generating units, adhering to the constraints of the system. Optimization plays a key role in finding the most optimized solution with a balance between demand and supply. The economic load dispatch problem of the power system is realized as a nonlinear problem that can be solved using metaheuristic optimization methods.

In the present research, the economic load dispatch problem with an integrated system (renewable sources with EVs/BESSs) is considered for finding an optimum solution to curtail the operational fuel cost of thermal energy generation and maximize the efficacy of the system. Wind and solar plants used as sources of renewable energy are stochastic in nature meaning that their velocity, direction, and radiation go on changing with time. This uncertain stochastic nature could be fixed by using various statistical techniques and it is always preferred to use renewable energy sources in combination with conventional power plants. Researchers are constantly working on finding the most cost-effective ways to provide an efficient solution to this crucial problem of energy management in a complex stochastic environment.

This thesis deals with introductory aspects of the current power generation scenario and the significance of economic load dispatch in modern integrated power system. Also, this chapter includes various possible non-conventional alternatives for minimizing the dependency of modern society on conventional methods for energy generation. This chapter also includes an introduction to battery energy storage systems as ancillary sources of energy.

The ensuing chapter explores a literature review of recent optimization algorithms applied to various real-world problems including the economic load dispatch considering various aspects of renewable energy sources. The chapter covers research work starting from a few decades to recent developments and an intense review of the economic load dispatch problem along with advantages and disadvantages has been presented in order to explore the research gap. Finally, the chapter has concluded by exploring the scope of the proposed research work.

The succeeding chapter deals with various optimization methodologies to elucidate benchmark functions and design problems in engineering. In this chapter theoretical and mathematical concepts of various methodologies have been explored in depth. Two memetic optimizers have been developed using recent modern search algorithms such as Harris Hawk's optimizer (HHO), Slime mould algorithm (SMA) and random exploratory search method. Outcomes of the proposed memetic algorithms have been studied for standard uni-modal, multi-modal and fixed-dimension benchmarks including various sets of real-world engineering design optimization problems. To validate the efficacy of the suggested memetic algorithms the test results are compared with some recent algorithms such as GA, PSO, DE, GWO, GSA, MVO, ACO, MFO, and others.

The next chapter deals with the solution to the static economic dispatch problem (ELDP) for different cases categorized as small-scale, medium-scale, and large-scale power systems. Three, five, six, ten, thirteen, fifteen, twenty, thirty-eight and forty generating units are tested for optimum fuel cost using the proposed methods. The ELDP for thermal units has been solved considering the different realistic constraints of the power system by hybrid Harris hawk's optimizer-random exploratory search method and memetic slime mould-random exploratory search method. The dynamic load dispatch problem (DELDP) with five, six, seven and ten generating units with 24-hour demand has also been tested in this chapter using the proposed methods. Comparative analysis of the aforesaid systems is performed with other existing methods and has witnessed that the proposed methods are better or in competition with other heuristic and meta-heuristic search algorithms.

The next chapter deals with the solution to ELDP for six, seven and ten generating units with renewable energy sources (RESs), EVs/BEVs/BESSs using the proposed methods. The load dispatch problem for thermal units has been resolved by implementing HHO, SMA and proposed memetic approaches (hHHO-RES and hSMA-RES) for conventional ELDP with renewable energy sources like solar and wind energy and the impact of incorporating both renewable energy sources (RESs) and electric vehicles -PEV/BEV/BESSs for the optimal load dispatch problem has been studied using the proposed approaches. A comparison of the suggested approaches with other heuristic and meta-heuristic algorithms has been conducted for 6, 7, and 10-unit systems, and it is discovered that the suggested methods produce better results.

The last chapter summarizes the significance and contribution of the proposed research work. The major issue of power system optimization, operation, and control has been resolved by the implementation of the proposed methods/algorithms are systematically presented. A comparative result analysis including percentage cost saving for 6, 7, and 10 generating units with renewable energy sources (RESs) and EVs/BESSs-based ancillary services has been summarized. Finally, suggestions for the possible futuristic scope of the proposed research work have been included.

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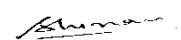
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Shivani Sehgal

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LIST OF SYMBOLS

Symbol	Description of Symbol
itn	iteration
$itn_{\max}$	Maximum iteration
r_1, r_2, r_3, r_4 and q	Random values between 0 and 1
$X_{pr}(itn)$	Position of prey in current iteration
$X_{rand}(itn)$	Randomly selected position of hawks
$X_m(itn)$	Mean position of Hawks
E_0	Initial energy in HHO
E_A	Escaped energy of prey in HHO
L_F	Levy Flights
μ, σ	Random value between (0, 1)
β	Default constant assumed as 1.5.
J_e	Jump Energy
$\vec{X}_A, \vec{X}_B$	Randomly selected positions of slime mould
$\vec{W}_s$	weights of masses in slime mould algorithm
$\vec{v}_b, \vec{v}_c, p$	constants in SMA
$S(i)$	Fitness of slime in i^{th} position
wF, bF	Worst and best fitness
R,r	Random values between 0 and 1
f^+, f^-, f	Fitness values using RES method
f_{final}	Final fitness value
$f_{\min}$	Optimum value
dim	dimension

$f(y), f(x), f(z)$	Objective functions of ED problems
$g_n(y), r_n(x), g_n(z),$	Constraints in ED problems
y_n, x_n, z_n	Design variables
$F(P^G)$	Fuel Cost
a_n, b_n, c_n	Cost-Coefficients
P_n^G	Power generated by n th unit
NG	Number of generators
φ_n, γ_n	Cost coefficients with VPLE
g_n, h_n, q_n	Heat co-efficients
$F_{Power}(P_n^G)$	Fuel cost from n units
$F_{Heat}(P_n^G)$	Total heat from all plants
$F_{Overall}(P_n^G)$	Total cost for combined heat and power
P^{Demand}	Power demand
P^{Loss}	Transmission loss
B_{i0}, B_{00}, B_{nm}	Loss matrix B co-efficients
$P_{n(min)}^G, P_{n(max)}^G$	minimum and maximum power limit of n th unit
UR_n, DR_n	Up and down ramp rate limit of n th unit
$P_n^{G_o}$	Initial power generated
$P_{n(max),m}^{POZ}, P_{n(min),1}^{POZ}$	Maximum and minimum value of POZs
$P^{Renewable}$	Power generated from renewable sources
$P^{BEVs/PEVs/BESS}$	Power of BEVs/PEVs/ BESSs
$NPEVs, NBEVs$	Number of plug in electric vehicles, battery electric vehicles

LIST OF ABBREVIATION

Abbreviation	Full Form
ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ALO	Ant Lion Optimization
ARSM	Adaptive Response Surface Method
AVR	Automatic Voltage Regulator
B&B	Branch and Bound
BA	Bat Algorithm
BBO	Biogeography Optimization
BESSs	Battery Energy Storage Systems
BEVs	Battery Electric Vehicles
BFO	Bacterial Forging Optimization
BM	Benchmark
BSA	Backtracking Search Algorithm
CDE	Chaotic Differential Evolution
CDV	Continuous Design Variable
CEED	Combined Economic Emission Dispatch
CGQBA	Cauchy Gaussian Quantum Behaved Bat Algorithm
CHPED	Combined Heat and Power Economic Dispatch
CMAES	Covariance Matrix Adaptation Evolutionary Strategy
CMVO	Chaotic Multi Verse Optimization
CPSO	Chaotic Particle Swarm Optimization
CS	Cuckoo Search
CSS	Charged System Search
DDV	Discrete Design Variable

DE	Differential Evolution
DEACO	Differential Evolution-Ant Colony Optimization
DED	Dynamic Economic Dispatch
DELC	Differential Evolution Level Comparison
DELD	Dynamic Economic Load Dispatch
DHS	Differential Harmony Search
DSA	Direct Search Algorithm
ED	Engineering Design
EELD	Economic Emission Load Dispatch
EHO	Elephant Herd Optimization
ELD	Economic Load Dispatch
ELDP	Economic Load Dispatch Problem
EP	Evolutionary Programming
ESSs	Energy Storage Systems
Evs	Electric Vehicles
FD	Fixed Dimension
FFA	Firefly Algorithm
FGA	Fast Genetic Algorithm
FPA	Flower Pollination Algorithm
GA	Genetic Algorithm
GBO	Gradient Based Optimizer
GCA	Group Correction Algorithm
GJO	Golden Jackal Optimization
GOA	Grasshopper Optimization Algorithm
G-QPSO	Gaussian Quasi Particle Swarm Optimization
GSA	Gravitational Search Algorithm
GWO	Grey Wolf Optimizer
HAS	Harmony Search Algorithm

HEAA	Hybrid Evolutionary Algorithm
HHO	Harris Hawk Optimizer
HNN	Hopfield Neural Network
HPSO	Hybrid Particle Swarm Optimization
IACO	Improved Ant Colony Optimization
IARSM	Improved Adaptive Response Surface Method
IHSA	Improved Harmony Search Algorithm
ISA	Interior Search Algorithm
LIM	Lambda Iteration Method
LSA	Lightening Search Algorithm
MBA	Mine Blast Algorithm
MDDE	Multitasking Distributed Differential Evolution
MDE	Modified Differential Evolution
MFO	Moth Flame Optimization
MGA	Modified Genetic Algorithm
MH	Meta-Heuristic
MKHA	Modified Krill Heard Algorithm
MM	Multi-Modal
MMA	Method of Moving Asymptotes
MO	Monkey Optimization
MODP	Multi-objective Design Problem
MOPSO	Multi-objective Particle Swarm Optimization
MVO	Multi Verse Optimization
NFLT	No Free Lunch Theorem
OPF	Optimal Power Flow
PEVs	Plugin Electric Vehicles
POZs	Prohibited Operating Zones
PSO	Particle Swarm Optimization

PVS	Passing Vehicle Search
RCGA	Real Coded Genetic Algorithm
RES	Random Exploratory Search
RESs	Renewable Energy Sources
RRA	Runner Root Algorithm
RRLs	Ramp Rate Limits
SA	Simulated Annealing
SAM	Secant-Approximation Based method
SBAT	Shuffled Bat Algorithm
SCA	Sine Cosine Algorithm
SCO	Single Candidate Optimizer
SD	Standard Deviation
SFLA	Shuffled Frog Leaping Algorithm
SFS	Stochastic Fractal Search
SHO	Spotted Hyena Optimizer
SI	Swarm Intelligence
SMA	Slime Mould Algorithm
SMS	State of Matter Search
SOA	Seeker Optimization Algorithm
SOS	Symbiotic Organism Search
SPEA	Strength Pareto Evolutionary Algorithm
SPPO	Synergic Predator Prey Optimization
SQP	Sequential Quadratic Programming
SSA	Salp Swarm Optimization
TLBO	Teaching Learning Based Optimization
TS	Test System
TS	Tabu Search
UM	Uni-Modal

VPLE	Valve Point Loading Effect
VSA	Vortex Search Algorithm
WCA	Water Cycle Algorithm
WEO	Water Evaporation Optimization
WIPSO	Weight Improved Particle Swarm Optimization
WOA	Whale Optimization Algorithm
WSA	Weighted Superposition Attraction

INTRODUCTION

1.1 INTRODUCTION

Electrical energy is the utmost basic requirement for the economic expansion of a country. Due to the increased modernized growth in the social, industrial, and agricultural sectors; the demand for electrical energy is increasing continuously and there is an imperative need to produce surplus power to satisfy the consumer demand at the most economical cost while considering the environmental issues also. Nowadays, the electric power system is considered to be the most complex industrialized system of this civilized era and performs a foremost role in the proper functioning of modern societies. Therefore, the generation and the dispatch of electric power must be achieved reliably, efficiently, and in an environmentally safe mode. The planning, processing, and controlling of the electric power system (generation, transmission, and distribution) is a key challenge to electrical engineers all over the world.

The main objective in the operation, control, and planning of power system generation is to distribute the load/power requirement at the most optimum cost while meeting all the constraints in the system [1]. Reducing the environmental impact of power generation from thermal power plants is also an important issue concerning global warming. With the increase in the number of thermal power plants, the number of emissions in the atmosphere is also increasing and is a major cause of environmental pollution. Electrical energy is mostly produced from conventional sources like coal, oil, and natural gas along with nuclear and hydro sources. Globally, the major part of electricity is produced in fossil-based thermal power plants. Due to the unceasing increase in energy demand, fuel consumption is also amassed, decreasing the limited and irreplaceable existing fuel resources.

Economic load dispatch problem (ELDP) is among the decisive optimization problem in the operation of the electric power system to meet the required power with

minimum operating/fuel cost under various system and operating constraints and thus recommending the efficient schedule/dispatch of power from the generating units. Traditionally, the ELDP was concerned only with conventional thermal sources based on non-renewable resources of energy. Nowadays, due to inadequate fossil resources and environmental concerns alternate methods of energy generation have gained popularity over conventional thermal generation methods. Alternative energy-generating technologies such as solar and wind have gained popularity as a viable alternative to traditional thermal power generation [2]. The combined operation of thermal with renewable sources has achieved remarkable prominence in the recent research scenario.

In today's research scenario, renewable energy sources (RESs) have taken on a significant role and this leads to a reduction of emissions from thermal power plants along with the operational cost of power generated using these resources. The improbable combination of coal and solar or wind under proper situations provides a sophisticated solution for a large-scale generation with reduced emissions, gases, and pollutants. Although the capital investment in renewable sources like solar and wind are more in contrast to the operational cost and are reliant on weather conditions hence have uncertainties in delivering output. These resources always entail some backup technology when supply is less or unavailable due to their intermittent nature that varies the power widely in a short period. Despite all these concerns, the combination of renewable sources with the conventional thermal power plant is advantageous to each other and will lead to a cleaner and most efficient power generating system.

Electrification of the transport system is also effective to eradicate greenhouse gases and air pollutants from fossil-based conventional power plants. The use of electric vehicles (EVs) is an implicit way to reduce carbon emissions and noise pollution. Electric vehicles are becoming more popular in the motor vehicle market universally and will ascertain to be a successful solution to diminish pollution in a short time, but this is another new challenge to operate & control the power system. To increase access to EVs, large-scale electricity charging facilities are required to allow the vehicles to be plugged into the power system and charge the batteries directly [3]. An increased

number of these vehicles will cause significant uncertainties in the power system operations and control. This is due to the random nature of the charging behavior of electric vehicles and hence increasing the power demand. This rise in energy demand has inspired researchers to cogitate the power generation from RESs. Moreover, researchers agreed that more emphasis is required in this field to decrease the issues related to the escalating power demand and the environment like global warming and deprivation of the ecosystem. The idea of charging and discharging electric vehicles from the grid and to the grid has a significant role in contemporary power system. The continuous load demands have initiated the integration of plug-in electric vehicles and battery electric vehicles into conventional power system making it a smart grid and reducing the fuel cost of the entire power system. This additional power of standalone vehicles can be used as a source for battery energy storage systems.

In all three major sectors of the power grid, namely generation, transmission, and distribution, electric power systems have experienced continuous expansion. Electricity cannot be economically processed, so there must be a constant equilibrium between supply and demand. The key aim of load dispatch in a power system is to obtain the utmost profitable distribution of load among all the generators until all the constraints are satisfied. Engineers in the twenty-first century are fascinated by the growing complexities of social and technical problems related to solar power extraction, wind power, and load dispatch problem. A typical power system is massive, complicated, geographically concentrated, and affected by multiple unpredictable events, solving optimization problems for such systems is extremely difficult. To take full advantage of the benefits of simplifying the formulation and execution of the problem, it is important to use the most effective-optimization techniques.

Power system modeling approaches are becoming highly problematic in dealing with the dynamic challenge of delivering electricity to the grid effectively. These optimization tools are needed in a variety of fields, including scheduling, power plant management, analysis, and energy conservation. Traditional optimization procedures can be utilized to discover the exact solution for unconstrained maxima/minima of continuous and differentiable functions. Economic load dispatch is the most

challenging research area of electrical engineering and power system optimization. To solve the ELD problem, several approaches have been developed, which can be separated into traditional, stochastic, and memetic methods.

Linear programming (LP), Lagrange multiplier, and dynamic programming (DP) are some examples of traditional methods that use a deterministic approach. When dealing with more complicated challenges, these approaches have shortcomings or disadvantages [4]. Current techniques for solving optimization problems using stochastic methods have gained importance such as genetic algorithms, differential evolution, GBO (Gradient-Based Optimizer), KHA (Krill Herd Algorithm), WOA (Whale Optimization Algorithm), etc. These modern approaches include complementary strategies that aim to solve the shortcomings of traditional methods, attempting to solve their disadvantages, and are, preferred over conventional approaches. These stochastic methods can further be improved by combining different algorithms and are termed as memetic or hybrid approaches.

Inspired by the aforesaid research challenges, the intent of the proposed research work is to develop a new memetic meta-heuristic optimization method for the optimal solution of complex load dispatch problems of electrical power systems with due consideration of power demand using plug-in electric vehicles (PEVs) with renewable energy sources (RESs) and excess power can be used as battery energy storage systems.

1.2 ECONOMIC LOAD DISPATCH

The power sector strives to produce power at the least rate and at the same time meet all the limitations and restrictions placed on production units. One of several optimization issues in the power industry is related to economic load dispatch (ELD). ELD calculates the best and most accurate power solution with the lowest generation cost while still satisfying the load requirement. However, owing to environmental issues over emissions generated by fossil fuels in thermal power plants, power providers must now take environmental restrictions into account in addition to economic constraints. However, all goals, namely low fuel costs and low emissions, are contradictory. The ELD issue is a major issue in the operation and development of thermal and hydro power plants.

It is regarded as an optimization problem and further, it is characterized by minimizing the overall generation cost while meeting power demand under various linear and non-linear controls. The problem is divided into two types: convex ELD problems and non-convex ELD problems. The main objective of the former ELD problem is modeled as dropping the generator-cost functions in regard to linear constraints. Although reducing the cost function, the later categorized ELD problem reflects non-linear constraints in comparison to linear constraints. The linear constraints/limits are the generation capacity of the unit and power balance of the system; causing the ELD problem to be approximated and generalized with piece-wise linear characteristics. To model a more intricate, detailed, real and exact problem non-linear constraints/limits are considered. Prohibited operating zones-POZs, ramp rate limits-RRLs and valve point loading effects-VPLE [5] are the three significant non-linear constraints used in real ELD problems.

ELD problems are usually discontinuous, multimodal, and strongly nonlinear. While the expense curve of thermal generation systems is typically modelled as the input-output dynamics and are non-convex and nonlinear due to the effects like VPLEs, POZs and RRLs. Steam turbines with several valves are common in power plants and to maintain the power equilibrium, the steam valves are opened and closed resulting in a throttling process. This causes ripples or variations in the fuel price function with an additional sinusoidal term and is referred to as the valve point loading effect. Completely disregarding the outcomes of valve-point loading can result in erroneous generation dispatch.

Quite apart from that, the thermal power units may have a limited operating range due to physical constraints such as system unit limitations, steam valve vibration, and shaft bearing vibration, among others. The term POZs refers to load restricted areas means when a generating unit has POZs, the operational area of the unit is divided into discrete sub-regions, resulting in non-convex outcome space. Moreover, the operational spectrum of online units is constrained by RRLs. The rate of decrease or increase in power output or energy output of generating units is restricted to a range to maintain thermal improvements in the turbine within avoidable secure limits and deterioration

of life. The traditional load dispatch dilemma becomes a dynamic economic load dispatch (DELD) problem due to the ramp rate constraints. Because of the existence of these nonlinearities in functional generator action, solving the ELD problem becomes more difficult. Coal, gas, gasoline, and diesel are the primary energy sources of fossil-fired power plants. Many of the resources listed above produce toxic gases in the atmosphere. Coal emits smoke, CO_2 , SO_x and NO_x into the atmosphere. The fresh or cooling water used in nuclear power plants raises the temperature of the water, impacting sea life. Nuclear power stations release dangerous radiation into the atmosphere. Because of the above reasons, pollution reduction has emerged as a critical organizational goal.

Even while the majority of this energy demand is still met by fossil fuels, the globe is gradually shifting toward sustainable energy to improve the environment. The integration of electrical energy storage has been regarded as the most practical and promising approach out of the numerous studies that have been conducted to identify potential solutions to mitigate the intermittencies, including shifting the load through demand management, connecting external grid, electrical energy storage, etc. Energy storage system is the process of first transforming electrical energy into another form that can be stored, and then as needed, convert the accumulated energy to electricity. Energy storage systems may efficiently reduce the intermittencies produced by RESs by charging and discharging real power in accordance with the renewable intermittent production profile, hence enhancing reliability and power quality [6]. Additionally, they have the capacity to store any extra energy produced by RESs, hence reducing energy spillage.

Electric vehicles (EVs) are on the rise in recent years, becoming a very promising mode of transportation, with energy storage systems (batteries) serving as the primary power source. Additionally, the energy storage system has numerous utility-scale applications, including peak shaving, load balancing, offering backup power, uninterruptible power supply (UPS), etc. Recently, many nations have begun commissioning the numerous applications and services that ESSs provides by constructing large-scale storage systems.

Economic dispatch of power grid considering the renewable energy sources and electric vehicles is significant due to the deeper penetration of renewable energy and the increasing number of electric vehicles. The economic dispatch strategy is to reduce the operating cost of the grid system and maximize the use of energy storage systems. The charging loads from Plug-in EVs as well as the discharging output via the vehicle-to-grid (V2G) method can greatly affect the economic dispatch for all the energy sources in a power grid.

1.3 ANCILLARY SERVICES IN POWER SYSTEM

One of the key problems in overhauling of the electrical market engraving more attention is the awareness of the electrical supply's dependability. The electrical power system is experiencing many uncertainties and frequency degradation as a result of the massive integration of renewable energy sources produced by wind or photovoltaic (PV) arrays. The following explanations might be stated as the main causes of uncertainties and frequency degradation:

First, conventional fossil-fuel-based power is being replaced by inexpensive and clean renewable energy. Second, these variable resources are heavily dependent on weather conditions, which makes them very unpredictable and intermittent. With the advent of renewable energy sources (RESs) in liberalized electricity markets and a significant increase in the content of electrical transactions, the task of ensuring the security and dependability of electrical planning has become much more difficult. Some form of service required to facilitate transactions from the manufacturer to the user while maintaining reliability and assuring the required degree of supply quality in order to have essential supply-demand equilibrium. The duties to enable the safe and sufficient availability of supply are termed as ancillary services and are categorized as frequency control services, voltage control services and emergency services [7].

Ancillary Services are support or backing services that are necessary to improve and enhance the electrical power system's dependability and security. The electrical sector cannot function without these services as these have evolved all over the world based on the current configuration of the electric resource infrastructure and functioning

procedures. Regarding vertically integrated utilities, one company is responsible for generation, transmission, and distribution of electric power, therefore ancillary services are considered as an integral part of electrical supply. The resources required for reliable operation have been considered as an added service that other industries must provide to the system operator.

1.3.1 BESSs Based Ancillary Services

Battery energy storage systems (BESSs) is an electrochemical process that is similar to all energy storage systems (ESSs). Its purpose is to capture energy and store it for later use. These systems complement intermittent sources of energy including wind, tidal, and solar power to balance energy production and consumption. As a result of energy storage, peak electrical system demand is lowered; other advantages include a small track, no geographical limits, and ease of installation [8].

To decrease the volatility and intermittency of renewable energy systems, various solutions are employed and the most optimal option is to use electric storage systems (ESSs). ESSs can accumulate excess renewable energy to be used in future when it is more cost-effective or technically feasible. The use of ESSs allows for energy trading, power quality boosting, load flow, voltage and frequency stability improvement, operational cost reduction, and rescheduling of expansion reserves. BESSs is the greatest option among the many energy storing system technologies, owing to its technological maturity and capacity to provide both energy and power densities.

Renewable energy sources (RESs) have been integrated into the electricity grid in response to the current environmental requirement to minimise greenhouse gas emissions. The installed capacity of renewable energy sources is rapidly growing, yet it still has drawbacks such as variability, intermittency, and uncertainty in electric power output. BESSs is now widely employed in electricity markets as a cost-effective way to reduce the negative impacts of renewable energy sources.

BESSs capacity installed for power system applications is expected to continuously increase, not only for utility-scale but also for distributed small-scale applications, where a huge number of BESSs will be connected to PV systems and behind the supply. The extensive use of electric vehicles, helped by expansions in vehicle-to-grid and grid-to-vehicle technology, is expected to accelerate the current trend of BESSs. Also, cost reduction is possible using BESSs technology and is projected to play a major role in their increased usage.

1.3.2 Classification of Ancillary Services

The three primary categories of ancillary services are (a) real power support service or frequency support services/load following, (b) voltage or reactive power support services, and (c) black start support services. These are adopted to improve the reliability, security and stability of electric power system. The Federal Electricity Regulatory Commission (FERC) defined six ancillary services:

- (i) *Scheduling, control, and dispatch*: The system operator of a control area provides this service to schedule the transfer of electricity through, out of, inside, or into the control area.
- (ii) *Reactive supply and voltage control from generation service*: this service Produce or absorb reactive power to sustain transmission voltages within acceptable limits.
- (iii) *Regulation and frequency response service*: To keep the frequency at a nominal level, generation and non-generation resources adjust their output or demand to maintain power balance (i.e., guarantee that power supply equals demand)
- (iv) *Energy imbalance service*: this provides a source of energy balance when there is a difference between the actual and scheduled delivery of energy.
- (v) *Operating reserve—synchronized reserve service*: Power generators are kept in reserve, but in a way that allows them to produce power fast (usually within 10 minutes) if a system failure occurs (an online power generator trips and goes offline).
- (vi) *Operating reserve—supplemental reserve service*: Power generators kept in reserve, but in a way that didn't allow for fast response (i.e., they had to be started up), but would be ready in a set time, usually 15 or 30 minutes.

A grid operator contracts ancillary services in addition to energy and capacity from generators to operate the grid in a reliable way with minimal frequency and voltage aberrations and without power service outages. In many markets, these services are auctioned among a pool of qualified generators, with mandatory participation in some territories for certain services, and existing power grid standards ensure that power plants meet the appropriate specifications, such as ramp rates and controls. Generators are compensated over a set length of time for keeping capacity (positive or negative) for these services accessible to the grid operator on demand. To summarize, all activities on interconnected grid that support electricity transmission and generation while maintaining dependable operation and guaranteeing the requisite level of quality and safety are referred to as ancillary services. Ancillary services, according to the Indian electrical grid code, are services that are required to support power system or grid operation in order to maintain grid quality, dependability, and security.

1.4 SCOPE OF OPTIMIZATION IN POWER SYSTEMS

Artificial Intelligence (AI) and machine learning-based problems are discrete and continuous-based problems in nature with the unconstrained and constrained types of behaviour. For these types of researches, there have been a few challenges in dealing with a variety of concerns in utilizing traditional techniques and consistent strategies. Some research has attempted to show that these approaches are insufficiently practical or persuasive to deal with a wide range of non-differentiable and non-continuous issues. This encourages the use of metaheuristic and memetic techniques to evaluated large number of challenges that are fundamental in nature and easily executed.

In recent years, heuristics and metaheuristic algorithms have gained interest and cognizance of success and effectiveness in different fields. However, the NFLT-No Free Lunch theorem [9] states that all the proposed developments in optimizers/algorithms show similar performance in rate if we apply them to all possible activities. According to the NFLT, theoretically no algorithm is considered as the best general-purpose planner. Therefore, the NFLT encourages the search for the development of highly efficient algorithms/optimizers. As a result of the NFLT, apart

from extensive researches on the efficacy, performance features, and consequences of traditional classical methods, new optimizers with exclusive exploitation and exploration in terms of global/local search approaches emerged in recent years involved an inclusive variety of researchers and experts in several fields [10].

In a power grid, the impact of overload occurs due to increased power demand requirements. Therefore, an electric system requires an improved structure to produce and fulfill the load demand of customers at the least possible cost by the use of an accessible framework. With the limited fuel resources for conventional power plants and change in load demand throughout the day, it has been necessary to generate power at a minimum cost and satisfy the customer's demand for power requirement [11]. This can be achieved by using advanced optimization methods that can give the most optimum solution by exploring the complete search space. Currently, professionals are working in a wide range of fields on a variety of methods to maximize the effectiveness and efficacy of these algorithms and overcome the inefficiencies of existing methods.

1.5 OUTLINE OF THE DESSERTATION

In the present research work efforts has been done to develop a memetic algorithm for the cost benefit solution to ELDP considering impact of renewable energy, electric vehicles/battery energy storage systems. To investigate optimum solution strategy for economic operation of power system, two memetic optimization strategies have been employed. Further, to check the proficiency of local and global search abilities, developed strategies have been applied on standard test benchmarks and real-life engineering design (ED) optimization challenges. One memetic algorithm consists of the combination of Harris hawk's optimizer and random exploratory search method and second memetic algorithm consist of hybrid combination of random exploratory search method and slime mould optimizer. The potentiality of the suggested work has been explored by testing different IEEE test system for static, dynamic and integrated ELDP. The different test cases have been categorized as (a) small-scale, (b) medium- scale and (c) large-scale power systems. The detailed research work has been organized chapter-wise in the thesis as follows: the

Chapter-1 deals with introductory aspects of the current power generation scenario and presents the various effects of utilizing the conventional fossil-based fuels on society and environment. This chapter also presents various possible non-conventional alternatives for energy generation and its utilization in transport sector. It also includes the introduction to ELDP, need of RESs and BESSs for ancillary services. Further, it includes the benefits and scope of utilizing vehicle to grid technology in reducing the excessive burden on grids to satisfy the tremendous increase in load or power demand.

Chapter-2 includes the literature review of several methods effectively applied to various problems including the economic load dispatch problem. The chapter covers research work till date and an intense review of the economic load dispatch problem and optimization methods along with its advantages and shortcomings. This is further used to explore the research gaps. Also, research objectives have been framed to accomplish the proposed research work. Finally, the chapter concluded by exploring the scope of the proposed research work.

Chapter-3 explores the need for optimization and various optimization methodologies. This is further elucidated on different benchmark functions and some engineering-based design problems. In this chapter, theoretical and mathematical concepts of various methodologies have been explored in depth. Two memetic optimizers have been developed using recent modern search algorithms such as Harris Hawk Optimizer (HHO), Slime mould algorithm (SMA), and Random Exploratory Search (RES) method. The suggested algorithms/methods have been tested for 23 benchmark problems and various engineering design (ED) challenges. The efficacy of the suggested method is validated by comparing the test results with other recent algorithms/methods.

Chapter-4 deals with the solution to static ELD problems categorized under small, medium and large-range power system. It includes the application of proposed methods to find the optimum fuel cost in case of three, five, six, ten, thirteen, fifteen, twenty, thirty-eight and forty generating units system. The ELD problem for thermal

power units has been solved for various realistic constraints of power systems by hybrid Harris hawk optimizer-random exploratory search method and memetic slime mould-random exploratory search method. Also, four dynamic ELD problems (DELDP) comprising five, six, seven, and ten units with 24-hour demand has also been tested in this chapter using the proposed methods. A Comparative analysis for the said systems has been performed with other existing heuristic and meta-heuristic algorithms.

Chapter-5 deals with solution to ELD problem for six, seven and ten generating units with renewable energy sources (RESs), Electric vehicles/BESSs using the proposed methods. The ELD problem for thermal units has been solved by implementing memetic hHHO-RES and memetic hSMA-RES for conventional ELD with RESs (solar and wind) and the impact of incorporating renewable energy source and electric vehicles -EVs/BESSs. A comparative analysis for 6, 7 and 10-unit system has also been performed and compared to other heuristic and meta-heuristic algorithms.

Chapter-6 concludes the proposed research accomplished to develop a cost-effective solution strategy for ELD problems incorporating BESSs/PEVs/BEVs operation under uncertain renewable energy sources. Further, suggestions for future work are also been included.

REVIEW OF LITERATURES

2.1 INTRODUCTION

Economic load dispatch is amongst the top momentous problems in refining the performance of the power system, with the aim of recommending a more efficient production system to meet energy demand with minimal operating cost under a variety of system and operational barriers. Previously, the ELD problem was limited to conventional thermal power producers that used non-renewable energy sources. Due to restricted fuel resources and environmental distresses, alternative energy generation technologies such as solar and wind have grown in favor as an alternative to traditional thermal power generation. Currently, these sources have taken on a significant role with emphasis on curtailing fuel price and emissions. The emissions from this fossil based traditional power plants will be decreased with the increase in power generated from renewable energy sources. Electric vehicles are also gaining popularity in the global motor vehicle market and will prove to be a promising alternative for reducing pollution in a short period of time. Electric vehicles, on the other hand, are posing a new challenge to power system management and control. To make electric vehicles more accessible, large-scale electrical charging stations are required, allowing vehicles to connect to the power grid and charge their batteries directly. Because of the unpredictable nature of their charging habits, a rise in the number of these vehicles will cause significant uncertainty in power system performance, thus increasing power demand. As a result, the ever-increasing energy requirement has impelled researchers to survey and examine RESs in combination with conventional sources to produce enough power most economically and utilize the power of standalone vehicles as a source to charge the BESSs. Many research efforts have intensely explored the conventional ELD problem by implementing different solution methodologies and investigations are continuously going on to discover more optimal and efficient methods using heuristics and metaheuristics methodologies. The literature relevant to the proposed research work is presented in the succeeding sections.

2.2 REVIEW OF LITERATURE

This section reveals the literature review of significant investigation done in field of optimization methods, ELD with due consideration of renewable sources –RESs in power system. It also includes the review of electric vehicles (PEVs/ BEVs) with substantial battery energy storage systems (BESSs). The brief overview of some research achieved in related field with several methodologies has been explored in the following sub-sections.

2.2.1 Review of Literature - Economic Load Dispatch

This section reviews different optimization approaches used to obtain optimum solution to model practical and scalar ELD problems from the researchers presented in the field of power systems. The following review has been taken into consideration to explore the effective research studies for scalar objective economic load dispatch problem. The overall review of literatures has been divided into two broad categories viz. traditional methods for Economic Load Dispatch and Stochastic methods for economic load dispatch and has been described in the following sub-sections:

2.2.1.1 Traditional Methods for Economic Load Dispatch

Numerous derivative-based strategies assuming monotonically increasing piecewise linear cost function, have been successfully used to solve the ELD problem. These traditional methods include the classical Lagrangian relaxation-based optimization methods [12], quadratic programming (QP) [13] , branch and bound method [14], lambda iteration method (LIM), gradient method, co-ordination equation [5], linear programming(LP) [15], and dynamic programming (DP) [16] The conventional optimization approaches, on the other hand, are quite susceptible to starting locations and frequently converge to local optimums or diverge entirely. Applying DP to ELD problem solutions may result in extraordinarily huge dimensions, requiring a lot of computing work. These approaches are not applicable to real-world systems and are unable to find the global optimum solution since the actual ELD problem has nonlinear properties including ramp rate restrictions, discontinuous POZs, and non-smooth cost functions like VPLE. An analytical approach (quadratic programming) was introduced

to address the non-smooth and non-convex ELD problem. Due to many restrictions and the extremely nonlinear nature of the ELD problem, the traditional calculus-based approaches are unable to deliver satisfactory results and are instead trapped at a local optimum. Therefore, it becomes imperative to design a robust, enhanced, and reliable strategy in order to address these shortcomings and tackle such challenges.

2.2.1.2 Stochastic Methods for Economic Load Dispatch

To overwhelm the drawbacks of traditional approaches, artificial intelligence-based methods such as Hopfield model, adaptive Hopfield based on neural networks, fuzzy logic, etc have been successfully developed to solve the ELD problems. But these methods suffer from excessive numerical iterations, due to which more quick and reliable methods are needed. With the advancement in technology, more advanced population-based methods also known as heuristics /stochastic optimization methods are used to solve the ELD problems using random variables. Some of the heuristic stochastic optimization approaches are discussed as follows:

Tzong Su et al. (2000) [17]: This paper discussed a new method based on Hopfield-Model for the power system's economic dispatch issue which entails specifying an energy function that accounts for massive gap in power, overall fuel costs, and transmission line losses. Computational outcomes demonstrate that this system can find precise solutions more quickly and effectively than the traditional LI method.

Attaviriyapap et al. (2002): This paper introduced a novel hybrid approach for dealing with DELD. The proposed approach is structured in such a way that basic evolutionary programming (EP) is used as a standard search to provide the way to global solution, and quadratic programming acts as local search solver to obtain the best result and effectiveness for a 10-unit test system is verified.

Abido et al. (2003) [18]: The SPEA approach is presented to resolve the economic/environmental power dispatch dilemma. To solve the issue of premature convergence and search bias, this approach employs the diversity-preserving mechanism. The proposed methodology is contrasted with traditional methods.

Sinha et al. (2003) [19]: This research work has introduced evolutionary programming methods which are used to solve economic load dispatch problems for 3-, 13- and 14-generator systems with valve-point loading effect. The efficiency of the suggested

methodology is analyzed for ELD problems with modifications to the core technique where adaptation is based on scaled cost and evolutionary programs are built with an empirical learning rate adaptation.

Gainareet et al. (2003) [20]: The PSO is introduced for the ELD problem taking into account the RRLs and the POZs for realistic generating systems. The suggested method's efficiency is evaluated for three different test systems and evaluated in comparison to the GA method in terms of computation feasibility and solution consistency.

Rahman et al. (2004) [21]: presented an adaptation of the Artificial Immune Systems approach of colonel selection to solve the economic dispatch problem. The affinity calculation is based on the total generation expense, which is regarded as an objective function. A few modifications were made before applying the algorithm: there is no specific antigen to be discovered, but an objective feature is to be optimized; all antibodies are to be chosen for cloning, and the number of cloned produced by the antibodies is equal. The algorithm has been tested on both binary and real number representations.

Victoire et al. (2005) [22]: This paper deals in a probabilistically driven PSO algorithm for the solution of dynamic ELD problem with VPLE. Since the valve-point effects are interpreted and imposed in the cost function as rectified sinusoidal elements, the objective (cost) function of the generating units is non-convex. The method proved its effectiveness in comparison to other algorithms.

Chiang et al. (2005) [23]: This paper proposed an enhanced genetic algorithm for solving and dealing with scalar ELD problems with multi fuel generation units and valve-point loading effect (VPLE). The suggested algorithm incorporates a more advanced genetic algorithm as well as multiplier analysis and proved better performance than classical GA.

Sudhakaran et al. (2007) [24]: This paper has introduced a PSO approach for scalar economic dispatch problems that are both efficient and effective. The proposed algorithm is implemented on 3- and 6-unit thermal systems, and it has been generalized to three plant systems with one as co-generation plant. The analysis of results

demonstrates that the proposed approach is capable of effectively achieving better and superior quality solutions for ELD problems in less computing time.

Lakshmi Devi et al. (2008) [25]: This paper presented PSO and GA approaches for the CEED to reduce running fuel costs and emissions while meeting operational constraints and load demand. This multi-objective dilemma is simplified to a single objective problem using the price penalty factor method.

Musirin et al. (2008) [26]: In this paper a novel ACO method is used for ELD problems. The suggested method was tested in this analysis using the IEEE 26-Bus standard, and the findings showed that the suggested technique has excellence in achieving the optimum solution for such problems.

Coelho et al. (2008) [27]: This paper discussed the use of integrating Gaussian probability distribution functions, PSO with unpredictable schedules. In this framework, improved PSO methods were suggested considering nonlinearities like ramp-rate limits and prohibited operating zones. The PSO and its various versions were tested for 2-test systems (15-, and 20-thermal generation units). The proposed combination solution performed better in comparison to other metaheuristic optimization methods.

Tamilselvan et al. (2009) [28]: In this article, four adapted models of PSO were used to solve optimal load dispatch with valve-point effects. Different approaches - New PSO, Self-Adaptive PSO, and Chaotic PSO were suggested and Self-Adaptive PSO was found to be superior to other PSO strategies in terms of better convergence speed, solution, robustness and execution time, but it has more sudden and unexpected convergence.

Singh et al. (2009) [29]: In this research article, the author used the cardinal priority rating-based decision-making method to solve the economic pollution load dispatch issue. The weighting approach is used to generate non-inferior solutions, allowing for straightforward trade-offs between target amounts for each non-inferior solution. Regression analysis and Decoupled load flow analysis are performed to find the best solution between the cardinal priority ranking and simulated weights and the loss coefficients and the transmission losses respectively. The feasibility of the method is implemented on IEEE 11-bus system with 3-generators.

Kumari et al. (2009) [30]: This paper described a Fast Genetic Algorithm (FGA) solution to the ELD problem. This algorithm function is appealing when extended to ELD with large systems. The findings were illustrated for three, six, twenty and thirty eight generator systems with and without system losses. In all cases, the FGA exhibited consistent convergence. The final effects were comparable to those of traditional GA.

Chaturvedi et al. (2009) [31]: In this paper, to regulate the local and global scope and avoid premature convergence in traditional PSO, the author used PSO with a function of time acceleration coefficient for non-convex economic dispatch.

Abido et al. (2009) [32]: MOPSO methodology was used in this paper by reformulating the world best and global preeminent entities in the multi-objective optimization area. The clustering algorithm was used to control the size of the Pareto-optimal (PO) set, and the fuzzy approach was used to find the lowest cost and the least amount of emissions. In terms of the accuracy of the evaluated Pareto-optimal solutions, this method outperforms other multi-objective techniques.

Duman et al. (2010) [33]: This research paper proposed a new meta-heuristic algorithm named as Gravitational-Search-Algorithm (GSA) by taking valve point effects into consideration to solve economic load dispatch. The suggested algorithm has been implemented on the various test systems taking fuel cost function into consideration.

Bhattacharya et al. (2010) [34]: This article suggested biogeography (BBO) method to solve non-convex and convex load dispatch problems in a power grid. To demonstrate the benefits of BBO, it is used in four different test schemes to solve economic dispatch problems for 40-, 20-, 10- and 6-generating units. The suggested approach gives far better results than the traditional one.

Bhattacharya et al. (2010) [35]: This article introduced a BBO methodology for resolving EELD in power system. In this study, various pollution compounds (NO_x , CO_x , SO_x) are considered. This algorithm has been used to solve EELD for three and six generator systems with valve point results.

Selvi et al. (2010) [36]: This paper compared the most efficient optimization techniques inspired by ACO, PSO and SI - Swarm Intelligence. An in-depth comparative analysis was performed to create these algorithms with fitness sharing as to increase the performance and applications.

Rayapudi et al. (2011) [37]: This research paper presented an intelligent water drop (IWD) algorithm to solve the basic ELD problem. To illustrate the utility of the projected algorithm, it was tested on 6 and 20 generating unit test systems with valve-point-loading effects.

Pandi et al. (2011) [38]: The authors presented the solution for complex economic load dispatch problem using a hybrid algorithm based on swarm intelligence and harmony search algorithm for convergence improvement. The algorithm's accuracy was evaluated using different benchmark test schemes of 5 units, 10 units, and 30 units.

Shaw et al. (2011) [39]: In this article a novel SOA (seeker optimization algorithm) is discussed with an effective method for solving ELD problems in various test systems. A review of the obtained simulation outcomes using the SOA with those reported in literature was also compared for better efficiency.

Rahmat et al. (2012) [40]: In this paper, authors presented DEACO approach to optimize the cost of thermal load distribution in power system and showed better results as compared to ACO.

Swain et al. (2012) [41]: This paper proposed GSA, the gravitational search algorithm to solve the thermal dispatch problem. Tests were carried out on multiple systems with different generators and comparisons were made with other commonly used methods. It is observed that the proposed methodology showed vitality, rapid convergence, and ability over other existing techniques.

Yang et al. (2012) [42]: In this article, firefly algorithm (FA) is used to solve ELD problem while taking into account various non-linear constraints and power loss. The suggested algorithm was considered on four altered test strategies, and the outcomes indicated that the FA proved to be more cost-effective.

Tankasala et al. (2012) [43]: This paper presented an ABC - artificial bee colony algorithm as the best approach for achieving a near-global optimal solution but at a high computational cost. However, with careful selection of the iteration, population size selected and idle bees, the computational results proved to be better.

Hardiansyah et al. (2012) [44]: This paper suggested a PSO strategy for thermal load dispatch problem that is both efficient and consistent. The findings for ELD of

conventional 3- and 6- generator systems with and without transmission losses is proved to be robust and effective.

Subramanian et al. (2013) [45]: This paper proposed an efficient and dependable FFA-firefly algorithm to solve the ELD problem. The proposed approach was tested on six separate generating systems, and the outcomes were compared to other population-based optimization strategies such as differential evolution, virtual annealing, PSO, biogeography-based- optimization, GA and artificial bee colony optimization. This approach demonstrated higher solution consistency, improved numerical performance, and stable convergence characteristics.

Prabha et al. (2013) [46]: This paper proposed two algorithms named as bacterial foraging and firefly optimization algorithm for ELD problem with VPLe. The aforesaid algorithms was tested on different generating systems (3- and 13-unit) with different load demands in MW as 1800, 900 and 850. In terms of performance, precision, and time the outcomes from the bacterial foraging optimization algorithm were superior to those obtained from FFA.

Thenmalar et al. (2013) [47]: In this paper a firefly algorithm (FFA) approach for solving economic emission load dispatch for different power plants. The suggested approach is applied and evaluated on three, and six generating test systems. The problem is combined with load availability from renewable resources. The obtained results are contrasted to the ABC and PSO. Furthermore, the accuracy of the solutions and rate of convergence are found to be better than many other methods.

Younes et al. (2013) [48]: This paper suggested a novel hybrid algorithm using FFA and ACO for economic load distribution strategy. The ACO is used for global quests, while the FFA for local. The approach was investigated for IEEE-30 bus system and proved better than other techniques with simplicity, stability, less computation time and less iterations.

Serapiao et al. (2013) [49]: The authors implemented the Cuckoo Search (CS) algorithm to thermal ELD problem for two different test schemes. CS simulation-performance results for 3- and 6- generating units are compared with other swarm-based intelligence algorithms.

Wan,g et al. (2013) [50]: This article introduced Harmony Search (HSA) and Differential Evolution (DE) which are combined to form the differential –harmony-search algorithm (DHSA) and used to solve the ELD problem. The projected algorithm's robustness and efficacy were shown by simulation findings and similarities with other known algorithms.

Dubey. et.al (2013) [51]: This paper discussed an innovative algorithm PSO-GSA algorithm for thermal load division. This algorithm blended PSO's societal thought feature with GSA's local search capability. The observed findings verified the algorithm's reliability and robustness against other known techniques.

Tiwari et al. (2013) [52]: In this article authors proposed an efficient alternative using PSO for the large scale nonlinear optimization problems and proved to have good results in comparatively less iterations.

Effatnejad et al. (2013) [53]: In this article, the ACO method is seen to be more capable of producing higher-quality results. The developed ACO is contrasted to others, including DE-OBL, DE, ABC, GA and ACO-OPF. It is evident that the developed framework can be a suitable method for medium-scale systems.

Secui et al. (2014) [54]: This paper developed a new modified/improved harmony search algorithm -IHSA to resolve the load dispatch issue considering valve point loading. The effectiveness of the suggested algorithm is assessed on 6-, and 38-thermal power generation systems.

Kherfane et al. (2014) [55]: This article discussed a new algorithm based on GA and MGA for ELD problem by integrating the wind power to the grid. The GA determined the global foremost solution, while the MGA searched the local foremost solution. The proposed algorithm is tested on 30-buses as well as a section of the Algerian power network in the west.

Kaur et al. (2014) [56]: A genetic algorithm-GA is revealed to be capable of optimizing any kind of problem, irrespective of power demand. The obtained results demonstrate a substantial reduction in generator fuel costs while satisfying different equality and inequality constraints.

Singh et al. (2014) [57]: In this article, GA outperforms LIM by providing more reliable findings with faster convergence characteristics. GA is crucial in determining

the best solution in a fraction of a second. It has been discovered that GA outperforms LIM. Specifically, GA demonstrates that it is the fast algorithm that produces true optimum generations of both transmission line losses and running costs in the power system.

Sahu et al. (2014) [58]: In this article, GA was added to the generation cost in an electric power network in order to find the best load dispatch approach (ELD). GA can have highly optimal solutions while also reducing computation time compared to iterative methods. The versatility provided by the GA solution in modelling both time-dependent and coupling constants is one of its advantages. Another feature of the GA method is the ease of handling arbitrary restrictions and objectives.

Mahdad et al. (2014) [59]: The authors introduced an improved ABC optimization approach for realistic economic dispatch including valve-point loading (VPL) effects and achieved better results.

Upadhyay et al.(2014) [60]: In this paper BBO (Biogeography-Based Optimization) algorithm is discussed for non-convex and convex ELD problems for fossil based thermal plants. The BBO gives optimum solution with improved convergence characteristics and computational performance.

Wong et al. (2014) [61]: Grey Wolf Optimizer (GWO), a novel meta-heuristic method is presented in this paper and tested on 20 generating units and the results outperformed many other algorithms.

Prakash et al. (2014) [62]: In this paper author thrown light on the economic load dispatch (ELD) method for fulfilling the load requirements at minimal costs & losses simultaneously. The diverse limitations are available in the functional generation units. The rectification of ELD issues can be done using enormous quick optimization techniques. In this, two methodologies namely PSO and BFO persuaded by biological evolution of living organisms. The ELD problem for IEEE 13- bus system is solved.

Sahoo et al. (2015) [63]: This paper introduced the cuckoo search algorithm, and evolutionary algorithm applied to non-convex ELD problems. In contrast to the solution efficiency and execution time achieved by five test systems for six, fifteen, thirty, one hundred forty, and three hundred twenty-unit power systems. Cuckoo search algorithm

converges better than PSO and GA and also offers the cheapest generation plan, making it a very powerful and time-consuming algorithm for online applications.

Nischal et al. (2015) [64]: In this article, an ant lion optimization (ALO) algorithm is presented to solve the optimal load dispatch problem. The proposed methodology is used to solve the problem for 3-, 6-, and 20-unit test systems. Numerical outcomes indicate that the applied approach has better convergence and solution efficiency than other algorithms.

Sharma et al. (2015) [65]: In this paper introduced Grey wolf optimization GWO is implemented to convex ELD problem with two different test systems. The simplicity, dependability, and performance of the GWO algorithm make it ideal for practical applications.

Reddy P et al. (2015) [66]: The authors proposed the FFA to solve the ELD problem with the VPLe considering with three- and five-generating units. The investigated effects of the approach are compared to those of other methods such as lambda iteration and ABC.

Tran et al. (2015) [67]: This paper also includes a cuckoo search approach(CSA) for the optimal load dispatch systems implemented on different test cases. The findings are compared to other methods to prove the worth of the proposed method.

Saka et al. (2017) [68]: This paper suggested a vortex search algorithm (VSA) for optimal load sharing problem with VPLe, losses, RRLs, and POZs restrictions The VSA findings were compared to CPSO, PSO, WIPSO, GA, MRPSO, and MFO techniques making it a very efficient and useful tool.

Lin et al. (2015) [69] : Intelligent PSO for economic dispatch with VPLe is presented in this article. The direct search algorithm (DSA) is used to adjust and evaluate the optimal solution at a low computational cost and showed better performance of the suggested IPSO.

Kamboj et al. (2015) [70] : The solution of a non-convex and complex ELDP of an electric power grid using GWO is discussed in this article. The performance is assessed for small-, medium-, and large-scale categories of power plants. GWO has been successfully resolved various ELD problems and GWO is capable of converging to a higher quality near-optimal solution.

Trivedi et al. (2016) [71] : In this article, the Moth-Flame- Optimization (MFO) algorithm with levy flights is proposed for ELD problems with RRLs, POZs and VPLe. The proposed approach is examined on three different systems and proved to be more reliable and effectual than standard MFO.

Tyagi et al. (2016) [2]: Optimum scheduling of integrated solar-wind-thermal power system using backtracking search algorithm (BSA) is discussed in this paper. BSA with two new operators - crossover and mutation, for exploring and exploiting the search space is suggested.

Hassan et al. (2017) [72]: This author proposed the genetic algorithm and dynamic programming to solve the unit commitment problem. Based on this, the shuffled bat (SBAT) technique was used as an evolutionary-based approach to solve the confined ELD problem of thermal plants. This author evaluates the solution accuracy, calculation performance, and feasibility of using the SBAT algorithm to solve the ELD problem for IEEE 30 bus system.

Rugema et al. (2020) [73]: In this research article author developed a novel technique to solve the load dispatch problem using (CGQBA) Cauchy-Gaussian-Quantum-Behaved-Bat-Algorithm. Due to its better convergence characteristics, the algorithm has been preferred over traditional multi-objective optimization techniques due to its better convergence. Six different prototype functions, including 3-, 6-, 20, 40-, 110-, and 160-generating modules, are tested to demonstrate the CGQBA's performance.

Wang et al. (2020) [74]: In this article author designed a real dynamic economic dispatch (DED) as it is complete and intelligent way out for demand management. DED is a contemporary concept that integrates advanced current demand modelling, dynamic load dispatch, metering, and bidding strategy with economic dispatch.

Parouha et al. (2020) [75]: In this paper author developed an innovative and revolutionary hybrid algorithm for ELD problems without and with valve-point loading. This algorithm is a combination of new DE (NDE) and a completely new PSO (NPSO). Additionally, NPSO is used to keep exploration and extraction going in the current population, followed by NDE to improve convergence accuracy. Different benchmark functions and nonconvex economic load dispatch issues involving 3-, 6-,

15-, 40-, and 140-unit test systems are evaluated and the effectiveness of the proposed algorithms is showed in terms of better-quality solutions and better performance.

Deb et al. (2021) [76]: In this paper, author focused on ELD problems with their outcomes. In addition to the prior metaheuristic optimization algorithms, the capability of Gradient-Based Optimizer (GBO) is analyzed and stimulated by newton's method. The proposed algorithm has certain pros like a good balance and maintenance between exploration and exploitation, infrequent stuck-in local optima, and premature convergence.

Kaur et al. (2021) [77]: This paper addressed and resolved complex economic load dispatch problems with non-linear generation, taking into account, the transmission losses using a new sophisticated method named modified krill herd algorithm (MKHA). The proposed method proved better than traditional meta-heuristic techniques.

Raj et al. (2021) [78]: In this article, author elaborated an intelligent whale optimization algorithm (WOA) for minimizing the issues related to static ELD (SELD) & dynamic economic load dispatch (DELD). The emulation of a streamlined collective structure gives rises to this WOA technique. This technique is majorly suitable in optimization related problems that cover the certainty & calculation time of the output. Comparing the WOA method with others like PSO, genetic algorithm & traditional optimization approaches, this technique holds well in numerous load dispatch problems with quality output taking less computational time.

Zhong et al. (2021) [79]: This paper demonstrated secant approximation-based method (SAM), to achieve successful convergence for non-quadratic cost functions which aroused unsatisfied with the traditional distributed algorithms. This approach seems to be advantageous for general convex cost functions since marginal cost functions usually exhibit linear properties for specific price intervals. A (DRC) dynamic-ratio-consensus approach can quickly achieve price for DERs with linear marginal cost functions. Results focused on real-world data revealed that when general convex cost functions are used, the convergence rate improves and performance improves in larger-scale platforms.

Navin et al. (2021) [80]: In this paper author utilized multi-agent fuzzy reinforcement learning (MAFRL), with numerous plug-in electric vehicles charging scenarios and

valve point loading of the respective thermal power generators, which is capable of solving the economic/environmental power dispatch (EEDP) challenge. In this, authors draw up a wide variety of system constraints such as the plug-in electric vehicle problems constraints, valve point loading effect, generator power limits or constraints, and ramp rate constraints are used to arithmetically rectify economic and environmental scheduling problems. The review of different ELD methodologies is also tabulated in Table 2.1.

Earlier the classical calculus-based methods were used which fails to respond to constrained non-linear problems satisfactorily. Then the researchers proposed the deterministic optimization techniques to solve the ELD problem, like lambda iteration method, gradient method, linear programming, lagrangian relaxation algorithm, Branch and Bound, quadratic programming, dynamic programming and non-linear programming [81][82]. The main limitations of these algorithms are theoretical assumptions and therefore not considered appropriate for non-convex and nonlinear problems. However, for a large-scale electric system with large number of generating units the Lagrangian relaxation algorithm becomes more complex and fails to achieve solution. Similarly, in the Branch and Bound (B&B) method a linear function represents the fuel cost and attains a lower and upper bound which result in the exponential growth in the execution time for systems of a large practical size. Unlike these algorithms, the dynamic programming method can solve the discontinuous and nonlinear cost curves but the major disadvantage is the complexity, size or dimensions of the problem and more computational time.

To overwhelm the limitations of traditional algorithms, later the researchers proposed methods based upon artificial intelligence like artificial neural networks (ANN), simulated annealing, tabu search, genetic algorithm, etc. and these are also categorized as evolutionary, heuristic and meta heuristic optimization algorithms. Improved and real coded GA [83][84][85], evolutionary programming (EP) [86], genetic algorithm (GA) [58], particle swarm optimization (PSO) [28] and modified PSO [87][88], Differential Evolution [89], biogeography-based optimization (BBO) [90], Bacterial Foraging (BF) [91], harmony search (HS) [38], improved harmony search

[92] and Hopfield neural network (HNN) [93]. The HNN technique reflects more constrictions, but it may suffer with poor numerical convergence due to its training procedure. Gravitational search algorithm [94], artificial bee colony [43], ant colony optimization [95], intelligent water drop algorithm [96], firefly algorithm [42], cuckoo search algorithm [49], grey wolf optimization [97] and many more. These algorithms have many advantages and disadvantages as compared with other methods. The main features and drawbacks of all the algorithms are based on their rate of convergence, global optima, computational time, robustness, effectiveness, easy to implement, global search ability and good exploration / exploitation capability. To overcome the drawbacks of existing methods there is always a need of developing new metaheuristic method.

To prevail over the disadvantages of the heuristic, meta-heuristic and evolutionary methods, researchers are trending towards the hybrid optimization obtained by combining two or more local and global optimization algorithms. These algorithms can have better exploration and exploitation properties. Some of these methods as implemented on electric power dispatch problems are PSO-SQP [98], hybrid GA-BF [99], PSO-GSA [100], hybrid GA-MGA [55], hybrid HAS [101], etc. to enlist a few. Nowadays, research is more emphasized on development of new optimization algorithms and memetic methods which perform better than the existing algorithms. From the literature it reveals that although many methods have been developed for the solution of economic load dispatch problem, but there is always a need for new metaheuristic algorithm that can achieve an improved result with exclusive features like robust performance, more reliable, global search capability, less data requirement, easy implementation, and no requirement of differentiable and continuous objective function. Population based algorithms are good in exploration and local search based methods are very efficient in exploitation. So to obtain the advantage of both hybridized technique is suggested by combining population based methods with local search methods known as memetic methods.

Table 2.1: Brief Review - Economic Load Dispatch (ELD) Problem

S No.	Author Name	Reference	Year	Brief Review	Algorithm	Test Systems Considered
1	Chopra et al.	[102]	2022	Golden Jackal algorithm is developed and tested on standard benchmarks and eld problems.	Golden Jackal Algorithm	40 unit system
2	Zhang et al.	[103]	2021	An improved Symbiosis is developed using conventional PSO for improving the local and global findings. This is further implemented to resolve ELD problems	Improved Symbiosis Particle Swarm Optimization	3 unit system with and without VPLe
3.	Sakhtivel et al.	[104]	2020	SSA algorithm for non-convex ED cases in power grids is proposed. The method proved to be proficient of obtaining greater quality solutions efficiently in large scale ELD systems.	Squirrel search Algorithm	Large scale Power systems
4	Maedeh et al.	[105]	2019	A phasor PSO algorithm is proposed which replaces the control parameters of PSO with a phasor to solve different convex/ nonconvex/ non-smooth ELD cases.	Phasor particle swarm optimization	10-unit system (multi- fuels with/without VPE); 15-unit system (POZs and transmission loss with/ without RRLs); 40 -and 80 unit system with VPE;140-unit large-scale test system.
5	Niazazari et al.	[106]	2019	Firework algorithm for ED cases in power grids is proposed. The method proved to be proficient of obtaining greater quality solutions efficiently in ELD systems.	firework algorithm	IEEE 24 bus reliability test system.
6	Sulaiman et al.	[107]	2019	An improved form of GOA (IGOA) with a better initialization strategy to balance the searching ability of original GOA is developed. The method proved to be better	Improved Grasshopper optimization Algorithm	ELD test cases with 1263MW, 600MW, 800MW and 2500MW demands

				in terms of convergence and superiority of response.		
7	Hamid et al.	[108]	2019	Chaotic improved harmony search algorithm is proposed to solve the EELD problem. The proposed method proved to be more robust, accurate and efficient also the statistical investigation confirms the quality and superiority of the algorithm.	chaotic improved harmony search algorithm	Test systems considering 6, 10, 13, 14, 40, and 140 generators
8	Zhang et al.	[109]	2019	Self-adaptable DE algorithm integrated with multiple mutation strategies for ELD systems is proposed. The exploration/exploitation capabilities of the DE is improved by three extensions.	Self-adaptable DE algorithm integrated with multi- mutation strategies (ADE-MMS)	38-unit PD = 6000 MW 13-unit with VPE PD = 2520 MW 40-unit with VPEPD = 10500 MW 6-unit with loss, PD = 2.834 p u 6-unit with loss, PD = 1200MW; 20-unit with loss, PD = 2500 MW; 10-unit with VPE , PD = 2000 MW; 15-unit with POZ, PD = 2630 MW; 140-unit with VPE, RRLs and multiple fuel PD = 49342 MW
9	Singh et al.	[110]	2018	The method is proposed based on Grey wolf optimization, random exploratory search and opposition-based learning to perform global search, search in the neighborhoods of visited search locations and to maintain good solutions and diversity among solutions respectively. The proposed method competes with the recent algorithms developed so far.	Amroilated Grey-Wolf Optimization	standard benchmark functions and medium to large electric power systems

10	Heris et al.	[111]	2017	A review on the application of heuristic and meta heuristic optimization algorithms for solving the CHPED problems is provided. The methods are compared on the basis of convergence speed, attained optimal solutions, and constraints.	Review and comparison of existing methods	N/A
11	Secui et al.	[112]	2017	Symbiotic Organisms Search based New SOS is suggested to solve the multi-area CEED problem. The results obtained proved the effectiveness of the proposed algorithm.	New Symbiotic Organism Search Algorithm	ELD 6-unit, 10-unit, 40-unit, 120-unit, 130-unit generating systems
12	Ali Bulbul et al.	[113]	2016	A novel and heuristic algorithm based on the herding behavior of ocean krill individuals combined with the opposition based learning for solving complex ELD problem. The method proved to be proficient and robust.	Opposition based Krill Herd Algorithm	6, 10,40, 140 units 6 unit multiple fuel
13	Singh.M et al	[114]	2016	An OGHS is used to solve non-linear multi objective power dispatch cases. In this initialization is done using opposition based learning method and fuzzy theory is used for decision making. The Wilcoxon signed-rank test implemented has proved the supremacy of the algorithm.	opposition-based greedy heuristic search	Medium and large power System
14	Singh et al	[115]	2016	Synergic predator-prey optimization (SPPO) algorithm to solve ELD problem for thermal units with practical aspects. This method has used collaborative decision for movement and direction of prey and maintains diversity in the swarm.	Synergic Predator Prey Optimization	Small-Medium-large range power system problems

				The quality of prey swarm is improved by implementing opposition-based initializing.		
15	Kamboj et al.	[116]	2015	The paper proposed a Grey Wolf Optimizer (GWO) to solve the ELDP. The algorithm proved to be very competitive.	Grey Wolf Optimization	Small-Medium-large range power system problems
16	Arul et al.	[117]	2014	This paper has proposed the three new versions of DHS algorithms to solve DELD and DEED problems. The results proved to be better than DHS, EP, and many other algorithms in terms of convergence, quality, and computational time.	Chaotic self-adaptive differential harmony search algorithm	IEEE-26 bus system IEEE-39 bus system
17	Mousa et al.	[118]	2014	This paper has described and implemented a hybrid multi objective quantum genetic algorithm to solve CEED problem the results revealed that the proposed algorithm outperforms many other heuristic algorithms in robustness, high success, fast convergence and excellent capability on global searching.	Hybrid Multi-objective Quantum Genetic Algorithm	IEEE 30-bus system
18	Basu et al.	[119]	2014	Teaching learning-based algorithm (TLBA) is proposed for solving multi-area economic dispatch systems. In comparison to DE, EP and RCGA, the proposed algorithm outperforms.	Teaching learning Based Optimization	2 area 3 generators with POZ 10 generators with VPL, multiple fuel and transmission losses
19	Reddy et al.	[120]	2013	This paper proposed a hybrid shuffled DE to solve large scale non-convex ELD problem. The algorithm proved to be superior, accurate and fast convergence as compared to other considered algorithms.	Shuffled Differential Evolution	13, 40, and 140-unit test system

20	Sayah et al.	[121]	2013	In this paper a hybrid DE-PSO approach is suggested to solve the practical economic dispatch problem. The proposed approach confirms the effectiveness by comparing with the approaches of recently published methods.	Hybrid DE-PSO	6 -generating units;10-generating units; 15-generating units
21	Hardiansyah et al.	[122]	2012	In this paper an effective and reliable particle swarm optimization (PSO) techniques used for the economic load dispatch and proved to be better than conventional quadratic programming method	Particle Swarm Optimization	3 generating unit and 6 generating unit with and without losses.
22	Basu et al.	[123]	2011	In this paper a multi-objective differential evolution approach is proposed to solve CEED problem. The results proved to be effective as compared to pareto DE, non-dominated sorting GA-II and strength pareto EA	Multi-objective differential evolution	6 -generating units 10- generating units 40-generating units
23	Bhattacharya et al.	[124]	2011	Combined DE - BBO approach is proposed to solve complex multi-objective CEED problems. The proposed method is used to increase the convergence rate to improve the quality of response	Hybrid Differential evolution (DE) and Biogeography-optimization (BBO) algorithm	3-generator system with NO _x and SO _x emission;6-generators system with NO _x emission, 6-generator system with both valve-point loading and NO _x emission
24	Haiyan Lu et al.	[125]	2010	A hybrid PSO method is invented by incorporating a real-valued- mutation (RVM) operator to enhance the global search capability. The mentioned algorithm is superior to most of the existing algorithms when implemented to ELD.	Hybrid PSO with RVM	6 typical benchmark functions 10-unit multiple fuels and VPLE 40-unit VPLE

25	Sharma et al.	[126]	2010	Evolutionary techniques for multi-area economic dispatch are compared. Search capability and convergence rate of Classical DE and its various strategies, Classical PSO and improved PSO are compared.	Review of evolutionary techniques implemented to multi area ELD problems	MAELD problems for two area and three area test power systems with 4, 10 and 40- generating units.
26	Chen et al.	[127]	2010	The proposed algorithm is used to solve EELD and multi-area EELD problems. The algorithm proved to be better than GA and conventional methods with reduced computational time.	Particle Swarm Optimization	IEEE 30 bus system for EELD problem; Four area 6 generators for multi area EELD problem
27	Manoharan et al.	[128]	2009	Performance of different evolutionary algorithms are analyzed on multi-area economic dispatch problems. The effectiveness and efficiency of these algorithms are compared. The CMAES performs better.	Evolutionary algorithms (RCGA, PSO, DE, CMAES)	4, 10, and 120 unit power systems
28	Musirin et al.	[95]	2008	The power dispatch problem is solved using ACO technique. The proposed technique proved better than the artificial immune system (AIS) in achieving the optimal solution.	Ant Colony Optimization	IEEE 26 Bus system
29	Younes et al.	[129]	2006	In this paper genetic algorithm is implemented to achieve optimum solution for load dispatch problem.	Genetic Algorithm (GA)	IEEE 9-bus system; 30 bus system and 57-bus model system
30	Chiang et al.	[23]	2005	An Improved GA & multiplier updating (IGAMU) algorithm is offered for the optimal solution of ELD problems with certain constraints. The algorithm verified its efficacy for large scale ELD problems.	Improved Genetic Algorithm	13 unit with VPLE 10 unit with multiple fuels 10 unit with both VPLE and multiple fuels

2.2.2 Plug-in Electric Vehicles and BESSs in Ancillary Services-A Review

Zenyal et al. [130] have incorporated EVs into power grids and the conventional ED problem is reformulated with EV's operational constraints and proved to be effectively reducing the total dispatch cost. Gupta et al. [131] presented a multi aggregator based charge scheduling strategy with collective charging and realistic conditions with variable energy purchase (VEP) and elimination charges. Qu et al. [132] proposed an original multi-objective evolutionary algorithm (EA) based on decomposition algorithm for solving multi-objective dynamic CEED problem considering EVs and uncertainties in wind power and proved to be effective. Zang et al. [133] reviewed the different optimization algorithms based on scheduling methods for the grid integration with electric vehicles. Hu et al. [134] proposed to use the recycled batteries as supply loads in the economic power dispatch considering wind energy as RESs. A method is also proposed to reduce the complexity in dispatch due to EVs and the operational cost is also reduced by using incentive and penalty (I&P) costs in improving the performance of EVs. Liu et al. [135] implemented the improved PSO to solve the multi objective ELD model of a micro-grid by combining the EVs with solar photovoltaic arrays, wind power, diesel engines, fuel cells and battery to reduce the total cost and emissions. Cheng et al. [136] discussed a new method of cooperative strategy of charging electric vehicles through smart charging station in dynamic electricity trade market and implemented the techniques based on mixed integer linear programming for the scheduling problem including charging and discharging of batteries. Pal et al. [137] presented a technique of scheduling EVs including the response for electricity demand with neighbour connection and invented a household model with some appliances that are shiftable and non-shiftable along with EVs for energy transfer. Gu et al. [138] discussed how to use PHEVs/EVs for system operation and regulation taking in view demand response and economic dispatch. The use of more renewable resources without violating the cost, reliability and safety of power systems is also discussed. Goyal et al. [139] explained the scheduling problem of charging the PEVs considering load change and tariff. Andervazh et al. [140] presented a probabilistic optimization framework for the economic emission dispatch of steam power plants with

due consideration to the stochastic demand of charging PHEVs, uncertain load demand and intermittent wind power. Monte Carlo simulation along with NSGA-II and SPEA-2 optimization techniques are employed to solve multi-objective load dispatch problem.

The main purpose of auxiliary services in energy systems is to maintain integrity and support the core business of delivering power to customers. Auxiliary services are real power generator control services used by the system operator at different times to maintain the required rapid and continuous balance between full energy production and load. Cheung et al. [141] proposed hybrid optimization algorithm based on sequential dispatch along with the joint dispatch for solving a multi-service electricity market dispatch problem in coordination with New England Power Pool. The proposed method is used to solve the energy and ancillary dispatch problem for 6-unit and 324-unit ISO-New England system. Lin et al. [142] proposed a system to extract the ancillary services from commercial building HVAC systems while maintaining indoor conditions. Sonnee et al. [143] discussed the evolution, implementation and benefits of ancillary services operations in Indian Electricity Market considering security, reliability, integration with renewable energy and congestion management. Behera et al. [144] suggested a social spider algorithm for load dispatch of PEVs with and without RESs for 10 unit DELD problem. Tariq et al. [145] proposed Bat algorithm and DBA algorithm for integrated renewable/EV system for seven generating units with different load situations with supremacy in the results.

2.2.3 Optimization Algorithms -A Comprehensive Review

Optimization is the action of using the resource most effectively by obtaining the optimum maxima or minima as a mathematical function. Nowadays in every research problem the solution is obtained using different optimization algorithms and has become one of the huge areas of research. The research is continued to develop new algorithms and also their hybrid methods to mitigate the drawbacks of the existing method and to achieve better and robust results. Following is the brief review of some modern optimization-based research papers to investigate the advantages and drawbacks of existing algorithms. The review includes ant colony optimization

algorithm [146], adaptive gbest-guided search algorithm [147], ant lion optimization [148], branch and bound method [14], bat algorithm [149], binary bat algorithm [150], biogeography based optimization [151], bacterial foraging optimization [152], bird swarm algorithm [153], cultural evolution algorithm [154], chaotic krill herd algorithm [155], backtracking search optimization [156], colliding bodies optimization [157], cuckoo search algorithm [158], binary gravitational search algorithm [159], dynamic programming [160], elephant herding optimization [161], dragonfly optimization algorithm [162], electromagnetic field optimization [163], earthworm optimization algorithm [164], exchange market algorithm [165], fireworks algorithm [166], firefly optimization [167], forest optimization [168], flower pollination algorithm [169], grasshopper optimization [170], genetic algorithm [171], grey wolf optimizer [172], hopfield method [173], gravitational search algorithm [174], , human group optimizer [175], imperialist competitive algorithm [176], interior search algorithm [177], invasive weed optimization [178], krill herd algorithm [179], lightning search algorithm [180], mine blast algorithm [181], mixed integer programming [182], monarch butterfly optimization [183], moth-flame optimization [184], multi-verse optimizer [185], seeker optimization algorithm [186], optics inspired optimization [187], particle swarm optimization [188], random walk grey wolf optimization (RWGWO) algorithm [189], runner-root algorithm [190], simulated annealing [191], sine cosine algorithm [192], stochastic fractal search [193], , search group algorithm [194], symbiotic organisms search [4], shuffled frog-leaping algorithm [195], salp swarm algorithm [196], tabu search [197], teaching-learning-based optimization [198], weighted superposition attraction [199], water cycle algorithm [200], wind driven optimization [201], virus colony search [202], whale optimization algorithm, water wave optimization [203], harris hawks optimization [204], animal migration algorithm [64], slime mould algorithm [205] the reviews of some of the stochastic, heuristic and meta-heuristics search algorithms are tabulated in Table 2.2 and Table 2.3.

Table 2.2: Brief Review - Optimization Algorithms

Year	Algorithm	Author(s)	Problems Considered	Number of benchmark functions considered	Ref. no.
2007	Variable neighborhood search	Fleszar et al.	Open vehicle routing problem	16	[86]
2008	Biogeography-Based -Optimization	D Simon	Real optimization Problem	14	[7]
2009	Gravitational Search Algorithm	Rashedi et al.	Various nonlinear functions	23	[169]
2010	Firework Algorithm	Ying et al.	Optimization problem	9	[22]
2012	Water Cycle Algorithm	Eskandar et al.	Engineering Optimization	19	[58]
2012	Artificial Bee Colony Optimization	Karaboga et al.	A comprehensive survey	NA	[71]
2012	Upgraded Artificial Bee Colony Algorithm	Ivona et al.	Constrained Optimization Problems	5	[72]
2012	Multi-start methods	Rafael et al.	combinatorial optimization	NA	[87]
2012	Krill Herd	Gandomi et al.	Optimization tasks	20	[174]
2015	Fuzzy Optimization Technique	Shahriar et al.	Unit Commitment Problem	NA	[78]
2013	Animal Migration Optimization	Li et al.	Global , constrained, multi-objective	23	[203]
2013	Cultural Evolution Algorithm	Kuo et al.	Reliability Engineering Problems	7	[13]
2014	Binary PSO-GSA Optimization	Mirjalili et al.	Real World Problem	22	[204]
2014	BBO Train Multilayer perceptron	Mirjalili et al.	Bio-medical Optimization	6	[205]

2014	. Chaotic Krill Herd Method	Wang et al.	Constrained Optimization Problems	14	[14]
2014	Competition Over Resources	Mohseni et al.	Optimization problems including smart antenna, wireless sensor network, and pattern recognition.	8	[206]
2014	Forest Optimization Algorithm	Ghaemi et al.	Feature weighting	4	[163]
2014	Exchange Market Algorithm	Ghorbani et al.	Non-linear Optimization Problems	12	[21]
2014	Symbiotic Organism Search	Cheng et al.	Engineering Optimization	26	[190]
2014	Stochastic Fractal Search	Salimi et al.	Engineering Optimization	23	[188]
2014	Grey Wolf Optimizer	Mirjalili et al.	Engineering Optimization	29	[167]
2014	Interior Search Algorithm	Gandomi et al.	Engineering Optimization	14	[172]
2015	Bird Swarm Approach	Meng et al.	Optimization problem	18	[149]
2015	Electromagnetic Field Optimization	Beheshti et al.	Optimization Problem	30	[158]
2015	Elephant Herding Algorithm	Wang et al.	Optimization tasks	15	[157]
2015	Lightning Search Optimization method	Shareef et al.	Constraint Optimization Problems	24	[175]
2015	Moth-flame Optimization Method	Mirjalili et al.	Engineering Optimization	29	[179]
2015	Binary GWO	Hossam et al.	Feature Selection	18	[207]
2015	Multi-verse Search Algorithm	Mirjalili et al.	Engineering Optimization	19	[180]
2016	Sine Cosine Algorithm	Mirjalili et al.	Aircraft Wing Design	19	[187]

2016	Virus Colony Search Method	Li et al.	Engineering Optimization	30	[195]
2016	Whale Optimization Algorithm	Mirjalili et al.	Engineering Optimization	29	[196]
2016	Oppositional Artificial Bee Colony Algorithm	Dhaliwal et al.	Optimization of Digital IIR Filter	NA	[208]
2016	Grid Classification Based Optimization	Panag et al.	Identification of Fields Under WSN	NA	[209]
2017	Grasshopper Optimization Algorithm	Saremi et al.	Engineering Optimization	19	[26]
2017	Hybrid GWO-SCA	Singh et al.	Bio-medical Optimization	22	[68]
2017	Salp Swarm Algorithm	Mirjalili et al.	Engineering Optimization	19	[192]
2017	Lion Optimization Algorithm	Narendra et al.	Engineering Optimization	NA	[79]
2017	Electro-Search algorithm	Tabari et al.	Engineering Optimization	10	[80]
2018	Binary whale optimization algorithm	Reddy et al.	Unit Commitment Problems	NA	[210]
2018	Barnacles Mating Optimizer	Sulaiman et al.	Engineering Optimization	23	[211]
2018	Emperor Penguin Optimization	Dhiman et al.	Engineering Problems	44	[212]
2018	Coyote Optimization Algorithm	Juliano et al.	Engineering Optimization	40	[213]
2019	Artificial Bee Colony Algorithm	Chen et al.	Economic Dispatch Problems	NA	[214]
2020	Slime Mould Algorithm	Li et al.	Standard benchmarks/ Engineering Optimizations	27	[215]

Table-2.3: Brief Review - Stochastic, Heuristics and Meta-Heuristics Search Algorithms

S.No	Year	Algorithm	Nature of Algorithm	Author's Name	Publisher	No. of Test Benchmark	Benchmark Problems solved	Name of Engineering benchmark problems	Ref
1	2015	DE-Random Search approach	Stochastic	Kamboj et al.	Springer	23	Unimodal:7 Multimodal:06 Fixed Dim: 10	NA	[216]
2	2006	Ant Colony Optimization	Meta-heuristic	Dorigo et al.	IEEE	NA	NA	NA	[217]
3	2017	Adaptive Cuckoo search algorithm	Meta-heuristic	Mareli et al.	Elsevier (Appl. Comp.	14	Unimodal:5 Multimodal:9	NA	[218]
4	2014	Grey Wolf Optimization	Meta-heuristic	Mirjalili et al.	Elsevier	23	Unimodal:7 Multimodal:06 Fixed Dim 10	Tension/compression spring design, Welded beam design, Pressure vessel design	[219]
5	2015	Ant Lion Optimization	Meta-heuristic	Mirjalili et al.	Elsevier	23	Unimodal:07 Multimodal:06 Fixed Dim: 10	Three-bar truss , Cantilever beam, and Gear train design problem	[142]
6	2015	Moth-flame optimization algorithm	heuristic	Mirjalili et al.	IEEE	29	Unimodal:07 Multimodal:06 Composite: 12	Welded beam, Gear train, Three-bar truss & I-beam design problems	[179]
7	2014	Adaptive gbest-guided GSA	heuristic	Mirjalili et al.	Springer	25	Unimodal:05 Multimodal:9 Composite:11	Tension/compression spring design, Welded beam design	[141]
8	2014	Water Wave Optimization	Meta-heuristic	Zheng et al.	Elsevier	30	Unimodal:03 Multimodal:13 Hybrid:06 Composite:08	Application in high-speed train scheduling	[220]

9	2013	Animal migration optimization	heuristic	Li et al.	Springer:	23	Unimodal:07 Multimodal:06 Fixed Dim: 10	NA	[203]
10	2014	Autonomous Particles Groups for PSO	Meta heuristic	Mirjalili et al.	Springer	23	Unimodal:07 Multimodal:05 Fixed Dim: 10	NA	[221]
11	2013	Bat Algorithm with Lévy Flights	Meta heuristic	Xie et al.	Hindawi (CI&N))	14	Unimodal:5 Multimodal:9	NA	[222]
12	2011	Multi-objective Bat algorithm	Meta heuristic	Yang et al.	Elsevier	NA	NA	Welded beam design	[223]
13	2012	Binary Bat Algorithm	Meta heuristic	Nakamura et al.	IEEE	NA	Unimodal:07 Multimodal:05 Fixed Dim: 10	NA	[145]
14	2014	Biogeography-based optimization with chaos	heuristic	Saremi et al.	Springer	10	Unimodal:4 Multimodal:6	NA	[224]
15	2008	Biogeography-Based Optimization	heuristic	Dan Simon	IEEE	14	Unimodal:5 Multimodal:9	aircraft engine health estimation	[225]
16	2009	Bacterial Foraging Optimization	Meta heuristic	Das et al.	Springer	NA	NA	NA	[147]
17	2015	Butterfly-particle swarm optimization	Swarm inspired	Bohre et al.	IJSCMC	4	Sphere, Rastrigin, Rosenbrock, Griewank	NA	[226]
18	2009	Binary GSA	heuristic	Rashed et al.	Springer	23	Unimodel:7; Multimodel:6; Fixed Dim: 10	NA	[148]

19	2014	Binary optimization using hybrid GSA-PSO	Heuristic	Mirjaliliet al.	Springer	22	Unimodal:07 Multimodel:9 Composite:06	NA	[227]
20	2008	Binary Particle Swarm Optimization	Heuristic	Hossein et al.	The Journal of Computer Society of Iran	11	Unimodal:07 Multimodel:03 Composite:01	NA	[228]
21	2015	Bird Swarm Algorithm	Meta-heuristic	Menga et al.	Journal of Exp. & Theo. AI	18	Unimodal:07 Multimodal:06 Fixed Dim:05	NA	[229]
22	2013	Backtracking Search Optimization	Meta-heuristic	Pinar et al.	Elsevier	78	Unimodal:15 Multimodal:35 Hybrid Composite:11 Bound Constrained:3	NA	[150]
23	2011	Collective Animal Behaviour	Meta-heuristic	Cuevas et al.	Discrete Dynamics in Nature and Society	31	Unimodal:07 Multimodal:06 Fixed-dimensions:10 Used GKLS function:08	NA	[230]
24	2015	Colliding Bodies Optimization	Meta-heuristic	Kaveh et al.	Springer	2	NA	Design of welded beam, a pressure vessel & compression spring	[231]
25	2015	Cognitive behavior optimization	Meta-heuristic	Li et al	Elsevier	20	Unimodal:07 Multimodal:13	Tension/compression spring design problem, Welded beam design problem	[232]
26	2013	Cultural Evolution Algorithm	meta-heuristic	Kuo et al.	Elsevier	7	Unimodal:03 Multimodel:04	Serial-Parallel System, Bridge System	[152]
27	2016	Grouping evolutionary	heuristic	Kashan et al.	Springer	4	Computational experiments: 04	NA	[233]

28	2014	Chaotic Krill Herd algorithm	meta-heuristic	Wang et al.	Elsevier	14	Unimodal:5 Multimodal:9	NA	[153]
29	2016	Animals Behavioral Ecology	heuristic	Sina et al.	Springer	8	DeJong,,Michalewicz, Rastrigin, Rosenbrock Valley, Schwefel Griewangk Ackely funcions	NA	[234]
30	2009	Cuckoo Search via Levy Flights	meta-heuristic	Xin et al.	IEEE	10	Unimodal:2 Multimodal:8	NA	[235]
31	2015	Dragonfly algorithm	meta-heuristic	Mirjalili et al.	Springer	19	Unimodal:07 Multimodal:06 Composite: 06	Propeller Design	[156]
32	2015	Electromagnetic field optimization	Meta-heuristic	Hosein et al.	Elsevier	30	Unimodal:02 Multimodal separable:15 Multimodal non separable: 13	NA	[236]
33	2015	Elephant Herding Optimization	Meta-heuristic	Wang et al.	IEEE	15	Unimodal:2 Multimodal:13	NA	[237]
34	2014	Exchange market algorithm	Meta-heuristic	Ghorbani et al.	Elsevier	12	Unimodal:07 Multimodal:05	NA	[238]
35	2015	Earthworm optimization algorithm	Meta-heuristic	Deb et al.	Inderscience	48	High dimensional:22 Low dimensional:26	Real world engineering problem	[239]
36	2010	Fireworks Algorithm	Meta-heuristic	Ying et al.	Springer	9	Unimodal:02 Multimodal: 07	NA	[240]
37	2014	Fruit Fly Optimization Algorithm	Meta-heuristic	B. Xing and W.J. Gao	Springer	NA	NA	NA	[241]

38	2014	Forest Optimization Algorithm	Heuristic	Ghaemi, et al.	Elsevier	4	Multimodal:04	NA	[242]
39	2017	Grasshopper Optimization Algorithm	Meta-heuristic	Saremi et al.	Elsevier	19	Unimodal:07 Multimodal:06 Composite: 06	52 Three-bar truss Cantilever beam design problem & 3 bar truss design	[243]
40	2009	Gravitational Search Algorithm	Heuristic	Rashedi et al.	Elsevier	23	Unimodal:07 Multimodal:06 Fixed Dimension: 10	NA	[244]
41	2016	GWO based Back propagation Neural Network Algorithm	Meta-heuristic	Hassanin et al.	IEEE	5	2-Bit XOR dataset, 3-Bit XOR dataset, iris dataset, Wine dataset, Glass dataset	NA	[245]
42	2011	Human Group Optimizer with Local Search	Heuristic	Ran et al.	Springer	14	Unimodal:5 Multimodal:9	NA	[170]
43	2014	Interior search algorithm	Meta-heuristic	Gandomi et al.	Elsevier	14	Low dimension:07 High dimension:07	Welded beam, Pressure vessel, tension/compression spring design, 72 bar space truss & Gear train design	[246]
44	2010	Invasive Weed Optimization	Stochastic	Ahmed et al.	IEEE	NA	NA	NA	[173]
45	2016	JAYA Algorithm	Heuristic	R. Venkata Rao	IJIEC	30	Unimodal:12 Multimodal:18	NA	[247]
46	2016	JAYA Novel Optimization Algorithm	Heuristic	Hari Mohan Pandey	IEEE	NA	NA	NA	[248]

47	2012	Krill herd Algorithm	Meta-heuristic	Gandomi et al.	Elsevier	20	Low dimensional:10 High dimension: 10	NA	[249]
48	2013	League Championship Algorithm	Stochastic	Ali et al.	Elsevier	36	Large scale: 36	NA	[250]
49	2015	Lion Optimization Algorithm	Meta-heuristic	Yazdani et al.	Elsevier	30	Unimodal:03 Multimodal:13 Hybrid:06 Composite:08	NA	[251]
50	2015	Locust swarms optimizer	Meta-heuristic	Cuevas et al.	Inderscience	13	Unimodal:07 Multimodal:06	NA	[252]
51	2015	Lightning search algorithm	Meta-heuristic	Shareef et al.	Elsevier	24	Unimodal:07 Multimodal:12 traveling salesman problem :1	NA	[175]
52	2012	Mine blast algorithm	Meta-heuristic	Sadollah et al.	Elsevier	16	Engineering problem:08	Three-bar truss, Pressure vessel, Welded beam, Gear train , Speed reducer, Belleville spring, Rolling element bearing design	[176]
53	2008	Modified binary particle swarm optimization	Meta-heuristic	Lee et al.	Elsevier	10	Unimodal:05 Multimodal:05	NA	[253]
54	2016	Multi-objective ant lion optimizer	Heuristic	Mirjalili1 et al.	Springer	17	Unconstrained:05 Constrained:05 Engineering:07	Four-bar truss, Speed reducer, Disk brake, Welded beam, Cantilever, beam and Brushless DC wheel motor design problems, Safety Isolating Transformer design problem	[254]

55	2017	Multi-objective Bat Algorithm for Mining Interesting	Meta-heuristic	Eddine et al.	Springer	NA	NA	NA	[255]
56	2015	Multi-objective grey wolf optimizer	Meta-heuristic	Mirjalili et al.	Elsevier	10	Bi-objective:07 Tri-objective:03	NA	[256]
57	2015	A Minimum Population Search	Heuristic	Bolufé et al.	IEEE	8	Multimodal: 08	NA	[257]
58	2015	Multi-Verse Optimizer	Meta-heuristic	Mirjalili et al.	Springer	19	Unimodal:07 Multimodal:06 Composite:06	Welded beam design, Gear train design problem ,Three-bar truss design problem, Pressure vessel design problem and Cantilever beam design problem	[258]
59	2010	A Mean-Variance Optimization Algorithm	stochastic	Ganesh et al.	IEEE	5	Unimodal:05	NA	[259]
60	2015	A New Adaptive Cuckoo Search Algorithm	heuristic	Naik et al.	IEEE	23	Unimodal:07 Multimodal:06 Fixed Dimension: 10	NA	[260]
61	2014	Optics inspired optimization	Meta-heuristic	Ali et al.	Elsevier	26	Unimodal:12 Multimodal:14	Cantilever beam, Minimize I-beam vertical deflection, A 15-bar planar truss structure, 52-bar planar truss structure	[261]

62	2015	A particle-based simplified swarm optimization	Heuristic	Huang et al.	Elsevier	4	Reliability redundancy allocation problems (RRAPs):04	NA	[262]
63	2009	Leader/follower based Particle swarm optimization	Meta-heuristic	Wang et al.	Elsevier	4	Unimodal:04	NA	[263]
64	2015	Runner-root algorithm	Meta-heuristic	Bayat et al.	Elsevier	25	Unimodal:05Multimodal:9 Composite:11	NA	[185]
65	2009	Strategy Adaptation Differential Evolution (DE)	Stochastic	Qin et al.	IEEE	26	Unimodal:12 Multimodal:14	NA	[264]
66	2015	Sine Cosine Algorithm	Meta-heuristic	Mirjalili et al.	Elsevier	19	Unimodal:07 Multi Modal:06 composite: 06	Airfoil design	[265]
67	2006	Shuffled frog-leaping Algorithm	Meta-heuristic	Muzaffareus et al.	Engineering Optimization Journal	6	DeJong's function: 03 extended Rosenbrock's function: 01 Schaffer's function : 02	Gear problem, Cutting stock, Trim loss, Traveling-salesman problem	[266]
68	2014	Stochastic Fractal Search	Meta-heuristic	Salimi et al.	Elsevier	23	Unimodal:07 Multimodal:06 Fixed Dimension: 10	Tension/compression spring design problem, Welded beam, Pressure vessel.	[267]
69	2015	Search group algorithm	Meta-heuristic	Silva et al.	Elsevier	6	6 truss optimization benchmark problems	Bars design problem	[189]
70	2013	States of Matter based Algorithm	Meta-heuristic	Cuevas et al.	Springer	14	Unimodal:04 Multimodal:7fixed-dimension:03	Optimum locations:05 Used GKLSfunctions:08	[230]

71	2007	Seeker Optimization Algorithm	Heuristic	Chen et al.	Springer	NA	NA	Digital filter design	[181]
72	2014	Symbiotic Organisms Search	Meta-heuristic	Cheng et al.	Elsevier	26	Unimodal:12 Multimodal:14	Cantilever beam, Minimize I-beam vertical deflection, A 15-bar planar truss structure, 52-bar planar truss structure	[261]
73	2017	Salp Swarm Algorithm	Heuristic	Mirjalili et al.	Elsevier	19	Unimodal:07 Multimodal:06 Composite:06	Cantilever beam, I- beam Speed reducer, Three-bar truss, Pressure vessel, Tension/ compression spring design	[268]
74	2012	Hybrid PSO - GSA	Heuristic	Mirjalili et al.	Elsevier	3	The N bits parity (XOR) problem Function Training neural networks	NA	[269]
75	2012	Improved teaching-learning-based algorithm	Heuristic	Rao et al.	Elsevier	23	Unimodal:07 Multimodal:06 Fixed Dimension: 10	NA	[270]
76	2013	Teaching learning orthogonal design based optimization	Heuristic	Satapathy et al.	Springer	20	Unimodal:07 Multimodal:13	NA	[194]
77	2015	Virus colony search	Heuristic	Li et al.	Elsevier	10	Unimodal:04 Multimodal: 06	Pressure vessel, Welded beam design Problem and Tension/compression spring design problems	[195]
78	2015	Water cycle algorithm	Meta-heuristic	Sadollaha et al.	Elsevier	4	Quadratic, cubic, polynomial and nonlinear	Speed reducer, Three-bar truss, Pressure vessel, Tension/compression spring design, Rolling element	[198]

79	2014	Water cycle algorithm	Meta-heuristic	Sadolla et al.	Springer	12	Multi objective problems	NA	[271]
80	2010	Wind Driven Optimization	Heuristic	Bayraktar et al.	IEEE	5	Sphere, Rotated Hyper Ellipsoid, Ackley, Rastrigin, Six-Hump Camel-Back	Complex electromagnetics design problems	[199]
81	2013	Improved Wind Driven Optimization	Heuristic	Bayraktar et al.	IEEE	4	Sphere, Rotated Hyper-Ellipsoid, Ackley, Rastrigin functions	E-shaped patch-antenna synthesis	[272]
82	2016	Whale Optimization Algorithm	Meta-heuristic	Mirjalili et al.	Elsevier	23	Unimodal:07 Multimodal:06 Fixed Dimension: 10	Welded beam, Pressure vessel, 3 bar truss and compression spring design	[273]
85	2016	Water wave optimization	Meta-heuristic	Zheng et al.	Elsevier	29	Unimodal:03 Multimodal:13 Hybrid:06 Composition:07	Application in high-speed train scheduling	[220]
86	2007	Imperialist Competitive optimization	Meta-heuristic	Kaveh et al.	IEEE	30	Unimodal:03 Multimodal:13 Hybrid:06 Composition:08	High-speed train scheduling	[200]
87	2015	Hybrid harmony search/random search algorithm	Meta-heuristics	Kamboj et al.	Elsevier	12	Unimodal:07 Multimodal:05	ELD 4, 10, 20 and 40 generating units	[123]
88	2019	Harris hawks optimization	Meta-heuristics	Heidari et al.	Elsevier	29	Unimodal:07 Multimodal:06 Fixed dim:10 Hyb composite:06	Three-bar truss, Tension/compression spring, Pressure vessel, Welded beam, Multi-plate disc clutch brake, Rolling element	[204]

Due to the constrained, unconstrained, continuous, or discrete nature of practical problems, it is difficult to solve these problems using traditional mathematical programming methods like the gradient method, quadratic programming, steepest decent, quasi-newton method, etc. Many researchers have proved that these methods are not always efficient on high-dimension multimodal, non-differential, and non-continuous problems. Consequently, metaheuristic approaches independent of gradient data came into existence due to their ease of implementation and simplicity and tackled these problems as an alternative competitive solver. Basically, algorithms are categorized as single solution-based and population-based methods. Population-based algorithms can often obtain an optimal or suboptimal solution that may be the same as the exact optimum or located in its neighborhood. These are further categorized as evolutionary algorithms, physics-oriented, human-oriented, and swarm intelligence algorithms. Despite different metaheuristic algorithms, the two stages of the search process-exploration (diversification) and exploitation (intensification) are common among all the algorithms. A proper balance between these two stages is required to make the algorithm more efficient and reliable, otherwise, the drawbacks of trapping in local optima and immature convergence increases. Some of the observations of existing methods are concluded as conventional approaches and memetic approaches for optimization and enlisted as:

Conventional Approaches for Optimization

- ❖ In *Genetic Algorithm* the problem exists in finding the global minima but is capable to give results in less time.
- ❖ *Evolutionary programming* is not suitable to deal with the multiple objective problems, the performance reduces and simulation time increases with increase in multiple objectives.
- ❖ *Hopfield Approach* is applicable to the systems with linear constraints only.
- ❖ *Simulated Annealing* simply converges near local optima with less simulation time but reaches near global minima in more time.
- ❖ *Particle Swarm Optimization* has very high search speed but it requires fine-tuning and choice of the parameters. The algorithm converges to local optima

in less time and is used for local searching.

- ❖ *Pattern search algorithm* stuck in the local minima but can be operated with high efficiency and fast speed.
- ❖ *Differential Evolution Algorithm* is complex method but results in globally optimal values with least convergence time. This is also superior in term of exploration, exploitation and convergence.
- ❖ *Harmony search method* is applicable to complex, non-linear optimization problems within a reasonable time but suffers from slow local convergence speed and requires more iterations for optimal solution.
- ❖ *Gravitational search algorithm* is simple and ease in implementation with low computational time but it very easily stuck into local optima and the rate of convergence reduces in the later search phase.
- ❖ *Bat-inspired algorithm* is simple with easy application and requires less execution time and search better values at high convergence rate but due to local optima this algorithm leads to improper convergence.
- ❖ *Artificial bee colony algorithm* is simple and flexible. Also uses fewer control parameters but has slow convergence speed for the local minima and sometimes premature convergence occurs due to poor exploitation.
- ❖ *Ant Lion Optimization* proved high convergence rate and less computational time for multi-modal problems but sometime converges prematurely.
- ❖ *Whale Optimization Algorithm* is much better in comparison with other algorithms but sometime stuck in local optima.

Memetic Approaches for Optimization

- ❖ *Firefly-PSO algorithm* gives a superior solution efficiently and exactly with fast rate of convergence.
- ❖ *GA-TS-SA algorithm* performs well for simple small systems but takes more time to converge for large scale systems with more number of constraints.
- ❖ *SO-SA algorithm* has the ability to escape easily from the local minima point with better computational quickness and high convergence rate.
- ❖ *DE-BBO algorithm* improves the search capacity of differential evolution (DE) by hybridizing BBO and performs better in comparison to individual methods.

- ❖ *GA-DE algorithm* has the benefit of having good convergence speed with no premature convergence and good simulation time.
- ❖ *DE-HS algorithm* also performs better than individual methods with superior searching ability.
- ❖ *EP-SQP algorithm* is used for optimal solution by considering EP initially for global search region and incorporating SQP for local search in that region. This algorithm also showed superior performance and efficiency.
- ❖ *PSO-GSA algorithm* has improved computational efficiency which making the control parameters more robust. It has superior convergence characteristic without trapping in local optima.

2.3 RESEARCH GAPS

The analysis of surveyed literature reveals that numerous optimization methods are available and are used to address the economic load dispatch problem. The solution of these real-world problems is difficult to solve using traditional mathematical programming methods like the gradient method, quadratic programming, steepest decent, quasi-newton method, lagrangian method etc. This is due to the constrained, unconstrained, continuous, or discrete nature of these problems. Many researchers have proved that these methods are not always efficient on high-dimension multimodal, non-differential, and non-continuous problems. Consequently, metaheuristic approaches independent of gradient data came into existence due to their ease of implementation and simplicity and tackled these problems as an alternative competitive solver. Some of these algorithms have the drawback of being less sensitive to the tuning of parameters and some may not always converge to the global optimum. These algorithms are categorized as single solution-based and population-based methods. Population-based algorithms can often obtain an optimal or suboptimal solution that may be the same as the exact optimum or located in its neighborhood. A proper balance between these exploration and exploitation is required to make the algorithm more efficient and reliable, otherwise, the drawbacks of trapping in local optima and immature convergence increases. Swarm intelligence (SI) optimization methods also have some drawbacks related to exploration which must need to be solved [206].

Further, there are lot of flaws detected in the metaheuristics search algorithms, which need to be rectified in the upcoming research. According to the no free lunch theorem, no algorithm can be considered as a general-purpose best optimization algorithm. This encourages the researchers to search and develop more efficient and better optimizers with specific global and local search strategies. Another important concern in swarm intelligent algorithm is regarding exploration, which is an important feature in optimization.

The literature investigation reveals that significant efforts has been made to solve the classical ELD problem of electric power system using different optimization methodologies, but require substantial efforts for the solution of ELD problem with due consideration to renewable sources and the demand of electric vehicles (PEVs/BEVs/BESSs). This seriously affects the load demand pattern and optimality of the results. Further, the ELD problem with due consideration of PEVs/BEVs/BESS has not been solved using modern or hybrid meta-heuristics search algorithm, which seriously effects the optimality of results. According to the no free lunch theorem no optimization algorithm is suitable for solving all kinds of optimization problems efficiently and there is still potential for progress in order to improve existing methods and solve the optimization problem more effectively. Thus, in view of all the above prospective, the objective of the present research problem is to develop a memetic meta-heuristic search algorithm by combining local search and global-search proficiency of the existing algorithms and to improve the exploration-exploitation capability of the prevailing algorithms for the cost-effective solution to economic load dispatch problem with due consideration of PEVs/BEVs/BESSs. The efforts are therefore required in persisting the proposed study. The research proposal therefore presents a “memetic meta-heuristic optimization for economic load dispatch in BESS based ancillary services”.

2.4 RESEARCH OBJECTIVES

The intend of the proposed research is to develop an efficient and powerful memetic meta-heuristics optimization algorithm, which will provide the reliable and cost-effective

solution for economic load dispatch problem (ELDP) with due consideration of electric vehicles (PEVs/BEVs/BESSs) and renewable energy sources (RESs). The objectives of the proposed research work are outlined as below:

- (i) To develop a memetic optimization algorithm and evaluate its performance for standard benchmark functions and engineering optimization problems.
- (ii) To solve economic load dispatch and scheduling problem of electric power system using the proposed hybrid optimization algorithm.
- (iii) To solve economic load dispatch and scheduling problem of electric power system by considering the impact of renewable energy sources using proposed hybrid optimization algorithm.
- (iv) To solve the economic load dispatch problem of electric power system by considering the impact of Plug-in electric vehicles/battery electric vehicles or any other battery energy storage system using proposed hybrid optimization algorithm.
- (v) To analyze and validate the results obtained using the proposed algorithm.

2.5 CONCLUSION

This chapter explores the comprehensive review of literatures for various advancements and solutions for ELD issues in power system. It also gives a brief tour of various conventional and modern optimization techniques developed in recent years. The shortcomings and benefits of different search techniques categorized as stochastic, heuristics and metaheuristics are also explored in this chapter. The review in this chapter also tabulated the various benchmark functions, real world problems like engineering design issues handled by different optimization algorithms. The in-depth study of various literatures has been explored to search the research gaps of scalar objective economic load dispatch problem. After identifying the research gaps the research objectives has been framed for this research work. In the succeeding chapters, the proposed objectives will be achieved to develop suitable memetic algorithm and implement them to solve the scalar economic load dispatch problem with and without incorporating renewable energy and BESS/BEVs/EVs based ancillary services of an integrated power system.

OPTIMIZATION METHODOLOGIES

3.1 INTRODUCTION

Optimization is an efficient tool for determining different possibilities to find the most precise solution under certain constraints. It is the process of finding a better and improvised solution in almost all fields including engineering design problems. For solving any type of simple or complex problems, optimization helps in selecting an appropriate solution. Optimization process can be executed with an expertise and is an effective way to provide systematic and efficient ways to create new design solutions in order to achieve an optimal design.

Optimization process generates most feasible solution and allows to execute same program to perform different task by just changing the design variables and subjected constraints. Optimization algorithm uses stored information and generates 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 adjustment of instructed commands and keep running the information in cycle form till the desired outcome is achieved. Optimization algorithms are progressively widespread in engineering design activities due to the availability and capability of high swift computers. After perceiving an appreciable knowledge, designers can utilize these optimization algorithms in solving various design problems with an objective of maximization or minimization.

Despite of numerous advantages of computational techniques such as accuracy, efficiency and reliability constrained optimization problems create probable obstacles in obtaining the solution in feasible regions. Moreover, classically linear and non-linear programming methods are found either incompatible or unfeasible while solving constrained optimization problems. Differentiability or convexity are the adverse results of uncontrolled computation due to increased problem size or constraint violation. For solving optimization problems involving real valued continuous parameters, Newton developed the gradient method, also known as steepest descent

algorithm that was capable of solving problems based on only continuous differentiable functions. But in real world applications, the problem may be discontinuous function with incomplete definition, the designer has to adopt other search algorithms [177], [207]–[209]. Optimization is decision-oriented task and designers requires expertized intelligence to take appropriate decisions. The foremost requirement of all such decisions is minimization or maximization of certain objective function subjected to related constraints. The process of optimization proceeds with initialization of problem formulation and continues till an optimum or desired solution is generated [193], [210], [211].

3.2 OPTIMIZATION PROBLEM FORMULATION

The major aspect for developing an optimal design process is to convert an idea or intend to mathematical format that can be examined by an optimization algorithm. 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 which may fail the optimization or cause it to converge to an undesirable or unrealistic optimum.

In the first step, description of system, statement of goals and requirements are written in a designed format. The next step is to collect all the possible data and information about the problem that is relevant to performance requirements and expectations. Adequate measures are needed to identify, gather and analyze all input and outputs to formulate a problem. Also, information of computational time in optimization is a repeated analysis process, along with the continuous process of information gathering and refinement, design variables, objective function and constraints. The three crucial and necessary entities are briefly elaborated as follows:

(i) Design Variables: The highly sensitive parameters with inherent ability of identifying and underlying 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 equation (3.1).

$$x = [x_1, x_2, \dots, x_{nx}] \quad (3.1)$$

The problem dimensionality depends upon number of x (design variables)

corresponding to different designs. The design variables should have specific identity such that optimizer can select the elements of x independently. This suggests that to have absolute control of optimizer, these decision variables should be fixed parameters throughout the entire optimization process.

(ii) Objective function: The main component of optimization method is objective function, is used to assess the performance of optimization problem for defined design variables. It is most important task for formulating any optimization problem. There may be different objective function associated with a particular type of design problem. Some function may be designed for minimization while other may require maximization. In such cases, principle of duality is applied which permits same algorithm to accomplish both the task using non-linear programming (NLP) [212]–[214].

(iii) Constraints: After choosing a specific objective function, the next step is framing of constraints associated with the design problem. These constraints may be of equality or inequality form under certain restrictions.

Generalized mathematical statement for single-objective optimization problem can be written using equation 3.2(a) & (b) given below.

$$\text{minimize } f(x)$$

$$\text{By varying } x_i^{\min} \leq x_i \leq x_i^{\max} \quad i = 1, \dots, n_x \quad (3.2a)$$

$$\text{Subjected to } \begin{array}{ll} g_j(x) \leq 0 & j = 1, \dots, n_g \\ h_l(x) = 0 & l = 1, \dots, n_h \end{array} \quad (3.2b)$$

The above mathematical statement articulates that minimize the objective function for the given set of defined decision variables within the minimum and maximum bounds subjected to some inequality and equality constraint. In the problem formulation, the design variables can be either only continuous or only discrete or both discrete and continuous variables. It is required to classify optimization problem for checking and choosing an appropriate optimization algorithm for solving particular design [215]. As no solitary algorithm is so efficient to solve all types of optimization problems, it is necessary to create solution for new optimization problem. In general prospect an optimization problem is classified on the basis of three main traits: (a) problem formulation (b) characteristics of the objective function and (c) types of constraints.

Design variables may be continuous, discrete or mixed; Objectives may be single objective or multi-objective; problems may be constrained or unconstrained. These can further be classified depending on smoothness, linearity, modality, convexity and stochasticity. Thus, the objective functions may be continuous, discontinuous, linear or nonlinear, uni-modal or multi-modal, convex or non-convex. These are also categorized as stochastic or deterministic methods. The deterministic algorithm searches the same points and converges to the same result for the same initial conditions but a stochastic optimization algorithm results in a different set of points from the same initial conditions even if run multiple times [211]. Deterministic algorithms are gradient in nature. For multiple model problems, information is required regarding the model and its integration with the optimizer at the initial state itself [216]. Thus, stochastic algorithms are gaining more popularity than deterministic approach and considered more suitable to solve optimization problems.

3.3 OPTIMIZATION METHODOLOGIES

Conventional discrete optimization algorithms are efficient for solving simple engineering design problems by employing basic techniques with the available accessibility and affordability of high-speed computation facilities. These algorithms are usually based on linear and nonlinear programming methods which search for an optimal solution near the initial starting point and require a lot of gradient information. Since the last three decades, several optimization algorithms have been developed to solve numerous numerical and engineering design optimization challenges. These algorithms utilize a specific approach to explore the global optimum in simple and ideal prototypes. Though, a variety of real-world problems based on engineering design (ED) are complex, multi-dimensional and tough to solve. These gradient search algorithms give worst performance if there are more than one local optimum and fail to find a global optimum. These search algorithms when employed to solve a specific design problem with a specific objective function and multiple constraints, creates computational difficulties that are not possible to accurately solve using traditional numerical methods.

Conventional methods like quadratic programming, conjugate gradient method and decoupled methods were found to be hard to handle such complex problems. These computational drawbacks of prevailing linear and non-linear approaches have motivated researchers to go for simulation-based meta-heuristic algorithms for solving multi-disciplinary engineering design problems. These meta-heuristic algorithms are simple, easy to implement and are efficient to solve continuous, discrete, constrained, or unconstrained problems. Meta-heuristic algorithms may be single solution based or population-based and evolve a set of solutions during each iteration.

Although linear optimization is able to tackle the optimization problem to some extent, those methods fail to provide the global optimal solution for all the search space. Further, these algorithms stuck at local minima. In order to improve the local and global search capability of the existing algorithm, the memetic algorithm approach has been utilized in this thesis, so that exploitation and exploration capability of the existing algorithm can be improved to the next extent. In design and engineering problems, precisely, local area stagnation is a major problem. This forces the optimizer to get entrapped in nearby local minima points and resists the algorithm to search most feasible solution. This reduces the proficiency of the optimizer to explore and exploit search space accurately. Researchers are continuously applying their efforts to develop advanced hybrid methods to enhance local search capability in order to find more efficient solutions for optimization problems.

Meta-heuristic approaches can be categorized into four main distinct groups. These are evolutionary algorithms, swarm based algorithms, physics-based, and human-based methods [217]. Evolutionary algorithms are established by reproducing biological evolution operators like crossover and mutation. Evolutionary programming, evolutionary strategy, Genetic algorithm, and differential evolution are some of the evolutionary approaches [218]. Swarm intelligence-based methods are encouraged by the food searching actions of animals moving in groups. Some of the famous swarm approaches includes PSO, grey wolf optimization, ant colony optimization, salp swarm algorithm, whale optimization algorithm, krill herd, butterfly optimization algorithm, seagull optimization algorithm, cuckoo search, harris hawk algorithm, etc. Based on the laws of physics like Newton's gravitational law and Archimedes' principle is the

next category of meta-heuristic algorithms. Simulated annealing [191], gravitational search algorithm [174], equilibrium optimizer [219], water cycle algorithm [200], sine cosine algorithm [220], Archimedes optimization algorithm [221] etc are among the bulging approaches of this class. The next category of metaheuristic approaches is based on the social behaviour of humans. Some algorithms under this category are teaching-learning-based optimization [222], political optimizer [223], group teaching optimization algorithm [224], etc. Some of the emerging hybrid methods include chaotic fruit fly [225], emended salp swarm algorithm [226] improved grey wolf algorithm [227] and many more.

In this chapter, two memetic optimization algorithms are proposed and analyzed to solve different benchmark and engineering optimization problems. In the first case, random exploratory search algorithm is combined with Harris hawk's optimizer and in another variant, slime mould optimizer has been combined with random exploratory search method. Initially, these memetic algorithms are verified on 23 standard benchmark (BM) problems and 10 multidisciplinary engineering design (ED) problems. In the upcoming chapters, these memetic algorithms will be used to find the optimum cost for the scalar economic load dispatch problem and also considering renewable energy sources (RESs) and BESSs based ancillary services by incorporating electrical vehicles. The following section presents detailed theory and mathematics of the optimization methodologies employed for solving standard benchmark (BM) functions and engineering design (ED) problems.

3.3.1 HARRIS HAWKS OPTIMIZER

The intelligent hunting birds, Harris Hawks, mostly found in the regions of United States and Mexico have a hunting nature for their survival and perform in clusters. The hunting process begins within group members by utilizing their ability communicate, encircle the target and outbreaks by making a huge number of hard and soft surroundings. Meanwhile if the target (rabbit) thrives in evading, hawks again arrange themselves for another occurrence by exchanging their points. At last, the fatigued prey drops all of its energy and get trapped by the hawk's group members [228]. Harris

Hawks optimizer (HHO) a meta-heuristic (MH) search process framed by Heidari et al. [204], based on the chasing strategy of Hawks to capture the escaping prey, most probably a rabbit.

HHO is a modest and easily applicable method and finds wide applications in MH and memetic variants developed by the researchers to answer different stochastic complexities. Some of the applications solved with HHO are related to issues like engineering design [204], environmental issues [229], power flow [230], solar PV modules [231], data-mining [232], image segmentation [233], medicine and drugs, materials [234], feature selection [235] and other variants and applications [236]. HHO is a stochastic/random search algorithm so initial values are not required for variables as in gradient search cases. It also has a capability to achieve a balance between exploration-exploitation for better solutions. The slow convergence of this algorithm also reduces its computational efficiency.

The primary feature of HHO is based on the combined hunting behavior using different steps - enclosing, surprise attack with soft and hard surroundings. It is an efficient and less time-consuming approach to solve complex optimization issues comprising of continuous or discrete constrained or unconstrained design functions problems. The key benefits of HHO are simple and easy approach, flexibility, improved performance and easily applicable to variety of problems.

The mathematical formulation of HHO is based on the different strategies of hawks and the escaping energy of the target, rabbit. The distinctive and successful chasing practice of Harris birds where they identify the food and chase it by using their sharp decisions while the prey do not know regarding hunter's plan. A successful hunt process acquired by hawks involves soft and hard encircles, soft and hard encircles with hard constraints.

Alike other metaheuristic methods HHO also embraces two phases, exploration (global search) and exploitation (local search) as represented in Fig 3.1. The pseudocode for HHO algorithm is given in Fig 3.2 and flowchart for the same is presented in Fig 3.3. The exploration phase has two stages but the exploitation phase is splitted into four stages as shown in Fig 3.1.

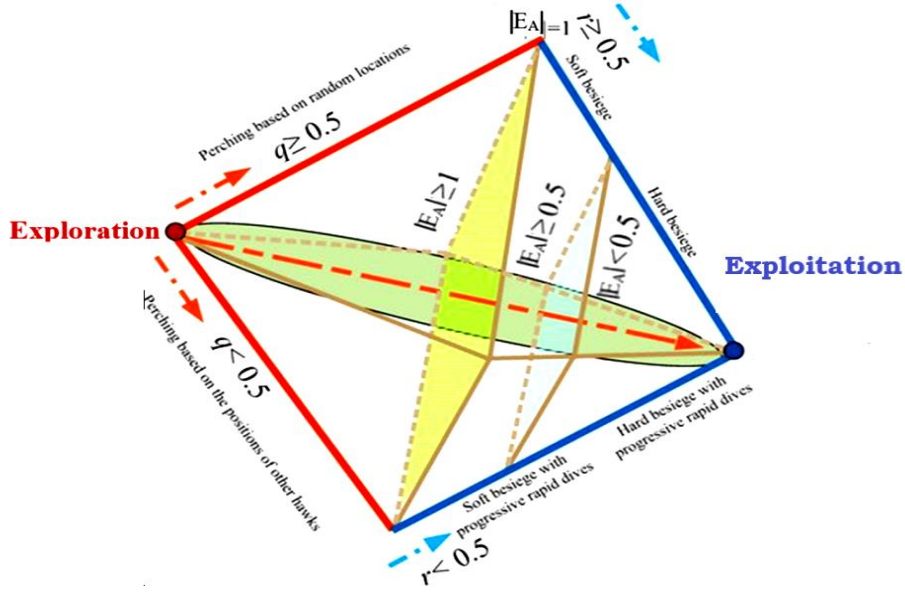


Fig 3.1: Exploration and Exploitation phases of HHO

(i) *Exploration Phase:* The exploring mechanism of HHO is put forward in this section. Because of their excellent vision, Harris' hawks can follow and find their prey, although occasionally it is difficult for them to see it and this might take many hours. In order to discover a prey, the hawks wait, watch, and monitor the desert area. The Harris' Hawks are the candidate solutions in HHO, and in each stage, the best candidate solution is considered as the intended prey or nearly the best. The Harris' hawks in HHO sit at random places and use one of two methods to wait for a prey to appear. Firstly, an equal chance q can be considered for each perching approach in which perch is based on the location of other group members (close enough while attacking) and the prey. This is modelled for $q < 0.5$. Secondly, the perch is based on the random locations within the range of the group and this is mathematically modelled for $q \geq 0.5$. This is modelled in equation (3.3a and 3.3b) [204]

$$\text{For } q \geq 0.5; X(itn+1) = \{X_{rand}(itn) - r_1 \times \text{abs}(X_{rand}(itn) - 2 \times r_2 \times X(itn))\} \quad (3.3a)$$

$$\text{For } q < 0.5; X(itn+1) = \{(X_{pr}(itn) - X_m(itn)) - r_3 \times (lb + r_4 \times (ub - lb))\} \quad (3.3b)$$

Here $X_{rand}(itn)$ represents randomly selected hawks corresponding to the vectors r_1, r_2, r_3, r_4 and q with random values between (0, 1) and modified in each iteration between its upper bound (ub) and lower bound (lb). $X(itn+1)$ implies the location of

hawks in the next iteration(itn); $X_{pr}(itn)$ gives the position of prey and $X_m(itn)$ symbolizes the mean position of Hawks which is determined by equation (3.4).

$$X_m(itn) = \frac{1}{N} \left(\sum_{i=1}^N X_i(itn) \right) \quad (3.4)$$

here, $X_i(itn)$ is the hawk's location/ position in each iteration with 'N' hawks in total.

(ii) *Shifting Phase (Exploration to Exploitation)*: The shifting mechanism from exploration to exploitation phase depends upon the energy of the prey during fleeing and is known as the escape energy of the prey(rabbit). When the prey tries to escape, there is a significant loss/decrease in this energy which is modelled as

$$E_A = 2 \times E_0 \times \left(1 - \frac{itn}{itn_{max}} \right) \quad (3.5)$$

Where, E_A is prey's avoidance energy, initial energy (E_0) of prey changing randomly between (-1, 1) and itn_{max} is maximum iterations. In this algorithm, the value of E_0 changes between -1 and 1 randomly. The value of E_0 between 0 and 1 signifies the strength of the prey while the value of E_0 between -1 and 0 signifies the physical flagging of the prey. The escaping/avoidance energy (E_A) decreases during the iterations. Therefore, the value of $|E_A| \geq 1$ means the exploration phase (hawks search different regions to explore the location of prey) and the value of $|E_A| < 1$ means the exploitation phase (hawks exploit the neighborhood of the solutions).

(iii) *Exploitation Phase*: Based on the prey's location searched in the previous phase, the hawks attack the prey in this phase. As the prey always tries to escape from these conditions, the hawks opt the different chasing styles to attain the target. According to the escaping actions of the prey and chasing plans of the hawks, four possible strategies are proposed. Let ($r < 0.5$) is the chance of a prey to flee successfully and ($r \geq 0.5$) is the chance that prey fails to escape before the surprise pounce. The attacking strategy based on the value of r and E_A is presented below:

(a) *Soft Besiege* ($r \geq 0.5 \& |E_A| \geq 0.5$)

In this the prey still has some energy to escape. Hence, the hawks softly encircle the prey and forces the prey to lose more energy before performing the surprise pounce. Soft besiege can be mathematically formulated as follows:

$$X(itn+1) = \Delta X(itn) - E_A \times \text{abs}(J_e \times X_{pr}(itn) - X(itn)) \quad (3.6)$$

$$\Delta X(itn) = (X_{pr}(itn) - X(itn)) \quad (3.7)$$

Where, $\Delta X(itn)$ is the change between present position of prey and hawk's position at itn iteration. The jump energy, $J_e = 2(1-r_5)$ varies randomly in every iteration and r_5 is the random number chosen within the range (0, 1).

(b) *Hard Besiege*: ($r \geq 0.5 \& |E_A| < 0.5$)

In this the targeted prey gets exhausted and have very low escaping tendency and fails to release from the surroundings. The hunter hawks hardly encircle the prey to perform the surprise attack. This stage of the hawks performing hard encircles is updated using the following equation (3.8).

$$X(itn+1) = X_{pr}(itn) - E_A \times \text{abs}(\Delta X(itn)) \quad (3.8)$$

(c) *Soft Besiege with advanced rapid dives*: ($|E_A| \geq 0.5 \& r < 0.5$)

In this stage the prey still has enough energy to escape from the attack but the hawk birds follow the zigzag path (Levy flight pattern) around the prey before the surprise pounce. The hawks do many group rapid dives encircling the prey and try to continuously correct their position and direction against the illusory movement of the prey. Therefore, the position of the hawk birds is modified in two steps during this stage. Firstly, the attacker tries to reach the prey by assessing the next move according to the rule stated in equation (3.9); secondly, decision is based on the comparison of the assessed result and previous dives that the dive is good or not. If the dive is not good than the hawks perform the abrupt and irregular dives based on the levy flight pattern to reach the prey. This is evaluated using equation (3.10).

$$Y = X_{pr}(itn) - E_A \times \text{abs}(J_e X_{pr}(itn) - X(itn)) \quad (3.9)$$

$$Z = Y + S \times L_F(Dim) \quad (3.10)$$

Here Dim = dimension, S = Range of fractal flight track with size ($1 \times Dim$)

The $L_F(Dim)$ is levy flight-based patterns which follow the rule given in equation (3.11) and equation (3.12)

$$L_F(x) = 0.01 \left(\frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}} \right) \quad (3.11)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)} \right)^{\frac{1}{\beta}} \quad (3.12)$$

Where, μ, σ are denoted as random value between (0, 1) and β is default constant assumed as 1.5. At this stage the prey has enough energy and encircles during this phase depends on levy flight (L_F) concept as modeled in equation (3.11). Hawks perform a soft encircle with rapid dives for $|E_A| \geq 0.5$ & $r < 0.5$ is modelled as follows:

$$X(itn+1) = \begin{cases} Y_l; & \text{if } F(Y_l) < F(X(itn)) \\ Z_l; & \text{if } F(Z_l) < F(X(itn)) \end{cases} \quad (3.13)$$

Where, Y_l and Z_l are the positions based on soft encircles.

(d) *Hard Besiege with advanced rapid dives*: ($|E_A| < 0.5$ & $r < 0.5$):

In this instance, the prey lacks the energy to escape and the Harris hawks make quick dives to get closer to the prey in an effort to narrow the gap before making a surprise pounce to capture it. In the event of a hard besiege, the hawks' movement is calculated as follows in equation (3.14) and perform hard encircles with rapid dives for $|E_A| < 0.5$ & $r < 0.5$.

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

$$Y'_l = X_{pr}(itn) - E_A \times \text{abs}(J_e X_{pr}(itn) - X_m(itn)) \quad (3.15)$$

$$Z'_l = Y'_l + S \times L_F(Dim) \quad (3.16)$$

Where, Y'_l and Z'_l are the positions centered on hard surroundings.

3.3.2 HYBRID HARRIS HAWKS OPTIMIZER

The detailed mathematical formulation for Harris Hawk's optimizer has been discussed in section 3.3.1. However, the local search of the basic HHO algorithm is

slow due to its poor exploitation capability. The major flaws are possibility of being trapped in local minima while dealing with large multimodal and composition optimization problems, improper balance between the global and local search, slothful performance in handling multi-dimensional problems [236]. These observations from the benchmark functions are consistent with the interpretations presented by Heidari et al. [204]. This motivated many researchers to form new modified and hybrid algorithms to enhance the performance of HHO.

Different variants of HHO achieved from the explicit research work has been selected to have fair interpretation and assessment. Some examples of memetic variant of HHO developed recently are chaotic multi-verse harris hawks optimization (CMVO-HHO) [237], improved HHO [238] formed by change in information between search agents and tested nine benchmark problems and seven engineering design problems, HHO-ANN [239] incorporated to evaluate the stability of soil slopes with improved fitted structure, robust hybrid algorithm by combining multi-verse optimizer with HHO and grasshopper optimizer is presented in [240]. Hybrid HHO [241] is used for tackling manufacturing optimization problems and for solving complications associated with cracks in cantilever beam design. CHHO [242] by combining chaos maps with HHO to improve exploration of original HHO, hybrid HHO-PSO [243] used for solving dispatch problem., SCA-HHO algorithm [244], Boosted HHO [245], enhanced HHO [246], Improved HHO [247], etc. More variants of HHO can be developed to improve the performance of original HHO algorithm.

From the literature studies, it has been revealed that the memetic modifications of HHO have been framed by the researchers to improve the search capability of original method. The solution accuracy of these algorithm depends on an appropriate balance between exploration and exploitation phase. It is also observed that slow rate of convergence is the most usual drawback of most heuristic algorithms and hence lowers the computational efficiency, as to modify the fitness value hybrid or memetic approaches are emerging immensely and improving the quality of solution. Also, in some standard benchmark functions exploitation has not reached to a significant level using classical HHO and hence failed to give precise results with inferior performance and premature convergence.

PSEUDO code of Harris Hawk Optimizer (HHO)

INPUTS: The population size taken as N and maximum iteration number is taken as itm_{max}
 OUTPUTS: The position of prey (rabbit) and its value of fitness
 Initialization of random population $X_i (i = 1, 2, 3, \dots, N)$
 While (iteration $< itm_{max}$)
 Calculation of the fitness value of Harris hawks
 Set the parameter X_{pr} as the best position of the prey (rabbit)
 for (each Harris hawks (X_i))
 Do Update energy at initial condition E_0
 if $|E_A| \geq 1$ then
 Position vector updated using $E_A = 2 \times E_0 \times \left(1 - \frac{itm}{itm_{max}}\right) \rightarrow \text{Phase of Exploration}$
 else if $q \geq 0.5$ then
 $X(itm+1) = \{X_{rand}(itm) - r_1 \times abs(X_{rand}(itm) - 2 \times r_2 \times X(itm))\}$
 else if $q < 0.5$ then
 $X(itm+1) = \{(X_{pr}(itm) - X_m(itm)) - r_3 \times (lb + r_4 \times (ub - lb))\}$
 if $|E_A| < 1$ then $\rightarrow \text{Phase of Exploitation}$
 $X(itm+1) = \Delta X(itm) - E_A \times abs(J_r X_{pr}(itm) - X(itm))$
 if $(r \geq 0.5)$ and $|E_A| \geq 0.5$ then $\rightarrow \text{Soft encircle}$
 Position vector updated using $\Delta X(itm) = (X_{pr}(itm) - X(itm))$
 else if $(r \geq 0.5)$ and $|E_A| < 0.5$ then $\rightarrow \text{Hard encircle}$
 Position vector updated using $X(itm+1) = X_{pr}(itm) - E_A \times abs(\Delta X(itm))$
 else if $(r < 0.5)$ and $|E_A| \geq 0.5$ then $\rightarrow (\text{Soft encircle with advanced fast dives})$
 Position vector updated using $Y = X_{pr}(itm) - E_A \times abs(J_r X_{pr}(itm) - X(itm))$
 else if $(r < 0.5)$ and $|E_A| < 0.5$ then $\rightarrow (\text{Hard encircle with advanced fast dives})$
 Position vector updated using $X(itm+1) = \Delta X(itm) - E_A \times abs(J_r X_{pr}(itm) - X(itm))$
 end
 end
 end
 end

Fig 3.2: Pseudocode – Harris Hawk Optimizer (HHO)

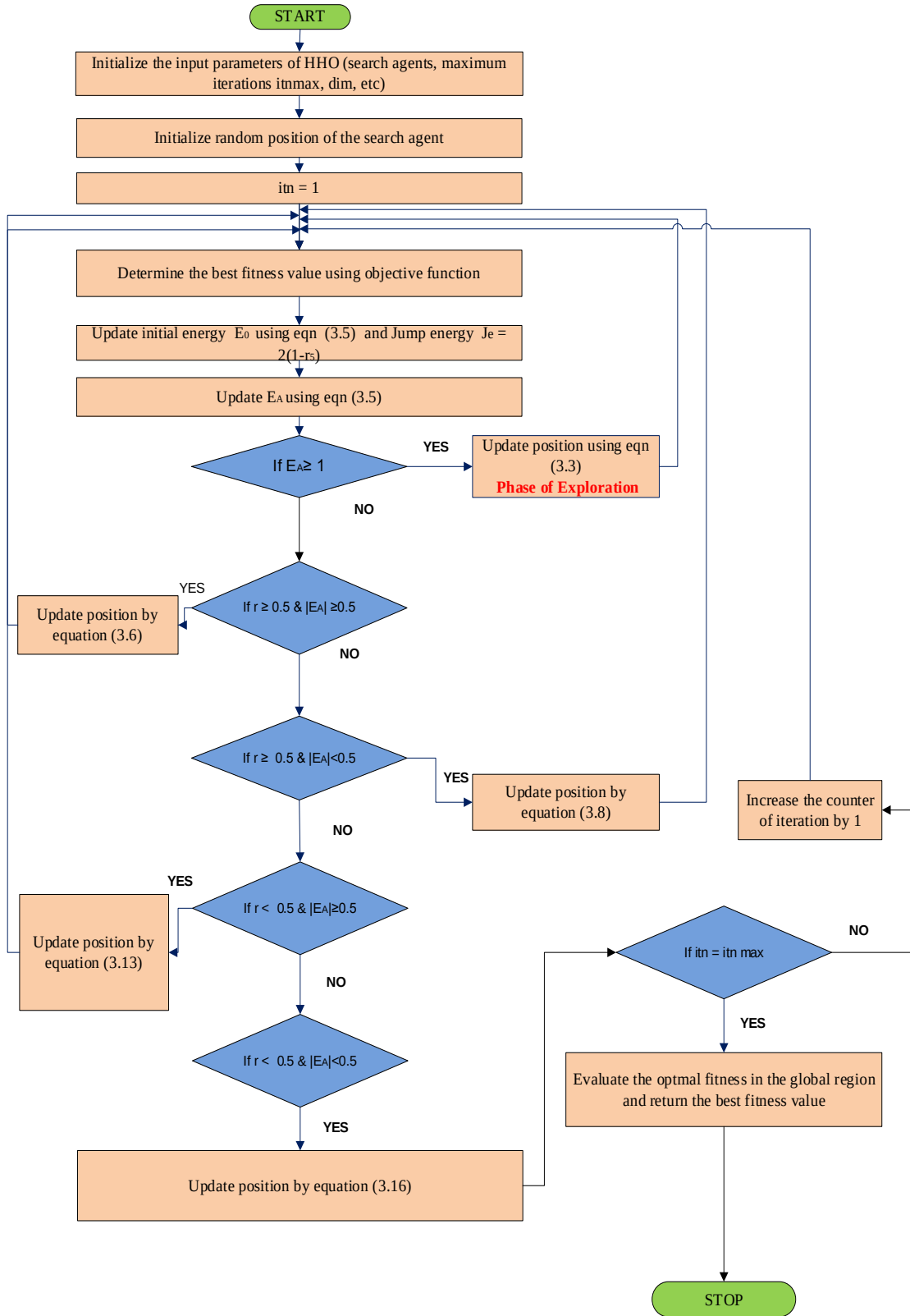


Fig 3.3: Flowchart for Harris Hawk Optimizer (HHO)

Therefore, this research study intends to offer a novel Random exploratory Search based HHO algorithm. The exploration and exploitation phase of HHO has been improved by combining harris hawk optimizer (HHO) with random exploratory search (RES) [248] algorithm. The resultant algorithm is called as memetic Harris Hawk's optimizer and abbreviated as hHHO-RES. In proposed method, exploration and exploitation phases of classical HHO has been enhanced by integration with RES algorithm. hHHO-RES helps HHO to explore the search space more intensively. Thus, prevents algorithm from any local minima stagnation and immature convergence. The pseudocode and flowchart of hHHO-RES is shown in Fig 3.4 and 3.5 respectively. The systematic steps to apply the hHHO-RES method are presented in the algorithm as defined below:

In terms of scalar objective function $f(X)$, the optimization problem is defined as:

$$\text{minimize } f(X) \quad (3.17)$$

$$\text{Subjected to } x_i^{\min} \leq x_i \leq x_i^{\max} \quad (i=1,2,\dots,N) \quad (3.18)$$

Where, $X = [x_1, x_2, \dots, x_N]^T$ is the set of design variables and 'N' is the number of design variables.

Algorithm

The procedure of optimization for the proposed memetic algorithm hHHO-RES consists of the following steps:

Step-1: Define the algorithm parameters.

Specify the input parameters required by HHO and RES algorithm to solve the optimization problem defined by Equation (3.17) such as- number of solution vectors, variables and parameters adjustment 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) and (lb) respectively.

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

Step-3: Initialization of exploration phase for each chance q , with condition $q \geq 0.5$ and $q < 0.5$ modelled by equation (3.3a) and (3.3b). Equation (3.4) gives the mean position of Hawks.

Step-4: Conversion from exploration phase to exploitation phase depends upon (E_A) , the evading energy and change of escape (r) as in equation (3.5).

Step-5: Various soft and hard encircles performed by hawks to capture the prey. For $|E_A| < 1$, exploration phase is completed and the new position vector is determined and the difference between current and updated position of prey and hawks is evaluated for each jump energy J_e in each iteration within the range of (0, 1) using equations (3.6) and (3.7).

Step-6: At this stage Hawks perform a hard encircles for $r \geq 0.5 \& |E_A| < 0.5$ using equations (3.8) to (3.10)

Step-7: Hawks perform a soft encircles with rapid dives for $|E_A| \geq 0.5 \& r < 0.5$ using equations (3.13) to (3.15)

Step-8: The Hawks are very close to prey and perform hard encircles with rapid dives using equation (3.16) for $|E_A| < 0.5 \& r < 0.5$.

Step-9: Update the position vector $X(itn+1)$ using random exploratory search (RES) algorithm.

Random Exploratory Search:

- The position vector $X(itn+1)$ is disturbed by Δ_i and new position vector $X[(itn+1)+\Delta_i]$ and $X[(itn+1)-\Delta_i]$ has been obtained.
- The variation of the parameter Δ_i is considered randomly within the local search space for exploiting the search space in a better way.
- Fitness resolution $f^+ \leftarrow f[X(itn+1)+\Delta_i]$ and $f^- \leftarrow f[X(itn+1)-\Delta_i]$ are considered with earlier fitness resolution $f \leftarrow f[X(itn+1)]$
- Ultimate fitness are estimated taking minimum values using equation $f_{final} \leftarrow \min(f^+, f^-, f)$.

PSEUDO code of the Proposed hHHO-RES algorithm

INPUTS: The population size taken as N and maximum iteration number is taken as $itn_{\max}$

OUTPUTS: The position of prey (rabbit) and its value of fitness

Initialization of random population $X_i (i = 1, 2, 3, \dots, N)$

While (iteration $< itn_{\max}$)

Calculation of the fitness value of Harris hawks

Set the parameter X_{pr} as the best position of the prey (rabbit)

for (each Harris hawks (X_i))

Do Update energy at initial condition E_0

if $|E_A| \geq 1$ **then**

Position vector updated using $E_A = 2 \times E_0 \times \left(1 - \frac{itn}{itn_{\max}}\right)$ $\rightarrow$ **Phase of Exploration**

else if $q \geq 0.5$ **then** $X(itn+1) = \{X_{rand}(itn) - r_1 \times abs(X_{rand}(itn) - 2 \times r_2 \times X(itn))\}$

else if $q < 0.5$ **then** $X(itn+1) = \{(X_{pr}(itn) - X_m(itn)) - r_3 \times (lb + r_4 \times (ub - lb))\}$

if $|E_A| < 1$ **then** $\rightarrow$ **Phase of Exploitation**

$X(itn+1) = \Delta X(itn) - E_A \times abs(J_e X_{pr}(itn) - X(itn))$

if ($r \geq 0.5$) and $|E_A| \geq 0.5$ **then** $\rightarrow$ **Soft encircle**

Position vector updated using $\Delta X(itn) = (X_{pr}(itn) - X(itn))$

else if ($r \geq 0.5$) and $|E_A| < 0.5$ **then** $\rightarrow$ **Hard encircle**

Position vector updated using $X(itn+1) = X_{pr}(itn) - E_A \times abs(\Delta X(itn))$

else if ($r < 0.5$) and $|E_A| \geq 0.5$ **then** $\rightarrow$ **Soft encircle with advanced fast dives**

Position vector updated using $Y = X_{pr}(itn) - E_A \times abs(J_e X_{pr}(itn) - X(itn))$

else if ($r < 0.5$) and $|E_A| < 0.5$ **then** $\rightarrow$ **Hard encircle with advanced fast dives**

Position vector updated using $X(itn+1) = \Delta X(itn) - E_A \times abs(J_e X_{pr}(itn) - X(itn))$

end

end

end

end

update the best fitness returned using RES algorithm

return best fitness

end

Fig. 3.4: Pseudocode for hHHO-RES

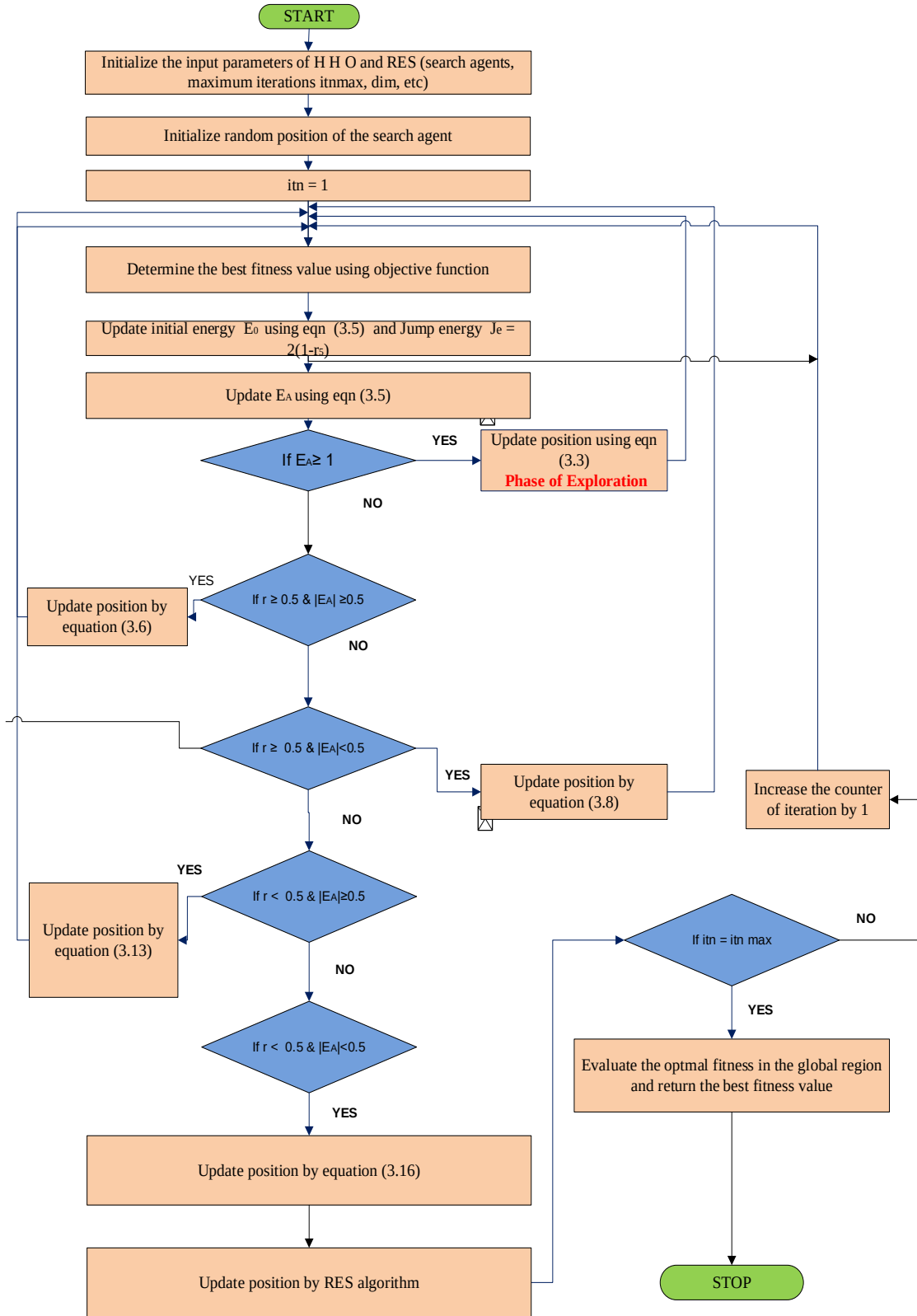


Fig 3.5: Flowchart for proposed hHHO-RES

3.3.3 SLIME MOULD ALGORITHM (SMA)

Slime mould algorithm (SMA) is the new meta-heuristic (MH) algorithm invented by Chen et al.[205] for solving stochastic optimization problems. SMA is a very simple and easily adoptable algorithm. The algorithm is formatted by mimicking the behavior of slime moulds and ability of searching, approaching, wrapping and grabbing food. The foraging behavior of *pysarum polycephalum* commonly known as ‘slime mould’ to search food sites have been competently implemented by researchers to frame new algorithms with diversified objectives.

A few research examples of implementing SMA approach are discussed below for a rational assessment. [249] identified the inherent ability of slime moulds to navigate through dissimilar channels and reach rich food sources via shortest path; reconfiguring transport networks by applying the foraging capability of moulds to obtain optimal routes transport networks has been developed [250]; study on ability of moulds to take decision for choosing optimal path was carried in [251] and [252] designed structural machines modal to solve complex computational problems. [253] used to rectify the fault signals in the telecommunication sector. [254] used in solving single and multi-path problems for avoiding emergencies and disasters. This approach has also been used in electrical applications for renewable system based optimal power flow [255] and PID-controlled DC motor and AVR system [256]. The complete life cycle of slime mould in SMA is restricted to its activity and physical changes when foraging. The organism's behavior was discovered to have been adopted and statistically modelled in order to solve unconstrained and non-convex mathematics. The plasmodium, in most cases, generates protoplasmic tubes that connect the masses of protoplasm to the food sources [245]. The front end of the relocation cycle extends into a fan-moulded, followed by an interlocking venous that allows cytoplasm to flow within, as shown in Fig 3.6. Moulds use their venous system to look for large amounts of food by secreting enzymes that ring the food sources. When there is enough food in the environment, moulds can grow to be above nine hundred sq. cm [251].

The slime mould even flows vividly in the situation of food shortage, which aids in understanding how slime mould locate, move, and link food in a changing

environment. Slime can detect the positive-negative response when a secretion approaches the target and choose the best path to grip food. This implies that slime mould may build a physical trail depending on the concentration of food. It desires to hunt in areas where there is a lot of food. The mould assesses the speed against the food concentration and environmental danger and decides to leave the former place while foraging.

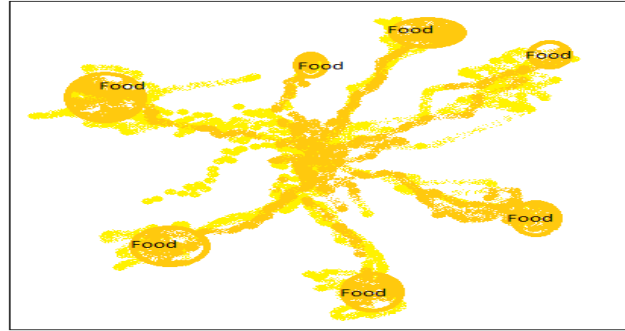


Fig 3.6: Food search arrangement of Slime Mould

The search process by moulds for the best food location is shown in Fig 3.7. The food searching process of slime moulds involves three main processes linked as approaching, wrapping and grabbing food. The following steps and mathematics are encompassed during food searching process of moulds [205]:

Step-1: In this step the moulds approaches the food and following equations are used for updating the position during the food search process. The selection criteria of the equations depends upon the values of r and p and is known as the contraction mode of the mould.

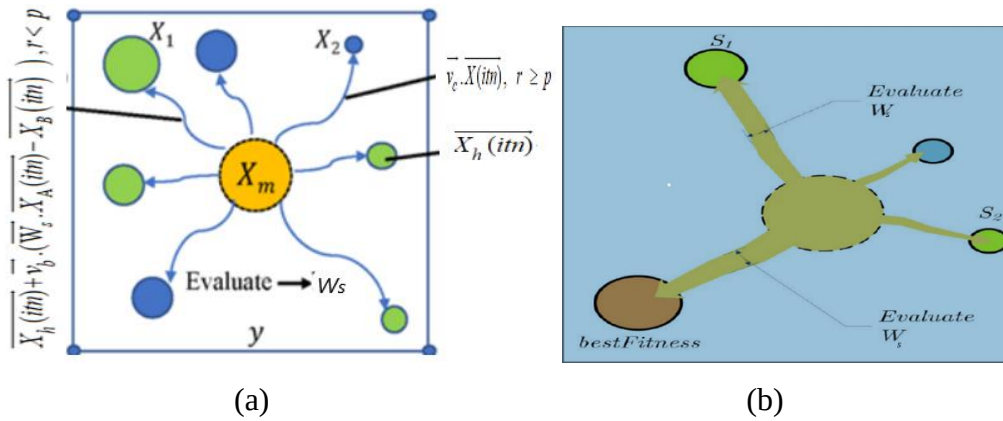


Fig 3.7: (a) Possible position of moulds (b) Fitness Evaluation

$$\overrightarrow{X(itn+1)} = \begin{cases} \overrightarrow{X_h(itn)} + \overrightarrow{v_b} \cdot (\overrightarrow{W_s} \cdot \overrightarrow{X_A(itn)} - \overrightarrow{X_B(itn)}) , r < p \\ \overrightarrow{v_c} \cdot \overrightarrow{X(itn)} , r \geq p \end{cases} \quad (3.19)$$

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

$$p = \tan h |S(i) - TF| \quad (3.20)$$

Where i changes from 1 to N; $S(i)$ represents the fitness of $\overrightarrow{X}$ and TF shows the total fitness from entire steps. $\overrightarrow{v_b}$ lies in the range $-a$ and a represented as

$$\overrightarrow{v_b} = [-a, a] \quad (3.21)$$

$$\text{Where } a = \arctan h \left(-\left(\frac{itn}{itn_{\max}} \right) + 1 \right) \quad (3.22)$$

$\overrightarrow{W_s}$, the weight of masses can be evaluated according to following

$$\overrightarrow{W_s}(\text{smell index}(i)) = \begin{cases} 1 + r \cdot \log \left(\frac{bF - S(i)}{bF - wF} + 1 \right), \text{condition} \\ 1 - r \cdot \log \left(\frac{bF - S(i)}{bF - wF} + 1 \right), \text{others} \end{cases} \quad (3.23)$$

$$\text{Smell Index} = \text{sort}(S) \quad (3.24)$$

Where, $S(i)$ ranks 1st half of the chosen population with r taken as random value chosen within 0 and 1; bF depicts the optimal fitness obtained in the current iterative process, wF represents the worst fitness attained in that iterative process and the function Sort (S) sorts the fitness values.

Step-2: This step involves the next process of detecting food known as wrapping of food. Mathematically this is modelled as follows for upgrading the positions of agents.

$$\overrightarrow{X^*} = \begin{cases} R \cdot (u_b - l_b) + l_b; R < z \\ \overrightarrow{X_h(itn)} + \overrightarrow{v_b} \cdot (\overrightarrow{W_s} \cdot \overrightarrow{X_A(itn)} - \overrightarrow{X_B(itn)}) ; r < p \\ \overrightarrow{v_c} \cdot \overrightarrow{X(itn)} ; r \geq p \end{cases} \quad (3.25)$$

Where u_b and l_b are the search limits, ' R ' and ' r ' denotes the random value within $[0, 1]$.

Step-3: This step represents the next searching process known as food grabbing. With the progress in the search process, the value of $\vec{v}_b$ vividly changes between $[-a, a]$ and $\vec{v}_c$ varies between $[-1, 1]$ and at last diminishes to zero.

The pseudocode and flowchart for SMA method is shown in Fig. 3.8 and 3.9 respectively describing various steps involved in this search algorithm.

3.3.4 HYBRID SLIME MOULD ALGORITHM

The comprehensive mathematical formulation for Slime mould algorithm along with its merits and demerits has already been discussed in section 3.3.3. Studies revealed that meta-heuristics (MH) approaches faces the problem of poor exploitation in some of the uni-modal and multi-modal benchmark function. Researchers have developed many hybrid approach in algorithms by combining different algorithms. Although, slow convergence and tendency to get trapped in local optima is amongst the common problem reported by many researchers [236].

<i>Pseudo-code for Slime Mould Algorithm (SMA)</i>
Initialization of the parameters (population size, search agents and max iterations (itn_{max})); Initialize the position of slime mould - $X_i (i = 1, 2, \dots, n)$; While ($itn \leq itn_{max}$) Evaluate the fitness of all slime mould; Update best fitness, X_h Calculate the W_i by Equation (3.23); For each search portion Update p, vb, vc ; Update positions by Equation (3.25); End For $itn = itn + 1$; End While Return bestFitness, X_h ;

Fig 3.8: Pseudocode for Slime Mould Algorithm (SMA)

From the literatures, it has been revealed that the solution accuracy of the algorithm depends on an appropriate balance between exploration/exploitation phases. Also, most

of the available studies till date reveals that basic SMA algorithm stuck in the local optima and leads to poor convergence. Therefore, this research study intends to offer a novel Random exploratory Search based SMA algorithm. The exploration and exploitation phase of SMA has been improved by combining Slime Mould Algorithm (SMA) with Random Exploratory Search (RES) algorithm. The resultant algorithm is called as memetic SMA and abbreviated as hSMA-RES. In proposed method, the exploitation phase of classical SMA has been boosted by integration with RES algorithm. hSMA-RES will help SMA to explore the search space and hence prevents the algorithm from any local minima stagnation and immature convergence leading to superior performance. The pseudocode and flowchart of hSMA-RES is shown in Fig 3.10 and 3.11 respectively describing the complete mathematical procedure. The algorithm for memetic SMA (hSMA-RES) describing the various steps is as follows:

Algorithm

The optimization procedure for the memetic algorithm hSMA-RES is described in the following steps:

Step-1: Define algorithm parameters.

Specify the input parameters required by SMA and random exploratory search (RES) to solve the optimization problem defined by equation (3.1) - population size, search agents and maximum iteration, upper bound and lower bound.

Step-2: Initialization of position of slime mould $X_i (i = 1, 2, 3, \dots, N)$

Step-3: Calculate the fitness of all slime mould and estimating the updated position of moulds till maximum iterations are reached using equation (3.19)

Step-4: Calculate W_s using equation (3.23).

Step-5: For each search iteration, the positions of p, vb, vc are updated.

Step-6: The equation for updating the positions of agents for wrapping food is calculated using equation (3.25).

Step-7: With the update in the search process, the stage changes to grabbing of food

in which the value of $\vec{v}_b$ changes vividly between $[-a, a]$ and $\vec{v}_c$ alters between $[-1, 1]$ and at last reduces to zero.

Step-9: Update the position vector $X(itn+1)$ using random exploratory search (RES) algorithm.

Random Exploratory Search:

- The position vector $X(itn+1)$ is disturbed by Δ_i and new position vector $X[(itn+1)+\Delta_i]$ and $X[(itn+1)-\Delta_i]$ has been obtained.
- The variation of the parameter Δ_i is considered randomly within the local search space for exploiting the search space in a better way.
- Fitness resolution $f^+ \leftarrow f[X(itn+1)+\Delta_i]$ and $f^- \leftarrow f[X(itn+1)-\Delta_i]$ are considered with earlier fitness resolution $f \leftarrow f[X(itn+1)]$
- Ultimate fitness are estimated taking minimum values using equation $f_{final} \leftarrow \min(f^+, f^-, f)$.

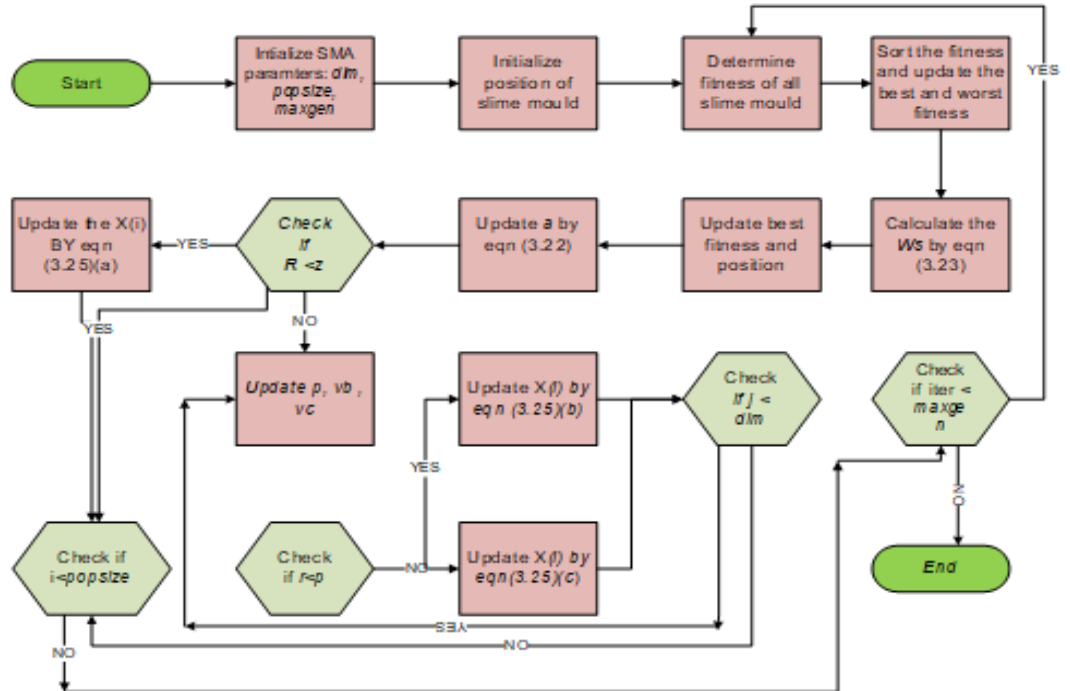


Fig 3.9: Flowchart for Slime Mould Algorithm (SMA)

Pseudo-code - hSMA-RES

Initialization of the parameters
(population size, search agents and max iterations (itn_{max}));
Initialize the position of slime mould - $X_i(i = 1, 2, \dots, n)$;
While ($itn \leq itn_{max}$)
 Evaluate the fitness of all slime mould;
 Update best fitness, X_h
 Calculate the W_s by Equation (3.23);
 For each search portion
 Update p, vb, vc ;
 Update positions by **Equation** (3.25);
 End For
 $itn = itn + 1$;
 Update position using RES;
End While
Return bestFitness, X_h ;

Fig 3.10: Pseudocode for hSMA-RES

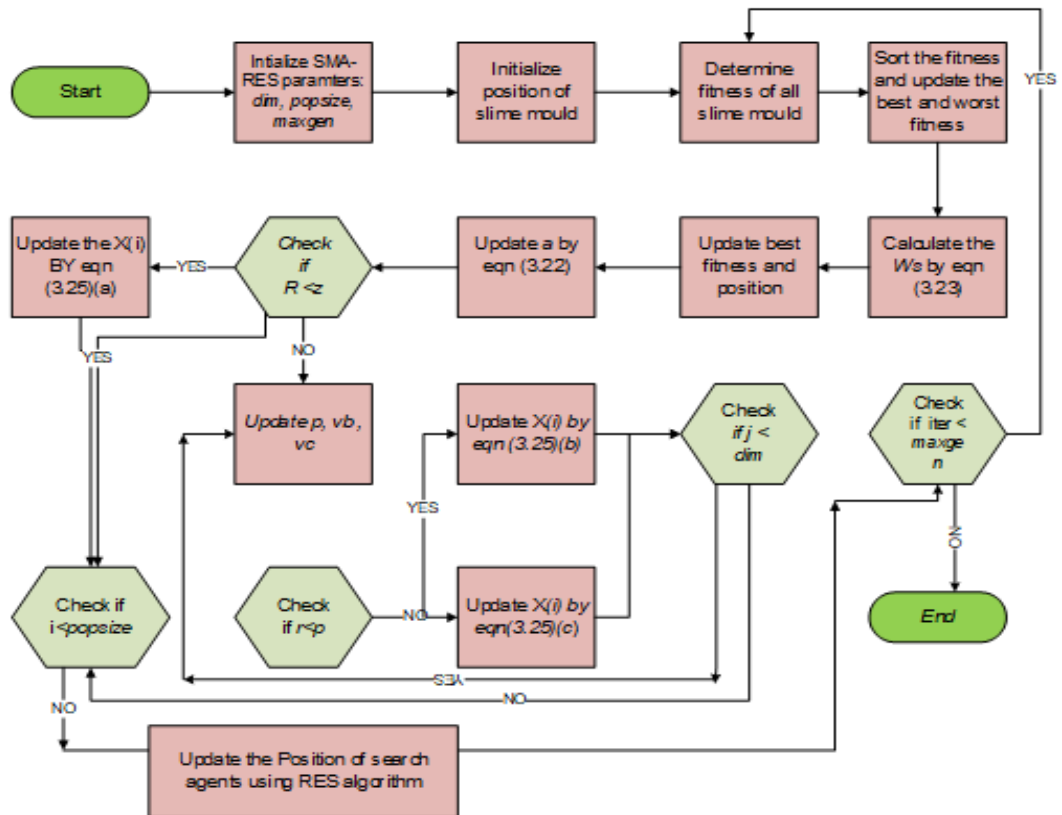


Fig 3.11: Flowchart for hSMA-RES

3.4 STANDARD BENCHMARK FUNCTIONS

In this section commonly used 23 standard benchmark (BM) functions has been discussed. The features of BM functions vary from each other in regard to searching ability, few BM functions perform better in local search region while some performs excellent in global search regions. Based on this the test functions have different global and local search capacities. Out of these standard functions; Levy, Griewank, Ackley, Schwefel, Rastrigin and Sphere functions are noted to have many local minima points whereas sum square and Zakharov functions have global minima points. These BM functions are categorized into three groups as unimodal (UM), multi-modal (MM) and fixed-dimension (FD) benchmark functions. The UM functions considered are from F_1 to F_7 , MM functions are represented from F_8 to F_{13} and FD functions are from F_{14} to F_{23} . The mathematical formulation and 3D view for each function of UM, MM and FD along with their range and optimal fitness value are illustrated respectively in Table TA.1 to Table TA.3 and Fig. FA.1 to FA.3 (AppendixA). These are regarded by their objective fitness in parameter space within a particular dimension range (Dim) and optimal value (f).

The proposed memetic algorithms have been tested for these benchmark functions in regard to best values, average values, standard deviation, worst values and median. Statistical non-parametric tests like Wilcoxon rank sum test and t-test has also been performed to validate the effectiveness of the proposed methods. Furthermore, the effectiveness of the proposed methodologies are performed with 30 independent trial runs for each benchmark. The variation in the values of trial runs a depicted graphically and box plots are plotted to depict the statistical analysis of the proposed algorithms. The existence and feasibility of these proposed methods have been analyzed by comparing the test results for each benchmark functions with other methods such as BA [257], BDA [258], MFO [184], GWO [172], GSA [174], BPSO [259], FEP [260], GOA [170], ALO [148], WOA [261], CS[262], GA [263], MVO [185], DA [258], BGSA [159], SCA [192], SSA [196], FEP [260]. The convergence curve of hHHO-RES and hSMA-RES is plotted and its comparative analysis with other algorithms has also been performed.

3.5 ENGINEERING DESIGN OPTIMIZATION

In this section ten real-world engineering design (ED) problems are discussed as listed in Table 3.4. The ED considered in this research work are “3-bar truss problem, speed reducer problem, pressure vessel design, tension-compression spring design, welded beam design [264], rolling element problem [204], [214], cantilever beam design problem [184], gear train design problem [264], multidisc clutch brake problem [200] and I beam design problem”[205]. Each design problem is simulated by applying the proposed memetic algorithms. The theoretical description of each design problem has been elaborated in section (A.2.1 to A.2.10) Appendix A. Also, mathematical analysis of each design problem along with associated constraints and optimization problems considered are deeply explored in section A.2 of Appendix A.

Table 3.1 – Details of Engineering Design (ED) Problem

S.No.	Engineering Design Problem	Objective
1	ED1 -Three-bar truss problem	Minimize weight
2	ED2 - Speed Reducer problem	Minimize weight
3	ED3 - Pressure Vessel	Minimize cost
4	ED4 - Spring Design	Minimize weight
5	ED5 - Welded Beam	Minimize cost
6	ED6 - Rolling Element Bearing	Maximize bearing capability
7	ED7 - Cantilever Beam Design	Minimize beam weight
8	ED8 - Gear Train	Minimize teeth ratio
9	ED10 - Multi plate Disc Clutch Brake	Minimize Weight
10	ED11- I beam structure design	Minimize beam deviation

3.6 RESULTS AND DISCUSSIONS

This section confers the outcomes of standard benchmark functions and engineering design (ED) problems. Twenty-three benchmark functions and 10 multidisciplinary engineering design problems discussed in section 3.4 and 3.5 are successfully tested by implementing the proposed memetic algorithms: hHHO-RES and hSMA-RES method. The simulation is executed in MATLAB 2018a Windows 10 environment with 2.10 GHz 4GB RAM Core i5. To verify the feasibility and reliability, simulation results are compared with standard existing algorithms.

To validate the results and to overcome the random or stochastic nature of the suggested memetic approaches (hHHO-RES and hSMA-RES), 30 independent trial runs are taken into consideration and each objective function has been assessed for index, best value, worst value, average value, median and standard deviation with maximum iterations 500. For statistical analysis of the proposed memetic algorithms, the non-parametric test (Wilcoxon rank-sum test and t-test) has been performed with its P and H values at 0.05 significance level. Further, for the validation of the results for 30 trial runs; the 1st, 2nd and 3rd quartile percent; semi-inter quartile deviations, outliers with maximum, minimum value and standard deviations has also been assessed.

3.6.1 Standard Benchmark Functions

The 23 standard benchmark functions categorized as uni-modal UM from F_1 to F_7 , multi-modal MM from F_8 to F_{13} and fixed dimension FD from F_{14} to F_{23} are tested using proposed memetic algorithms- hHHO-RES and hSMA-RES. Table 3.2(a), 3.3(a) and 3.4(a) depicts the results for UM functions (F_1 to F_7), multi-modal functions (F_8 to F_{13}) and fixed-dimension benchmark functions (F_{14} to F_{23}) respectively using hHHO-RES in the form of mean fitness, best fitness, worst fitness, median and standard deviation (SD). The index represents the best trial run. The statistical analysis for these functions is represented in table 3.2(b), 3.3(b) and 3.4(b) using hHHO-RES depicting the deviation in minimum and maximum values with 1st, 2nd and 3rd quartile, semi-inter quartile deviation and no. of outliers for 30 trial runs.

Table 3.2 (a): Results using hHHO-RES algorithm for UM benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F_1	5	1.20438E-94	2.2785E-109	57252E-93	5.0616E-100	6.52006E-94
F_2	9	1.04E-52	1.87E-61	1.95E-51	4.32E-55	3.72E-52
F_3	2	3.80308E-74	3.9248E-106	7.52618E-73	7.31863E-88	1.52241E-73
F_4	13	1.21201E-48	6.28117E-56	2.49184E-47	2.32362E-52	4.71646E-48
F_5	18	0.013967442	1.11076E-06	0.093245435	0.004325983	0.020457664
F_6	1	0.000194121	2.23602E-07	0.001956762	5.47528E-05	0.000385979
F_7	16	0.000179294	1.14314E-05	0.000722681	0.000136522	0.000184493

Table 3.2(b): Statistical Analysis using **hHHO-RES** algorithm for UM benchmarks

Function	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25th Percentile)	2 nd quartile (50th Percentile)	3 rd quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₁	2.30E-109	3.57E-93	1.20E-94	5.0E-100	1.10E-104	5.10E-100	5.40E-98	2.68E-98	6	6.50E-94
F ₂	1.87E-61	1.95E-51	1.04E-52	4.32E-55	6.08E-56	4.32E-55	7.90E-54	3.92E-54	5	3.72E-52
F ₃	3.90E-106	7.53E-73	3.80E-74	7.30E-88	6.61E-92	7.32E-88	3.50E-82	1.77E-82	6	1.50E-73
F ₄	6.28E-56	2.49E-47	1.20E-48	2.30E-52	3.63E-54	2.32E-52	1.30E-50	6.65E-51	7	4.70E-48
F ₅	1.11E-06	0.093245	0.01397	0.00433	0.002408	0.004326	0.01937	0.008483	1	0.02046
F ₆	2.24E-07	0.001957	0.00019	5.50E-05	1.30E-05	5.48E-05	0.00022	0.000101	2	0.00039
F ₇	1.14E-05	0.000723	0.00018	0.00014	4.32E-05	0.000137	0.00032	0.000137	0	0.00018

Table 3.2 (c): Test observations using **hHHO-RES** algorithm for UM Benchmarks

Function	Wilcoxon Rank Sum Test		T-Test	
	p- value	h-value	p-value	h-value
F ₁	2.510E-02	1	3.560E-01	0
F ₂	2.236E-02	1	2.716E-01	0
F ₃	5.201E-01	0	3.263E-01	0
F ₄	1.907E-01	0	3.381E-01	0
F ₅	8.187E-01	0	4.754E-01	0
F ₆	4.204E-01	0	9.622E-01	0
F ₇	8.073E-01	0	8.534E-01	0

Table 3.2 (d): Execution time using **hHHO-RES** algorithm for UM Benchmarks

Function	Worst Time (Secs)	Best Time (Secs)	Average Time (Secs)
F ₁	0.71875	0.171875	0.224479167
F ₂	0.296875	0.171875	0.2046875
F ₃	1.046875	0.890625	0.942708333
F ₄	0.234375	0.171875	0.198958333
F ₅	0.359375	0.28125	0.30625
F ₆	0.265625	0.203125	0.221875
F ₇	0.625	0.546875	0.574479167

To investigate the difference in the values, non-parametric tests has been performed and depicted in table 3.2(c), 3.3(c) and 3.4(c); the execution time for UM, MM and FD functions using hHHO-RES is presented in table 3.2(d),3.3(d) and 3.4(d) respectively in terms of best, worst and average time.

The trial solutions using the proposed hHHO-RES algorithm for uni-modal(UM), multi-modal(MM) and fixed-dimension(FD) benchmark functions are shown in Fig. 3.12, 3.13 and 3.14 respectively.

Table 3.3(a): Results using hHHO-RES algorithm for MM Benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F ₈	11	-12569.27	-12569.49	-12568.99	-12569.28	0.183013
F ₉	1	0.0	0.0	0.0	0.0	0.0
F ₁₀	1	08.88E-16	08.88E-16	08.88E-16	08.88E-16	0.0
F ₁₁	1	0.0	0.0	0.0	0.0	0.0
F ₁₂	4	9.50E-06	1.54E-08	8.87E-05	3.39E-06	1.82E-05
F ₁₃	6	8.08E-05	4.01E-08	0.000429	2.16E-05	0.000124

Table 3.3(b): Statistical Analysis using hHHO-RES algorithm for MM Benchmarks

Function	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25th Percentile)	2 nd quartile (50th Percentile)	3 rd quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₈	-12569	-12569	-12569	-12569	-12569	-12569	-12569	0.17702	0.0	0.18301
F ₉	0.0	0.0	0.0	0.0	----	0.0	----	----	0.0	0.0
F ₁₀	9.00E-16	8.90E-16	9.00E-16	9.00E-16	----	9.00E-16	----	----	0.0	0.0
F ₁₁	0.0	0.0	0.0	0.0	----	0.0	----	----	0.0	0.0
F ₁₂	2.00E-08	8.90E-05	1.00E-05	3.00E-06	7.00E-07	3.00E-06	9.00E-06	3.94E-06	3	1.80E-05
F ₁₃	4.00E-08	0.00043	8.00E-05	2.00E-05	6.00E-06	2.00E-05	0.0001	5.90E-05	2	0.00012

Table 3.3(c): Test observations using **hHHO-RES** algorithm for MM Benchmarks

Function	Wilcoxon Rank Sum Test		T-Test	
	p- value	h-value	p-value	h-value
F ₈	0.2643262	0	0.0142761	1
F ₉	-	-	-	-
F ₁₀	-	-	-	-
F ₁₁	-	-	-	-
F ₁₂	0.7731199	0	0.8470933	0
F ₁₃	0.9469559	0	0.3269023	0

Table 3.3(d): Execution time using **hHHO-RES** algorithm for MM Benchmarks

Function	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F ₈	0.40625	0.430208333	0.53125
F ₉	0.265625	0.291666667	0.328125
F ₁₀	0.09375	0.127083333	0.265625
F ₁₁	0.3125	0.339583333	0.421875
F ₁₂	1.234375	1.277083333	1.34375
F ₁₃	1.25	1.281770833	1.359375

Table 3.4(a): Results using **hHHO-RES** algorithm for FD Benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F ₁₄	7	1.031138073	1.9920309	0.998003838	0.18148368	0.998003838
F ₁₅	30	0.00036	0.000309	0.0007	0.00034	7.10E-05
F ₁₆	21	-1.03163	-1.031628	-1.03163	-1.03163	2.90E-09
F ₁₇	25	0.3979	0.397887	0.39803	0.397887	2.70E-05
F ₁₈	2	3	3	3	3	4.65E-07
F ₁₉	17	-3.85982	-3.862774	-3.84671	-3.86135	0.00398
F ₂₀	16	-3.1267	-3.299104	-2.95471	-3.14569	0.07794
F ₂₁	4	-6.19852	-9.967196	-4.9769	-5.05325	1.96247
F ₂₂	27	-6.43305	-10.29521	-5.07083	-5.08647	2.10408
F ₂₃	18	-6.08279	-10.36494	-5.09868	-5.12737	1.96502

Table 3.4(b): Statistical Analysis using **hHHO-RES** algorithm for FD benchmarks

Function	No. of trials	Minimum value	Maximum value	Mean Value	Median	First quartile (25th Percentile)	Second quartile (50th)	Third quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₁₄	30	0.998	1.99203	1.0311	0.998	0.998	0.998	0.998	1.01E-10	3	0.18148
F ₁₅	30	0.0003	0.0007	0.0004	0.0003	0.0003	0.0003	0.0004	2.58E-05	1	7.10E-05
F ₁₆	30	-1.0316	-1.0316	-1.0316	-1.032	-1.032	-1.0316	-1.032	1.65E-10	5	2.90E-09
F ₁₇	30	0.3979	0.39803	0.3979	0.3979	0.3979	0.3979	0.3979	1.80E-06	5	2.70E-05
F ₁₈	30	3	3	3	3	3	3	3	4.09E-08	4	4.65E-07
F ₁₉	30	-3.8628	-3.8467	-3.8598	-3.861	-3.863	-3.8613	-3.859	0.00157	3	0.00398
F ₂₀	30	-3.2991	-2.9547	-3.1267	-3.146	-3.189	-3.1457	-3.082	0.05366	0	0.07794
F ₂₁	30	-9.9672	-4.9769	-6.1985	-5.053	-8.674	-5.0533	-5.048	1.8131	0	1.96247
F ₂₂	30	-10.295	-5.0708	-6.433	-5.086	-9.347	-5.0865	-5.083	2.13188	0	2.10408
F ₂₃	30	-10.365	-5.0987	-6.0828	-5.127	-5.128	-5.1274	-5.119	0.00478	7	1.96502

Table 3.4(c): Test observations using **hHHO-RES** algorithm for FD benchmarks

Function	Wilcoxon Rank Sum Test		T-Test	
	p- value	h-value	p-value	h-value
F ₁₄	4.80E-02	1	2.14E-01	0
F ₁₅	3.11E-01	0	5.17E-01	0
F ₁₆	6.00E-02	0	3.97E-01	0
F ₁₇	3.18E-01	0	5.47E-01	0
F ₁₈	8.88E-01	0	5.30E-01	0
F ₁₉	1.00E+00	0	4.88E-01	0
F ₂₀	3.48E-01	0	1.86E-01	0
F ₂₁	6.95E-01	0	2.08E-02	0
F ₂₂	1.91E-01	0	5.07E-02	0
F ₂₃	1.22E-01	0	3.20E-01	0

Table 3.4(d): Execution time using **hHHO-RES** algorithm for FD benchmarks

Function	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F ₁₄	2.4375	2.473958333	2.53125
F ₁₅	0.171875	0.219791667	0.375
F ₁₆	0.171875	0.2078125	0.296875
F ₁₇	0.15625	0.211458333	0.59375
F ₁₈	0.140625	0.174479167	0.265625
F ₁₉	0.234375	0.253125	0.28125
F ₂₀	0.21875	0.2421875	0.265625
F ₂₁	0.265625	0.288541667	0.328125
F ₂₂	0.296875	0.344270833	0.421875
F ₂₃	0.359375	0.383854167	0.453125

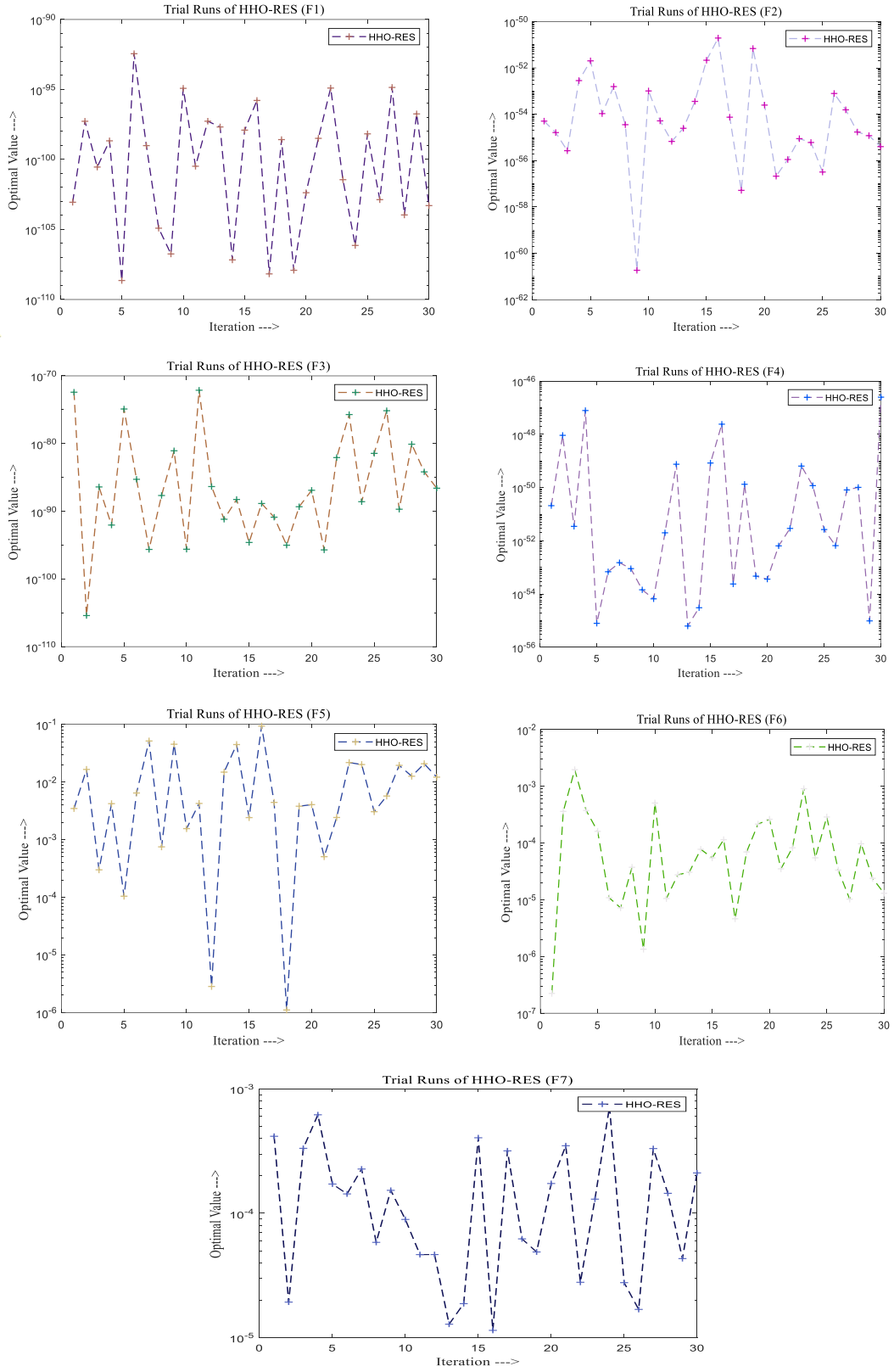


Fig 3.12: Trial Runs using hHO-RES for unimodal (F₁-F₇) Benchmark Functions

Table 3.5(a), 3.6(a) and 3.7(a) depicts the results for uni-modal (UM), multi-modal (MM) and fixed-dimension (FD) benchmarks respectively using hSMA-RES in terms of mean fitness, best fitness, worst fitness, median and standard deviation (SD). Index represents the best trial run among the 30 trial solutions.

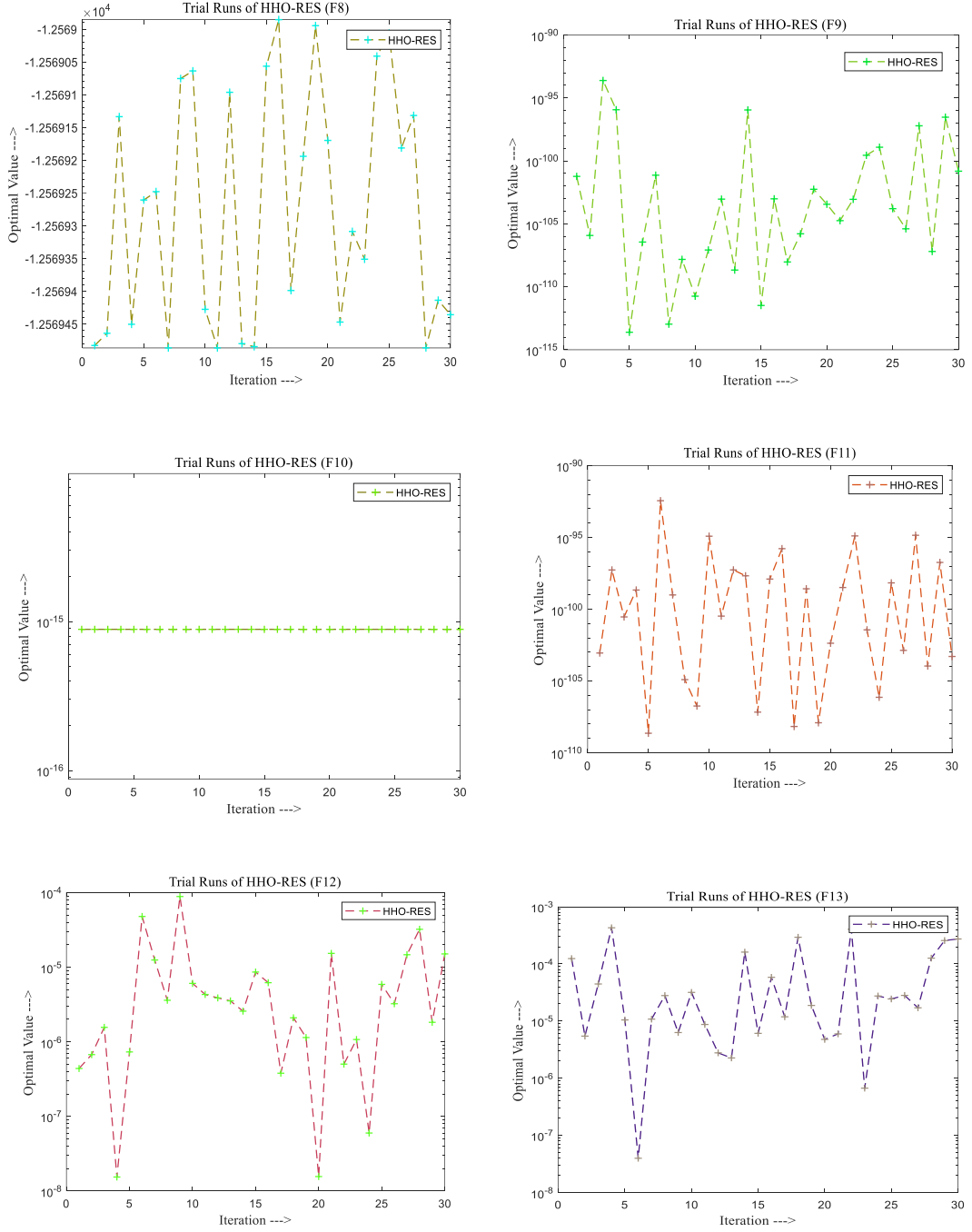


Fig 3.13 : Trial Runs using hHHO-RES for Multimodal (F₈-F₁₃) Benchmark Functions

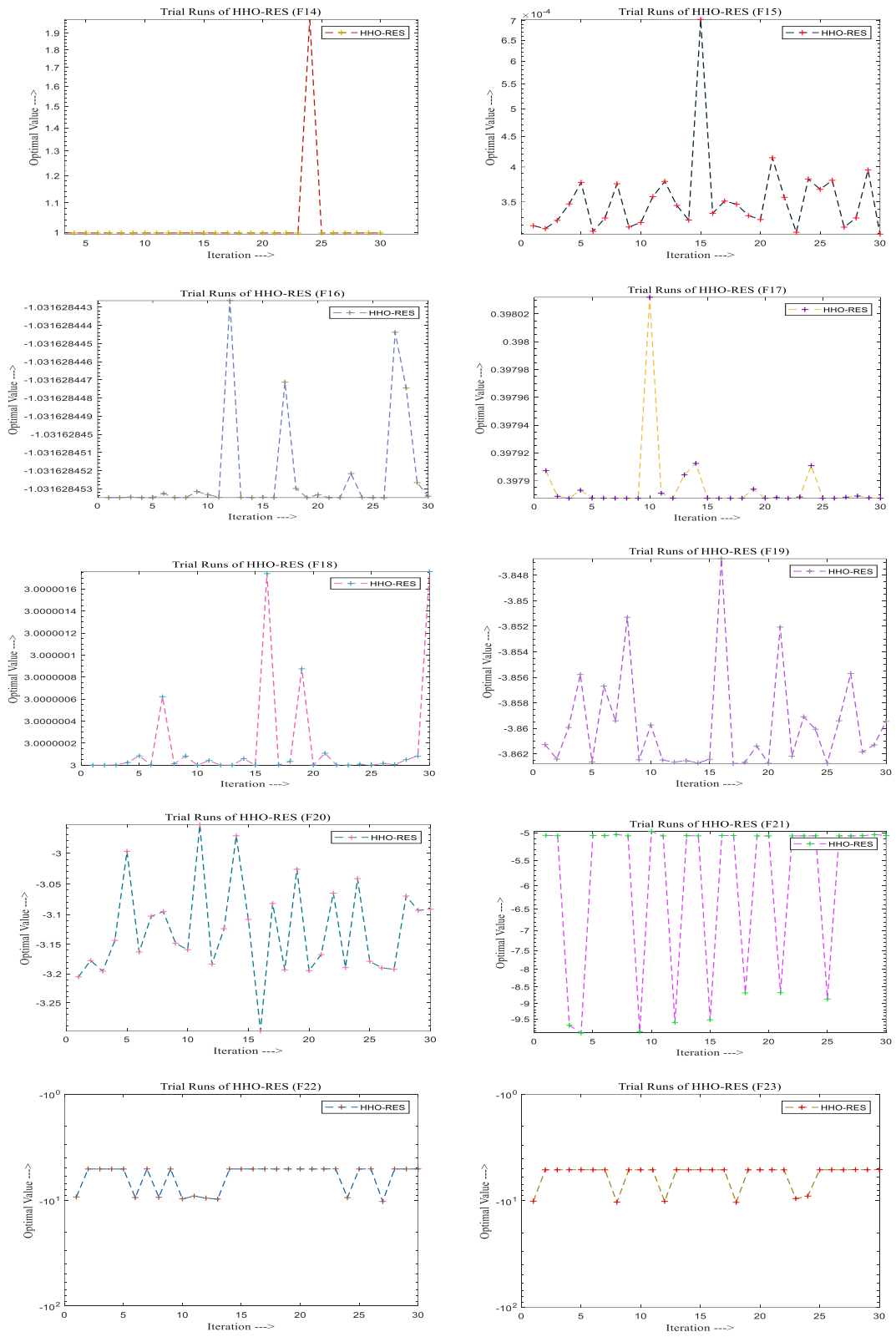


Fig 3.14: Trial Runs using hHHO-RES for Fixed Dimension (F₁₄-F₂₃) Benchmarks

Table 3.5(a): Results using **hSMA-RES** algorithm for UM Benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F ₁	1	0	0	0	0	0
F ₂	8	7.90E-153	5.96E-242	2.37E-151	8.23E-193	4.33E-152
F ₃	1	0	0	0	0	0
F ₄	8	4.81E-156	2.55E-292	1.44E-154	4.49E-205	2.63E-155
F ₅	26	7.69319736	0.004279901	28.50600101	1.26195418	11.48685579
F ₆	30	0.005692592	0.001845041	0.01338619	0.00464558	0.003188609
F ₇	5	0.000211641	6.13E-06	0.000853946	0.00015021	0.000197197

Table 3.5(b): Statistical Analysis using **hSMA-RES** algorithm for UM Benchmarks

Function	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25 th Percentile)	2 nd quartile (50 th Percentile)	3 rd quartile (75 th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₁	0.0	0.0	0.0	0.0	NA	0.0	0.0	NA	0	0.0
F ₂	6.0E-242	2.00E-151	8.00E-153	8.00E-193	2.14E-208	8.23E-193	3.58E-182	1.79E-182	7	4.0E-152
F ₃	0.0	0.0	0.0	0.0	NA	0.0	0.0	NA	0	0.0
F ₄	3.0E-292	1.00E-154	5.00E-156	4.00E-205	1.40E-223	4.49E-205	2.20E-188	1.10E-188	7	3.0E-155
F ₅	0.00428	28.506	7.6932	1.26195	0.912539	1.261954	8.915047	4.0012538	7	11.4869
F ₆	0.00185	0.01339	0.00569	0.00465	0.003198	0.004646	0.007137	0.0019695	0	0.00319
F ₇	6.10E-06	0.00085	0.00021	0.00015	7.24E-05	0.00015	0.00025	8.87E-05	2	0.0002

The statistical analysis for these functions is represented in Table 3.5(b), 3.6(b) and 3.7(b) respectively using hSMA-RES depicting the deviation in minimum and maximum values with 1st, 2nd and 3rd quartile, semi-inter quartile deviation and no. of outliers. The non-parametric tests (Wilcoxon rank sum test and t-test) for these benchmarks are presented in Table 3.5(c), 3.6(c) and 3.7(c) showing the statistical significance of the proposed method. The simulation time of the three categorized benchmarks using hSMA-RES is shown in Table 3.5(d), 3.6(d) and 3.7(d) respectively.

The p value obtained from non-parametric test in table 3.5(c), 3.6(c) and 3.7(c) reveals the statistical significance. The results for uni-modal functions strongly proves

the high exploitation and rate of convergence. The results of multi-modal functions and fixed dimension functions are also very competitive and represents high exploration and avoidance of local optima. The trial solutions using the proposed hSMA-RES algorithm for uni-modal, multi-modal and fixed-dimension benchmark functions are shown in Fig. 3.15, 3.16 and 3.17 respectively.

Table 3.5 (c): Test observations using hSMA-RES algorithm for UM Benchmarks

Function	Wilcoxon Rank sum Test		T-Test	
	p-value	h-value	p-value	h-value
F ₁	1.72E-12	1	0.3203	0
F ₂	3.02E-11	1	0.2697	0
F ₃	1.72E-12	1	0.32558	0
F ₄	3.02E-11	1	0.32419	0
F ₅	6.72E-10	1	0.00099	1
F ₆	3.02E-11	1	5.01E-10	1
F ₇	0.251881	0	0.6662	0

Table 3.5 (d): Execution time using hSMA-RES algorithm for UM benchmarks

Function	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F ₁	0.8438	0.9734	1.8594
F ₂	0.84375	0.925	1.75
F ₃	1.1875	1.215104167	1.296875
F ₄	0.84375	0.873958333	0.96875
F ₅	0.875	0.913541667	1.0000
F ₆	0.859375	0.8765625	0.921875
F ₇	1.03125	1.057291667	1.078125

Table 3.6(a): Results using hSMA-RES algorithm for MM benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F ₈	25	-12569.2	-12569	-12568.59	-12569.232	0.2312986
F ₉	1	0.0	0.0	0.0	0.0	0.0
F ₁₀	1	08.88E-16	08.88E-16	08.88E-16	08.88E-16	0.0
F ₁₁	1	0.0	0.0	0.0	0.0	0.0
F ₁₂	5	0.00527	1.48E-06	0.0196744	0.002071	0.0060793
F ₁₃	22	0.00557	2.23E-07	0.0319526	0.003123	0.0086447

Table 3.6(b): Statistical Analysis using **hSMA-RES** algorithm for MM benchmarks

Function	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25th Percentile)	2 nd quartile (50th Percentile)	3 rd quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₈	-12569.5	-12568.6	-12569.2	-12569.2	-12569.4	-12569.2	-12569.2	0.1323	2	0.2313
F ₉	0.0	0.0	0.0	0.0	NA	0.0	NA	NA	0	0.0
F ₁₀	08.88E-16	08.88E-16	08.88E-16	08.88E-16	NA	08.88E-16	NA	NA	0	0.0
F ₁₁	0.0	0.0	0.0	0.0	NA	0.0	NA	NA	0	0.0
F ₁₂	1.48E-06	0.01967	0.00527	0.002071	0.000661	0.002071	0.00882	0.0041	0	0.0061
F ₁₃	2.23E-07	0.03195	0.00557	0.003123	0.001031	0.003123	0.00546	0.0022	3	0.0086

Table 3.6(c): Test observations using **hSMA-RES** algorithm for MM benchmarks

Function	Wilcoxon Rank sum Test		T-Test	
	p-value	h-value	p-value	h-value
F ₈	0.68432259	0	0.02089996	1
F ₉	1.21E-12	1	1.33E-06	1
F ₁₀	1.21E-12	1	1.11E-120	1
F ₁₁	0.63261384	0	0.32682014	0
F ₁₂	2.1544E-10	1	5.3323E-05	1
F ₁₃	1.8567E-09	1	0.001579	1

Table 3.6(d): Execution time using **hSMA-RES** algorithm for MM benchmark

Function	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F ₈	0.890625	0.923958333	0.96875
F ₉	0.875	0.896354167	0.9375
F ₁₀	0.890625	0.901041667	0.9375
F ₁₁	0.90625	0.928645833	0.984375
F ₁₂	1.34375	1.371875	1.40625
F ₁₃	1.34375	1.372395833	1.421875

Table 3.7(a): Results using **hSMA-RES** algorithm for FD benchmarks

Function	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
F ₁₄	16	0.998004	0.998	0.998	1	2.66E-12
F ₁₅	15	0.000469	0.00031	0.0007	0	0.0001092
F ₁₆	2	-1.03163	-1.03163	-1.0316	-1	8.43E-10
F ₁₇	27	0.397887	0.39789	0.3979	0.4	2.32E-08
F ₁₈	6	3	3	3	3	3.10E-10
F ₁₉	17	-3.86278	-3.86278	-3.8628	-3.9	1.52E-06
F ₂₀	30	-3.24629	-3.32199	-3.1985	-3.2	0.0585877
F ₂₁	5	-10.1528	-10.1531	-10.152	-10	0.0003288
F ₂₂	30	-10.4026	-10.4029	-10.401	-10	0.000354
F ₂₃	15	-10.536	-10.5364	-10.535	-11	0.0002892

Table 3.7(b): Statistical Analysis using **hSMA-RES** algorithm for FD benchmarks

Function	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25 th Percentile)	2 nd quartile (50 th Percentile)	3 rd quartile (75 th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
F ₁₄	0.998004	0.998004	0.998004	0.998	0.998	1	0.998004	1.83E-13	2	2.66E-12
F ₁₅	0.00031	0.00069	0.000469	0.00045	0.0004	0	0.0005218	6.56E-05	0	0.000109
F ₁₆	-1.0316	-1.0316	-1.03163	-1.03163	-1.0316	-1	-1.031629	2.43E-10	3	8.43E-10
F ₁₇	0.39789	0.39789	0.397887	0.39789	0.3979	0.4	0.3978874	1.20E-08	2	2.32E-08
F ₁₈	3	3	3	3	3	3	3	1.81E-11	6	3.10E-10
F ₁₉	-3.8628	-3.8628	-3.86278	-3.86278	-3.8628	-3.9	-3.862782	1.43E-07	3	1.52E-06
F ₂₀	-3.322	-3.1985	-3.24629	-3.20309	-3.322	-3.2	-3.203056	0.0594631	0	0.058588
F ₂₁	-10.153	-10.152	-10.1528	-10.1529	-10.153	-10	-10.15269	0.000158	1	0.000329
F ₂₂	-10.403	-10.401	-10.4026	-10.4027	-10.403	-10	-10.40254	0.00014	2	0.000354
F ₂₃	-10.536	-10.535	-10.536	-10.5361	-10.536	-11	-10.53601	0.0001066	3	0.000289

Table 3.7(c): Test observations using **hSMA-RES** algorithm for FD benchmarks

Function	Wilcoxon Rank sum Test		T-Test	
	p-value	h-value	p-value	h-value
F ₁₄	5.07E-10	1	0.14643	0
F ₁₅	8.29E-06	1	0.16381	0
F ₁₆	2.00E-06	1	0.89897	0
F ₁₇	0.002051	1	0.01211	1
F ₁₈	0.001953	1	0.04135	1
F ₁₉	3.34E-11	1	1.59E-05	1
F ₂₀	1.60E-07	1	1.96E-06	1
F ₂₁	3.02E-11	1	3.73E-24	1
F ₂₂	3.02E-11	1	9.83E-19	1
F ₂₃	3.02E-11	1	4.03E-16	1

Table 3.7(d): Execution time using **hSMA-RES** algorithm for FD benchmarks

Function	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
F ₁₄	1.28125	1.30885	1.375
F ₁₅	0.40625	0.44115	0.48438
F ₁₆	0.375	0.39531	0.42188
F ₁₇	0.35938	0.3776	0.45313
F ₁₈	0.35938	0.38177	0.48438
F ₁₉	0.42188	0.44167	0.46875
F ₂₀	0.46875	0.48958	0.51563
F ₂₁	0.45313	0.47604	0.51563
F ₂₂	0.48438	0.5151	0.57813
F ₂₃	0.5	0.5276	0.57813

The statistical analysis of the proposed memetic algorithms shown in Tables 3.2(b), 3.3(b), 3.4(b) and Tables 3.5(b), 3.6(b) and 3.7(b) are depicted using the box plots. **Box plots** known as **box-whisker plots** are used to represent the graphical image of the data during different runs with extreme values and their deviation. The minimum-maximum values, median and 1st, 2nd and 3rd quartiles observed in statistical analysis are required for box plot and represented in Fig. 3.18(a) and 3.18(b) used for analyzing the closeness of data values for different test functions using HHO, SMA, hHHO-RES and hSMA-RES. The performance of the proposed memetic algorithms-hHHO-RES and hSMA-RES are verified by comparing the results (mean and standard deviation (SD)) with other well-known algorithms.

The comparison of unimodal (UM) benchmark functions with other recently developed metaheuristics algorithms GWO [172], GSA [174], FEP [260], ALO [148], SMS [265], BA [149], FPA [169], CS [266][167], FA [267], GA [263], GOA [170], MFO [184], BA [257], MVO [185], DA [162], BDA [162], BPSO [259], BGSA [159], SCA [220], BA [149], FPA [268], SSA [196], FEP [260], and WOA [261] in terms of average and standard deviation are shown in Table 3.8 and the convergence curve with comparison to other algorithms is shown in Fig. 3.19.

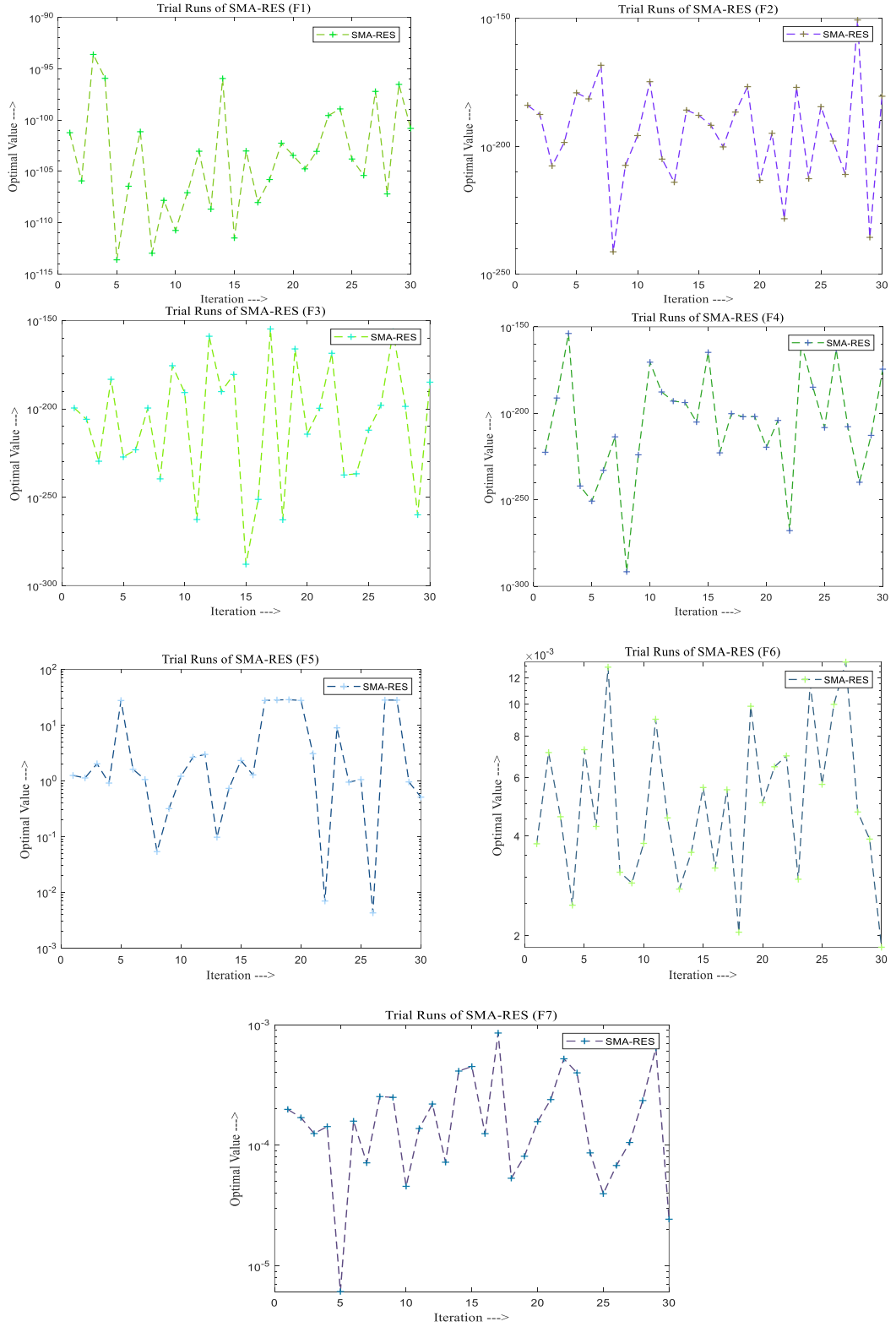


Fig 3.15: Trial Runs using hSMA-RES for unimodal (F₁-F₇) Benchmark Functions

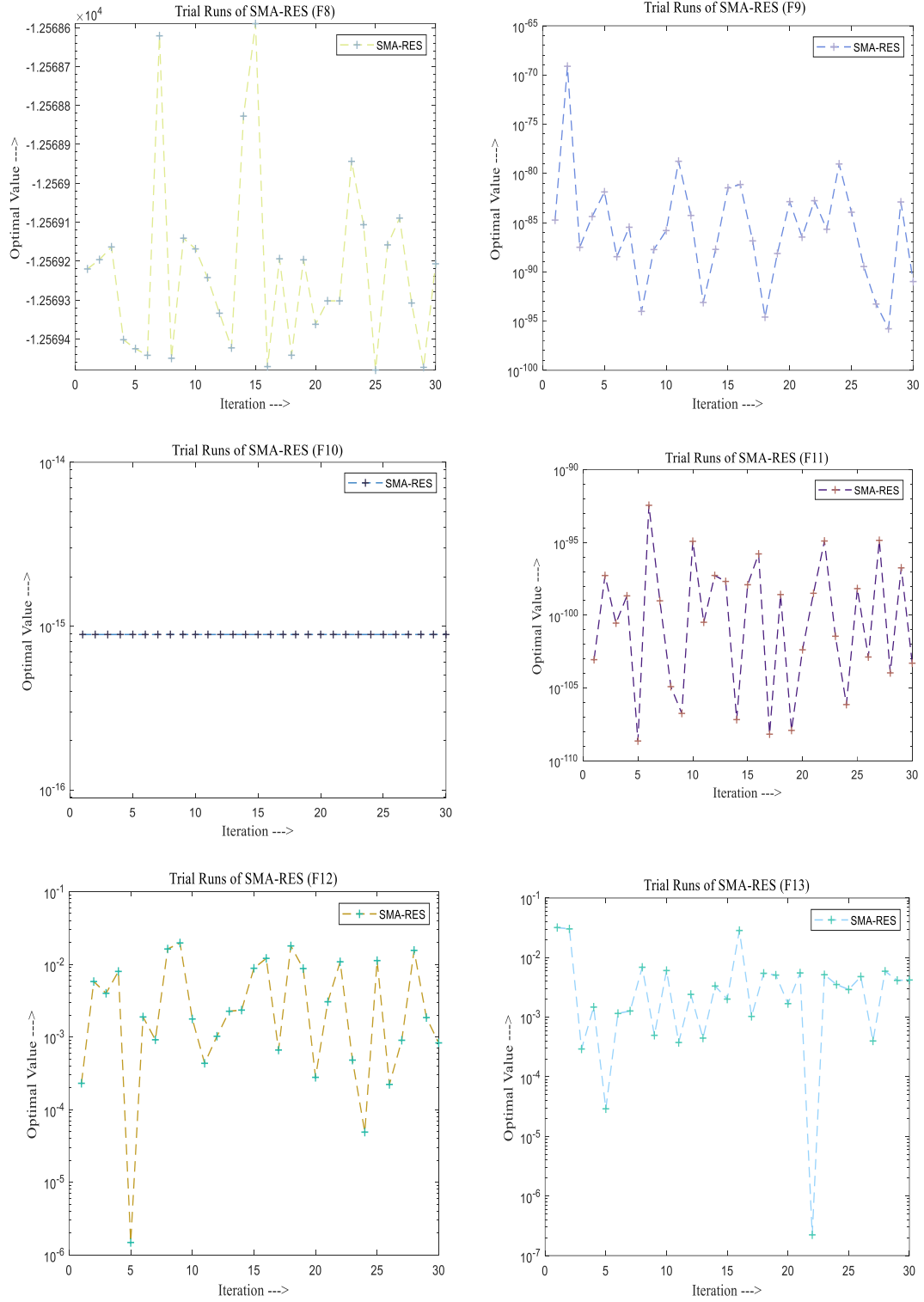


Fig 3.16: Trial Runs using hSMA-RES for Multimodal (F₈-F₁₃) Benchmark Functions

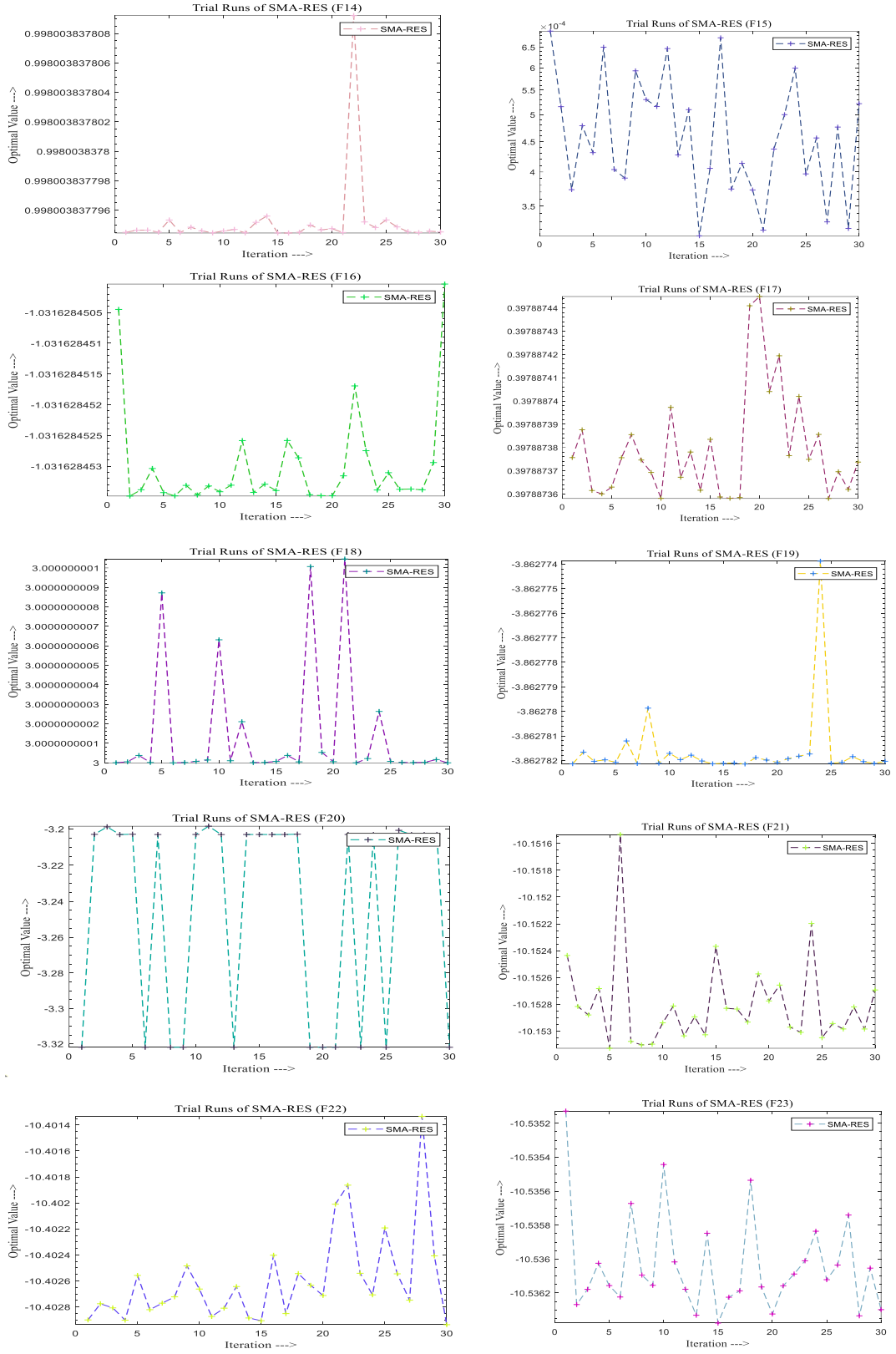


Fig 3.17: Trial Runs using hSMA-RES for Fixed Dimension(F₁₅-F₂₃) Benchmarks

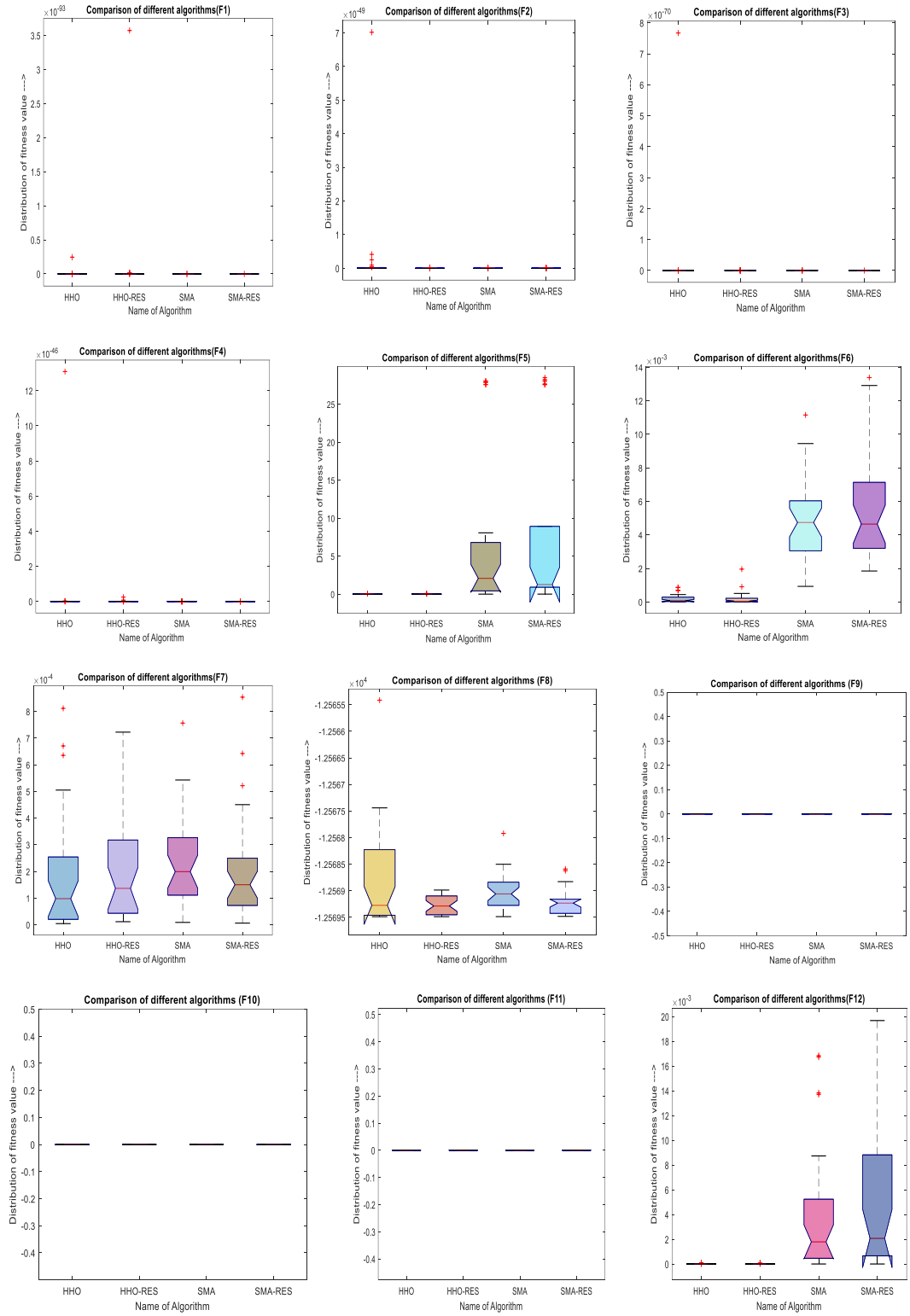


Fig 3.18(a): Box Plot for Benchmark Functions (F₁-F₁₂)

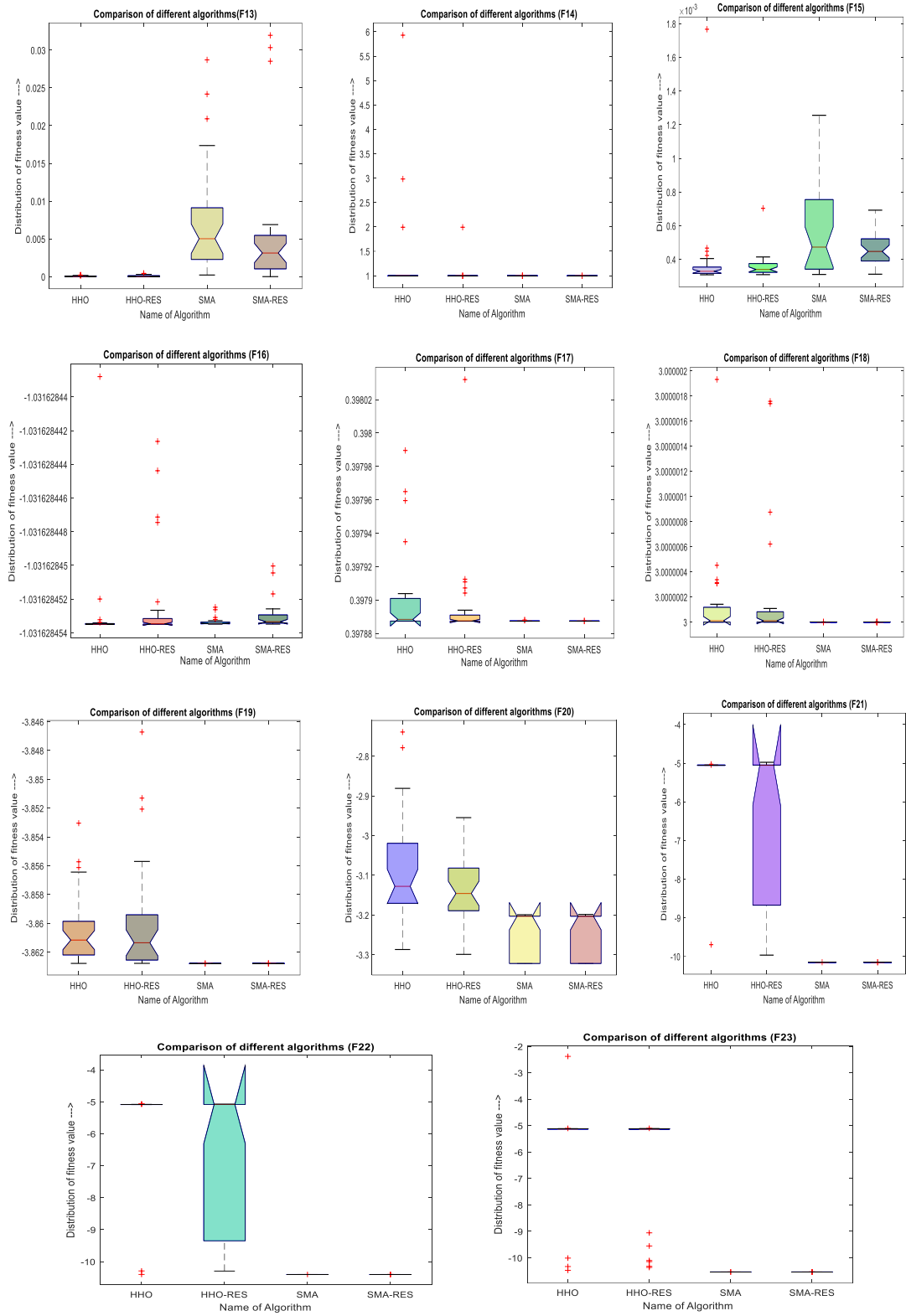


Fig 3.18(b): Box Plot for Benchmark Functions (F₁₃-F₂₃)

Table 3.8: Comparison of Unimodal (UM) benchmarks

Method	Mean/ SD	Uni-Modal (UM) Benchmark Functions						
		F ₁	F ₂	F ₃	F ₄	F ₅	F ₆	F ₇
GSA[174]	Mean	2.53E-16	0.055655	896.54	7.35487	67.5431	2.50E-16	0.08944
	SD	9.67E-17	0.194074	318.96	1.741452	62.2253	1.74E-16	0.04339
BGSA[159]	Mean	4.65 E-5	0.0016	26.29	1.28	3.8456	0.4584	0.0025
	SD	0.0	1.49E-07	4.64E+03	15.56	2.0474	0.0386	2.04E-06
PSO[269]	Mean	1.36E-04	0.042144	70.12562	1.086481	96.7183	0.0001	1.23E-01
	SD	0.0002	0.045421	22.11924	0.317039	60.1156	8.28E-05	0.04496
BPSO[270]	Mean	5.58903	0.196191	15.51722	1.895313	86.4463	6.98052	0.01175
	SD	1.97734	0.052809	13.68939	0.483579	65.8251	3.84911	0.00693
DA[258]	Mean	2.85E-18	1.49E-05	1.29E-06	0.000988	7.6	4.17E-16	0.01029
	SD	7.16E-18	3.76E-05	2.10E-06	0.002776	6.79	1.32E-15	0.00469
BDA[258]	Mean	0.281519	0.058887	14.23555	0.247656	23.5534	0.09531	0.01221
	SD	0.41772	0.069279	22.68806	0.330822	34.6822	0.12968	0.01462
GWO[172]	Mean	6.59E-28	7.18E-17	3.29E-06	5.61E-07	26.8126	0.81659	0.00221
	SD	6.34E-05	0.029014	79.14958	1.315088	69.905	0.00013	0.10029
MFO[184]	Mean	0.000117	0.000639	696.73	70.69	139.15	0.00011	0.09116
	SD	0.00015	0.000877	188.53	5.28	120.26	9.87E-05	0.04642
ALO[148]	Mean	2.59E-10	1.84E-06	6.07E-10	1.36E-08	0.35	0.34677	0.00429
	SD	1.65E-10	6.58E-07	6.34E-10	1.81E-09	0.11	0.10958	0.00509
FEP [260]	Mean	0.00057	0.0081	0.016	0.3	5.06	0.0	0.1415
	SD	0.00013	0.00077	0.014	0.5	5.87	0.0	0.3522
GOA [170]	Mean	0.0	0.002	0.001	0.0	0.0	0.0	0.0
	SD	0.0	0.001	0.0203	0.0	0.0	0.0	0.0
SCA[220]	Mean	0.0	0.0	0.0371	0.0965	0.0005	0.0002	0.0
	SD	0.0	0.0001	0.1372	0.5823	0.0017	0.0001	0.0014
MVO[271]	Mean	2.08583	15.92479	453.2	3.123005	1272.13	2.29495	0.05199
	SD	0.648651	44.7459	177.0973	1.582907	1479.48	0.63081	0.02961
SSA[196]	Mean	0.0	0.23	0.0	0.0	0.0	0.0	0.0028
	SD	0.0	1	0.0	0.66	0.0	0.0	0.0
WOA[269]	Mean	1.41E-30	1.06E-21	5.39E-07	0.072581	27.8656	3.11627	0.00143
	SD	4.91E-30	2.39E-21	2.93E-06	0.39747	0.76363	0.53243	0.00115
DE[269]	Mean	8.20E-14	1.50E-09	6.80E-11	0.0	0.0	0.0	0.00463
	SD	5.90E-14	9.90E-17	7.40E-11	0.0	0.0	0.0	0.0012
SCO[275]	Mean	0.0	0.0	7.94E-123	3.28E-20	2.85E+01	2.63E-01	2.87E-0-
	SD	0.0	0.0	4.35E-122	1.80E-19	9.48E-02	9.2E-02	2.69E-
GJO [102]	Mean	6.3E-41	2.23E-23	1.51E-20	1.28E-15	4.23E+00	1.91E-	0.000777
	SD	1.51E-40	4.3E-23	3.53E-20	1.27E-15	4.31E-01	3.81E-02	0.00065
HHO	Mean	3.95E-97	1.56E-51	1.92E-63	1.02E-47	1.32E-02	1.15E-04	1.40E-04
	SD	1.72E-96	6.98E-51	5.00E-64	5.01E-47	1.87E-02	1.56E-04	1.07E-04
SMA	Mean	5.90E-288	7.00E-142	8.39E-289	5.93E-157	7.11081	0.00473	0.00023
	SD	0.0	3.80E-141	0.0	3.12E-156	10.6984	0.00238	0.00017
hHHO-RES	Mean	1.20E-94	1.04E-52	3.80E-74	1.21E-48	0.01397	0.00019	0.00018
	SD	6.52E-94	3.72E-52	1.52E-73	4.72E-48	0.02046	0.00039	0.00018
hSMA-RES	Mean	0.0	7.90E-153	0.0	4.81E-156	7.6932	0.00569	0.00021
	SD	0.0	4.33E-152	0.0	2.63E-155	11.4869	0.00319	0.0002

Table 3.9: Comparison of Multi-Modal (MM) benchmarks

Method	Mean/ SD	Multi-Modal (MM) Benchmark Functions					
		F ₈	F ₉	F ₁₀	F ₁₁	F ₁₂	F ₁₃
GOA [170]	Mean	1	0	0.0975	0	0	0
	SD	0.0002	0.0007	1	0	0.0007	0
GWO[172]	Mean	-5.97E+03	2.19E+00	1.03E-13	8.57E-03	4.83E-02	5.96E-01
	SD	7.10E+02	3.69E+00	1.70E-14	0.006659	2.12E-02	2.23E-01
PSO[272]	Mean	-3.86E+03	2.87E+02	1.75E+01	1.70E+02	1.51E+07	5.73E+07
	SD	2.49E+02	1.95E+01	3.67E-01	3.17E+01	9.88E+06	2.68E+07
GA[263]	Mean	-1.26E+04	9.04E+00	1.36E+01	1.01E+01	4.77E+00	1.52E+01
	SD	4.51E+00	4.58E+00	1.51E+00	2.43E+00	1.56E+00	4.52E+00
BBO[273]	Mean	-1.24E+04	0.00E+00	2.13E+00	1.46E+00	6.68E-01	1.82E+00
	SD	3.50E+01	0.00E+00	3.53E-01	1.69E-01	2.62E-01	3.41E-01
FPA[268]	Mean	-6.45E+03	1.82E+02	7.14E+00	1.73E+01	3.05E+02	9.59E+04
	SD	3.03E+02	1.24E+01	1.08E+00	3.63E+00	1.04E+03	1.46E+05
BAT[257]	Mean	-2.33E+03	1.92E+02	1.92E+01	6.01E+02	4.71E+08	9.40E+08
	SD	2.96E+02	3.56E+01	2.43E-01	5.50E+01	1.54E+08	1.67E+08
FA[267]	Mean	-5.85E+03	3.82E+01	4.58E-02	4.23E-03	3.13E-04	2.08E-03
	SD	1.16E+03	1.12E+01	1.20E-02	1.29E-03	1.76E-04	9.62E-04
CS[266]	Mean	-5.19E+19	1.51E+01	3.29E-02	4.29E-05	5.57E-05	8.19E-03
	SD	1.76E+20	1.25E+00	7.93E-03	2.00E-05	4.96E-05	6.74E-03
MFO[184]	Mean	-8.48E+03	1.59E+02	1.74E+01	3.10E+01	2.46E+02	2.73E+07
	SD	7.98E+02	3.21E+01	4.95E+00	5.94E+01	1.21E+03	1.04E+08
GSA[174]	Mean	2821.07	25.97	0.06	27.7	1.8	8.9
	SD	493.04	7.47	0.24	5.04	0.95	7.13
SCO [275]	Mean	-8.25E+03	0	8.88E-16	0	2.60E-02	1.45E+00
	SD	5.86E+02	0	0	0	3.77E-02	591E-01
GJO [102]	Mean	-2298.22	0.604591	4.8E-15	0.01321	0.038206	1.30E-01
	SD	288.66	3.311	1.8E-15	0.039472	0.0185	9.59E-02
SMS [148]	Mean	-4.20735	1.32512	8.88E_06	0.70609	0.12334	1.35E_02
	SD	9.36E_16	0.326239	8.56E_09	0.907954	0.040898	2.88E_04
FEP [260]	Mean	-12554.5	0.05	0.02	0.02	0	0
	SD	52.6	0.01	0	0.02	0	0
ALO[148]	Mean	-1606.27643	0.273294621	0.007398721	0.0850216	0.0002657	3.67E-06
	SD	314.4302	0.068583	0.007096	0.040046	0.000553	3.51E-06
DA[162]	Mean	-2857.58	16.0188	0.23103	0.193354	0.031101	0.002197
	SD	383.6466	9.479113	0.487053	0.073495	0.098349	0.004633
HHO	Mean	-1.25E+04	0.00E+00	8.88E-16	0.00E+00	2.08E-06	1.57E-04
	SD	4.70E+01	0.00E+00	4.01E-31	0.00E+00	1.19E-05	2.15E-04
SMA	Mean	-12569.02	0.00E+00	8.88E-16	0	0.003921	0.007072
	SD	0.3565797	0.00E+00	0	0	0.005046	0.007286
hHHO-RES	Mean	-12569.27	0.00E+00	8.88E-16	0	9.50E-06	8.08E-05
	SD	0.1830129	0.00E+00	0	0	1.82E-05	0.0001241
hSMA-RES	Mean	-12569.22	0.00E+00	8.88E-16	0	0.005266	0.0055653
	SD	0.2312986	0	0	0	0.0060793	0.0086447

The comparison of multi-modal benchmark functions with other recently developed metaheuristics algorithms like GWO, GSA, FEP, ALO, SMA, FPA, CS, FA, BA, GOA, DA, GJO, SCO, etc in terms of average and standard deviation are shown in Table 3.9 and the convergence curve with comparison to other algorithms is shown in Fig. 3.20.

Table 3.10(a): Comparison of Fixed-Dimension (FD) benchmarks (F_{14} – F_{18})

Method	Mean/ SD	Fixed Dimension (FD) Benchmark Functions				
		F_{14}	F_{15}	F_{16}	F_{17}	F_{18}
GWO[274]	Mean	4.04	0	-1.03	3.98E-01	3
	SD	4.25	0	6.78E-16	1.69E-16	4.07E-05
PSO[274]	Mean	3.63	0	-1.03E+00	4.00E-01	3.10E+00
	SD	2.56	0	2.95E-03	1.39E-03	7.60E-02
GSA [274]	Mean	5.86	0	-1.03E+00	0.4	3
	SD	3.83	0	0	0	0
DE [274]	Mean	1	0	-1.03E+00	3.98E-01	3
	SD	0	0	6.78E-16	1.69E-16	0.00E+00
FEP [274]	Mean	1.22	0	1.03	0.4	3.02
	SD	0.56	0	0	0	0.11
GA[272]	Mean	9.98E-01	3.33E-02	-3.78E-01	5.24E-01	3.00E+00
	SD	4.52E-16	2.70E-02	3.42E-01	6.06E-02	0.00E+00
BBO[272]	Mean	9.98E-01	1.66E-02	-8.30E-01	5.49E-01	3.00E+00
	SD	4.52E-16	8.60E-03	3.16E-01	6.05E-02	0.00E+00
FPA[272]	Mean	9.98E-01	6.88E-04	-1.03E+00	3.98E-01	3.00E+00
	SD	2.00E-04	1.55E-04	6.78E-16	1.69E-16	0.00E+00
BAT[272]	Mean	1.27E+01	3.00E-02	-6.87E+00	3.98E-01	1.47E+01
	SD	6.96E+00	3.33E-02	8.18E-01	1.69E-16	2.21E+01
FA[272]	Mean	3.51E+00	1.01E-03	-1.03E+00	3.98E-01	3.00E+00
	SD	2.16E+00	4.01E-04	6.78E-16	1.58E-03	0.00E+00
CS[272]	Mean	1.27E+01	3.13E-04	-1.03E+00	3.98E-01	3.00E+00
	SD	1.81E-15	2.99E-05	6.78E-16	1.69E-16	0.00E+00
MFO[272]	Mean	2.74E+00	2.35E-03	-1.03E+00	3.98E-01	3.00E+00
	SD	1.82E+00	4.92E-03	6.78E-16	1.69E-16	0.00E+00
TLBO[272]	Mean	9.98E-01	1.03E-03	-1.03E+00	3.98E-01	3.00E+00
	SD	4.52E-16	3.66E-03	6.78E-16	1.69E-16	0.00E+00
SCO [275]	Mean	1.09E+00	4.53E-03	-1.03E+00	3.97E-01	3.00E+00
	SD	3.03E-01	1.15E-02	6.77E-08	6.00E-08	8.16E-08
GJO [102]	Mean	3.23E+00	1.40E-03	-1.03163	3.98E-01	3.00E+00
	SD	2.70E+00	1.47E-04	1.63E-06	1.88E-03	3.41E-05
HHO[272]	Mean	9.98E-01	3.10E-04	-1.03E+00	3.98E-01	3.00E+00
	SD	9.23E-01	1.97E-04	6.78E-16	2.54E-06	0.00E+00
SMA	Mean	0.9980038	0.0005506	-1.0316285	0.3978874	3
	SD	1.26E-12	0.0002552	2.34E-10	1.39E-07	2.91E-10
hHHO-RES	Mean	1.0311381	0.00036	-1.03163	0.3979	3
	SD	0.1814837	7.10E-05	2.90E-09	2.70E-05	4.65E-07
hSMA-RES	Mean	1.0311381	0.000469	-1.0316285	0.3978874	3
	SD	0.1814837	0.0001092	8.43E-10	2.32E-08	3.10E-10

Table 3.10(b): Comparison of Fixed-Dimension (FD)benchmark functions(F_{19} – F_{23})

Method	Mean/ SD	Fixed- Dimension (FD) Benchmark Functions				
		F_{19}	F_{20}	F_{21}	F_{22}	F_{23}
GWO[274]	Mean	-3.86	-3.25866	-8.64121	-10.4014	-10.0836
	SD	3.14E-03	0.064305	2.563356	0.000678	1.721889
PSO[274]	Mean	-3.86E+00	-3.11088	-4.14764	-6.01045	-4.72192
	SD	1.24E-03	0.029126	0.919578	1.962628	1.742618
GSA [35]	Mean	-3.86E+00	3.32	5.96	9.68	10.54
	SD	0	0.02	3.74	2.01	0
DE [274]	Mean	-3.86E+00	-3.27048	-9.64796	-9.74807	-10.5364
	SD	3.16E-15	0.058919	1.51572	1.987703	8.88E-15
FEP [274]	Mean	-3.86	3.27	5.52	5.53	6.57
	SD	0	0.06	1.59	2.12	3.14
GA[272]	Mean	-3.42	-1.61351	-6.66177	-5.58399	-4.69882
	SD	3.03E-01	0.46049	3.732521	2.605837	3.256702
BBO[272]	Mean	-3.78E+00	-2.70774	-8.32E+00	-9.38408	-6.2351
	SD	1.26E-01	0.357832	2.883867	2.597238	3.78462
FPA[272]	Mean	-3.86E+00	-3.2951	-5.21514	-5.34373	-5.29437
	SD	3.16E-15	0.019514	0.008154	0.053685	0.356377
BAT[272]	Mean	-3.84E+00	-3.2546	-4.2661	-5.60638	-3.97284
	SD	1.41E-01	0.058943	2.554009	3.022612	3.008279
FA[272]	Mean	-3.86E+00	-3.28105	-7.67362	-9.63827	-9.75489
	SD	3.16E-15	0.063635	3.50697	2.293901	2.345487
CS[272]	Mean	-3.86E+00	-3.322	-5.0552	-5.0877	-5.1285
	SD	3.16E-15	1.78E-15	1.78E-15	8.88E-16	1.78E-15
MFO[272]	Mean	-3.86E+00	-3.23509	-6.8859	-8.26492	-28.27083
	SD	1.44E-03	0.064223	3.18186	3.076809	3.576927
TLBO[272]	Mean	-3.86E+00	-3.24362	-8.64525	-10.2251	-10.0752
	SD	3.16E-15	0.15125	1.76521	0.007265	1.696222
SCO [275]	Mean	-3.86E+00	-3.30E+00	-9.47E+00	-9.61E+00	-9.54E+00
	SD	6.99E-05	4.98E-02	1.76E+00	2.07E+00	2.28E+00
GJO [102]	Mean	-3.85894	-3.04444	-8.08247	-9.44915	-9.18821
	SD	0.0028	0.1627	2.259	2.252	2.8269
HHO[272]	Mean	-3.86E+00	-3.322	-10.1451	-10.4015	-10.5364
	SD	2.44E-03	0.137406	0.885673	1.352375	0.927655
SMA	Mean	-3.862782	-3.24242	-10.152853	-10.402476	-10.536075
	SD	2.07E-07	0.057221	0.0003098	0.0002699	0.0002861
hHHO-RES	Mean	-3.85982	-3.1267	-6.19852	-6.43305	-6.08279
	SD	0.00398	0.07794	1.96247	2.10408	1.96502
hSMA-RES	Mean	-3.8627816	-3.24629	-10.152803	-10.402599	-10.53604
	SD	1.52E-06	0.058588	0.0003288	0.000354	0.0002892

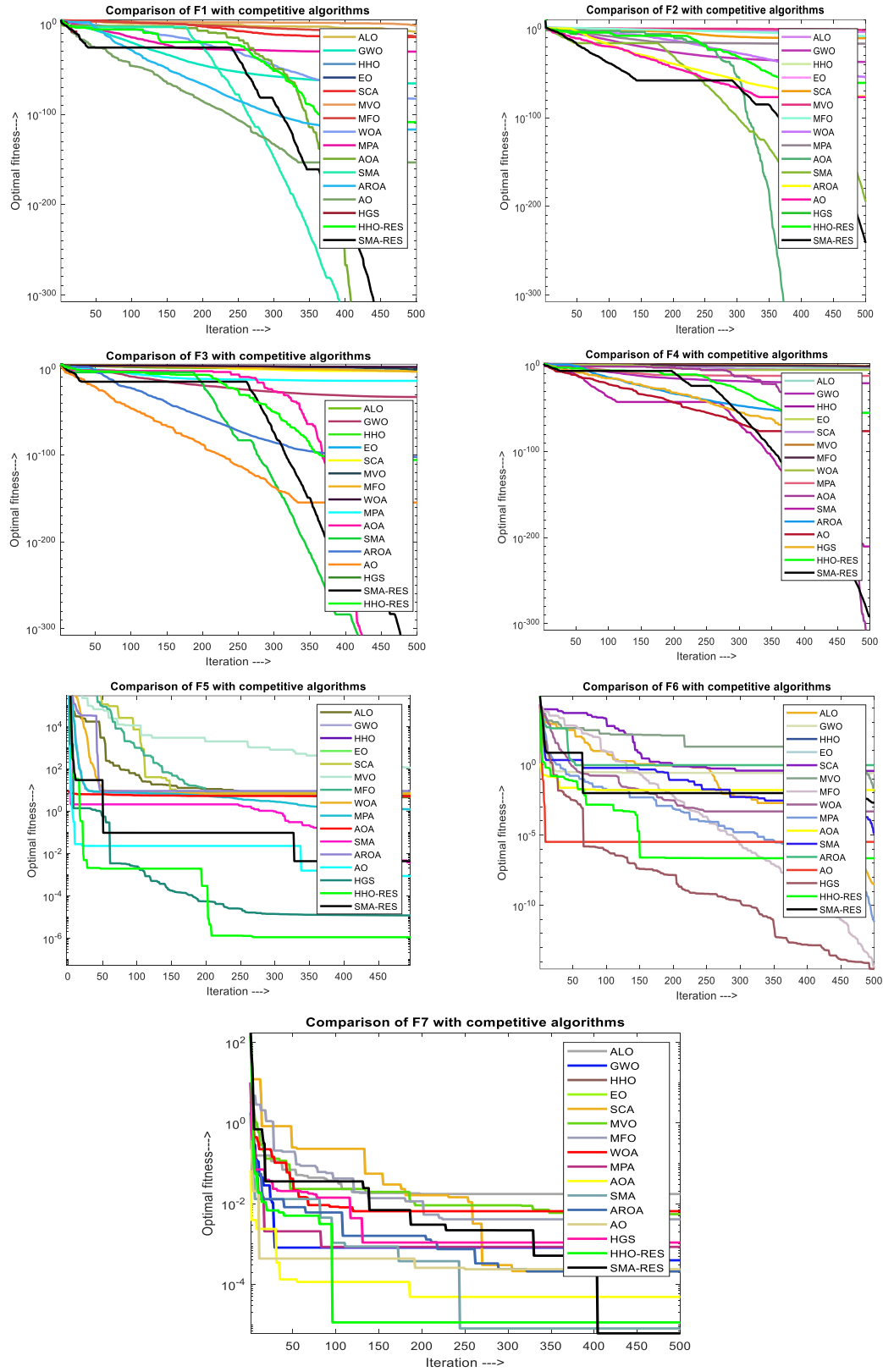


Fig. 3.19: Convergence Curves for Unimodal (UM) Benchmark Functions (F1-F7)

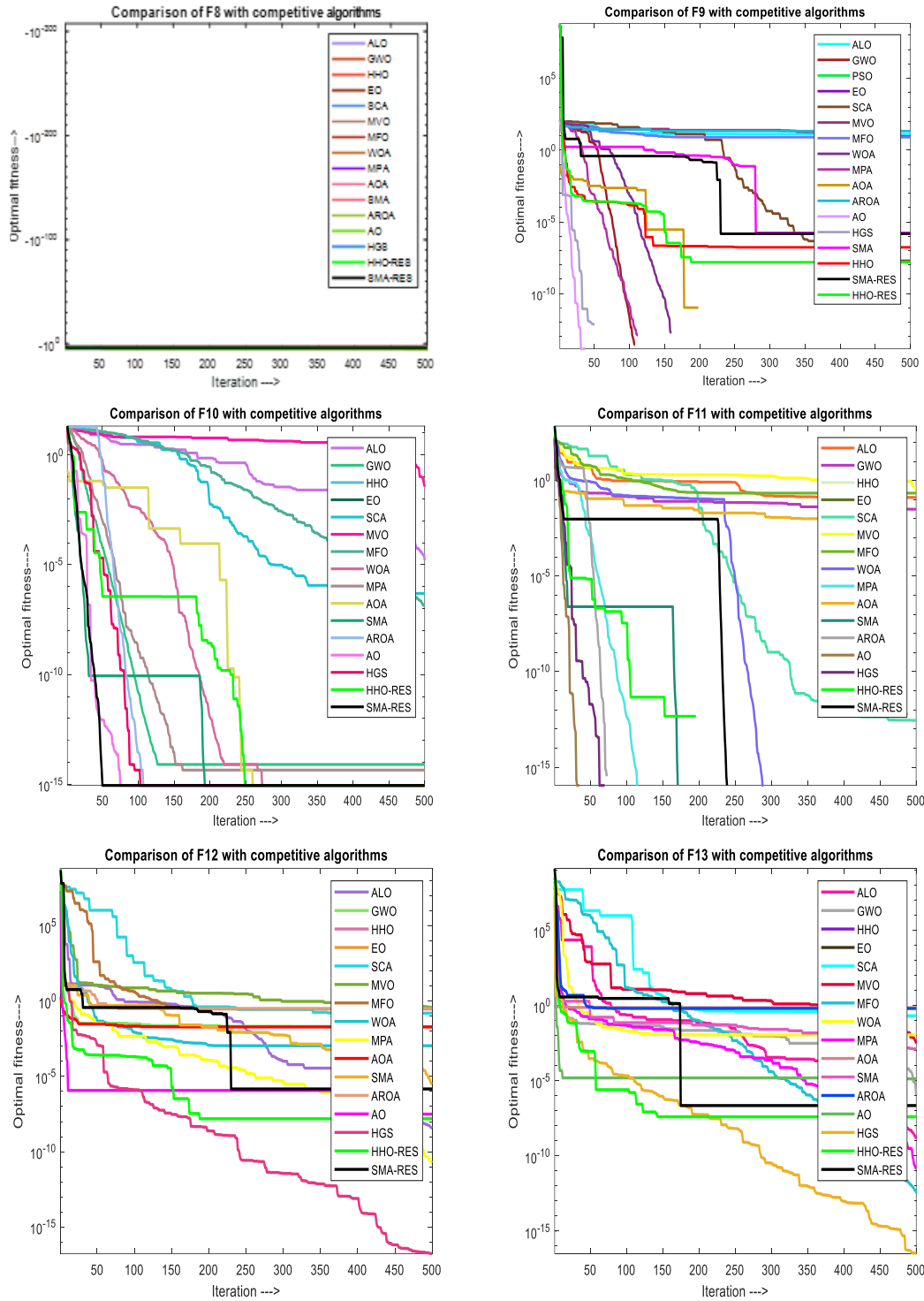


Fig 3.20: Convergence Curves for Multi-modal (MM) Benchmarks (F₈-F₁₃)

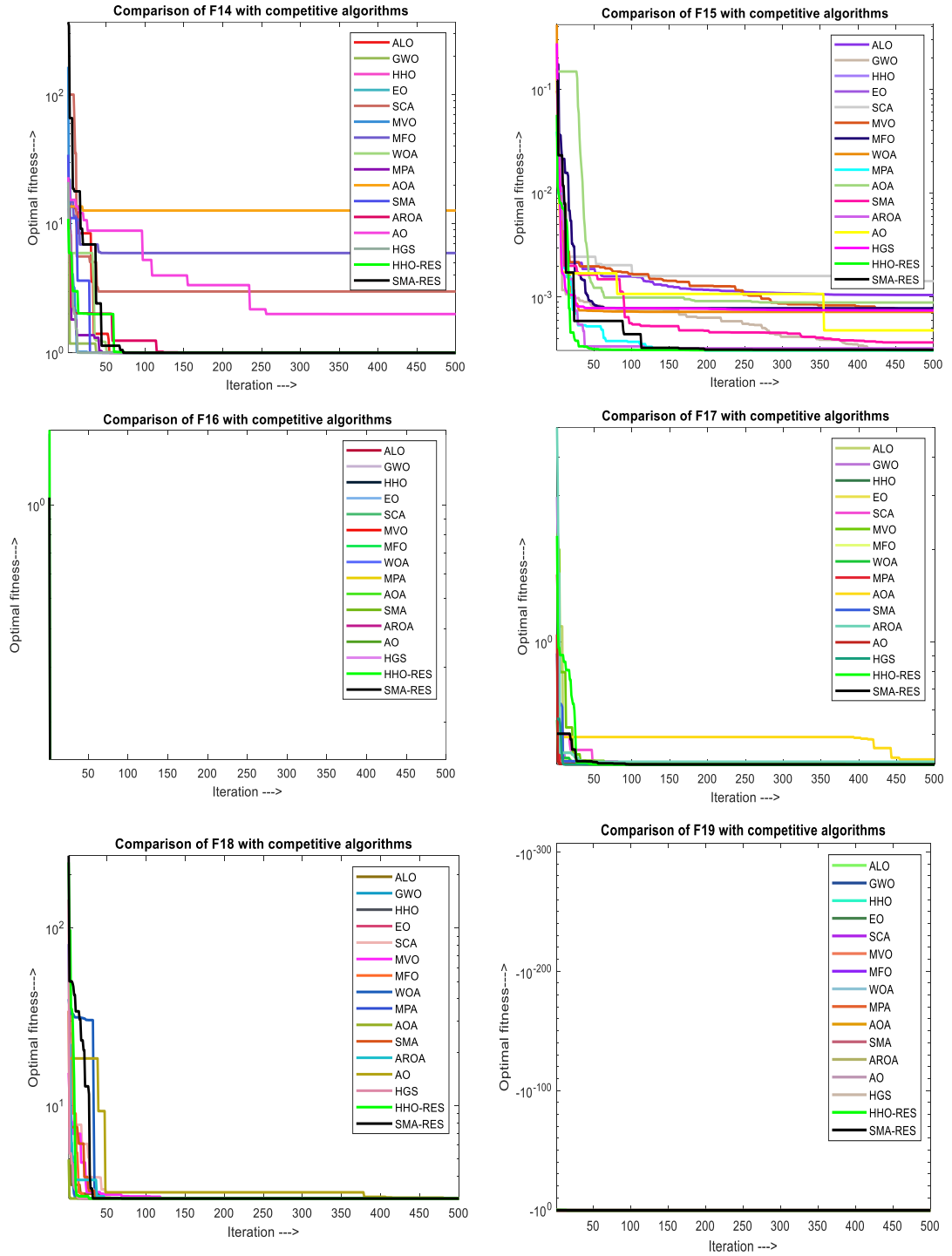


Fig 3.21(a): Convergence Curves for Fixed-Dimension (FD) Benchmarks (F₁₄-F₁₉)

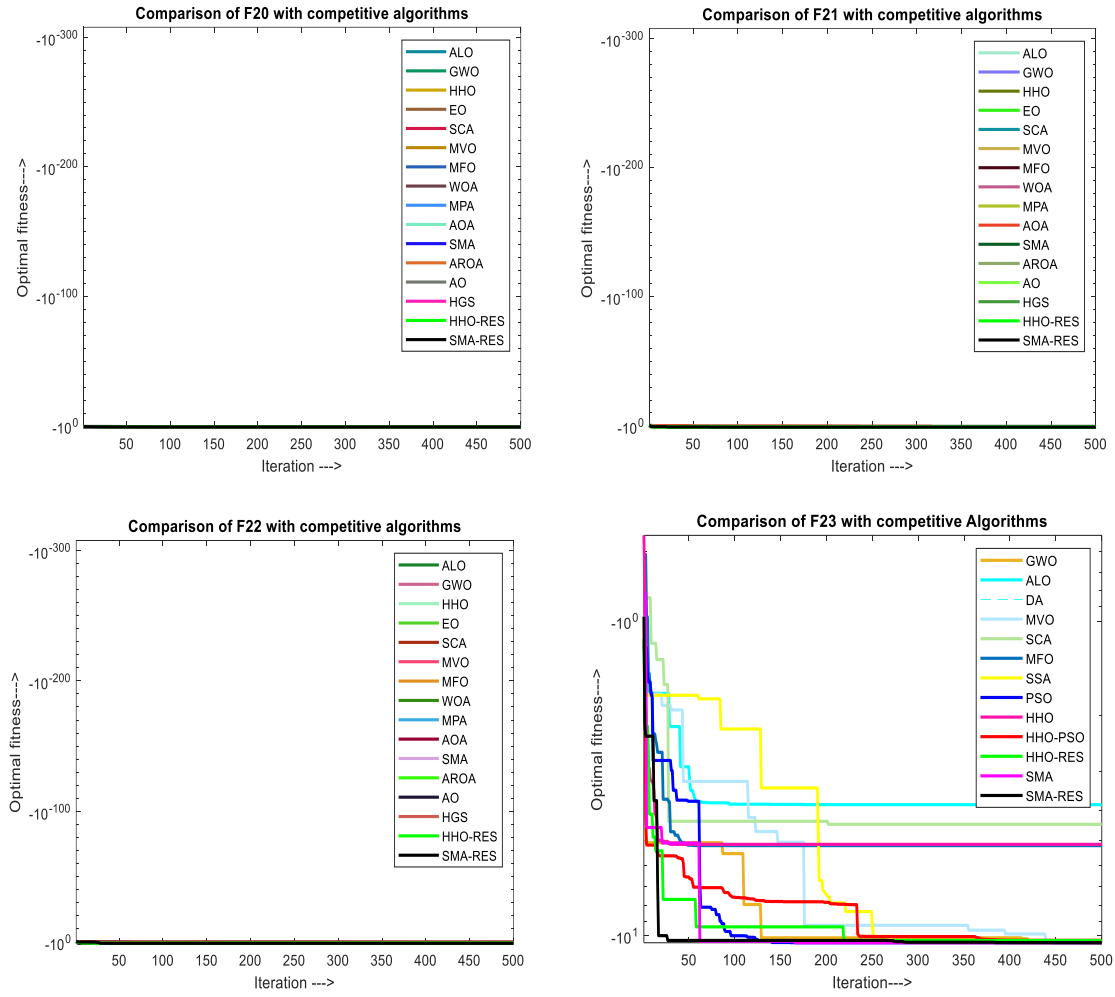


Fig 3.21(b): Convergence Curves for Fixed-Dimension (FD) Benchmarks (F₂₀-F₂₃)

The comparison of fixed-dimension (FD) benchmark functions with other recently developed MH algorithms like GWO, GSA, PSO, DE, CS, FA, MFO, TLOA, FPA, etc in regard to mean and standard deviation (SD) are shown in Table 3.10 and the convergence curve with comparison to other algorithms is shown in Fig. 3.21(a) and Fig. 3.21(b) and shows the competency of the proposed memetic algorithms.

3.6.2 Engineering Design Optimization Problems

This section discusses the outcomes of ten real-world engineering design problems mentioned in Table 3.1 and are tested using the proposed memetic approaches known as hHHO-RES and hSMA-RES. The design problems briefed in section 3.5 are simulated in MATLAB 2018a Windows 10, CPU (2.10 Ghz 4GB RAM Core i5)

processor environment. Test results are recorded with their best, mean, worst values, median and standard deviation (SD). The stochastic or random nature of complexity for the proposed memetic algorithms are investigated and justified by running the procedure for 30 independent trial runs and 500 maximum iterations. For statistical analysis of the proposed algorithm, the non-parametric test i.e. Wilcoxon rank-sum test has been taken into consideration at 0.05 significance level. The statistical significance has also been recorded using boxplot by evaluating the minimum, maximum, median values along with the 1st, 2nd and 3rd quartile values and no. of outliers for 30 trial runs.

Table 3.11(a): Results using hHHO-RES algorithm for ED problems

Engineering Design Problem	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
ED1	9	264.004	263.896	264.3632	263.9399	0.119602
ED2	14	3170.6	3029.11	3337.401	3173.261	87.94125
ED3	26	6687.49	6006.92	7335.803	6650.928	296.2704
ED4	10	0.01309	0.0127	0.01478	0.012917	0.000545
ED5	17	1.95535	1.74741	2.384857	1.890441	0.167895
ED6	11	82692.7	84714.5	72181.4	82982.7	2025.387
ED7	11	0.39716	0.38965	0.408251	0.395621	0.006062
ED8	1	0	0	0	0	0
ED10	9	1.30637	1.30451	1.30997	1.30634	0.001453
ED11	3	0.00663	0.00663	0.006626	0.006626	5.51E-17

The outcomes of different engineering design (ED) problems using memetic HHO approach (hHHO-RES) and memetic SMA approach (hSMA-RES) is compiled in Table-3.11(a) and 3.12(a) respectively; representing the best, worst and mean values with median and standard deviation (SD) for the ED optimization problems considered in this work. The statistical analysis using the proposed memetic HHO and SMA is depicted in Table-3.11(b) and 3.12(b) respectively with the evaluations of 1st, 2nd and 3rd quartiles with SD and no. of outliers.

Table 3.11(b): Statistical Analysis using hHHO-RES for ED Problems

Engineering Design Problem	No. of trials	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25th Percentile)	2 nd quartile (50th Percentile)	3 rd quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
ED1	30	263.9	264.36	264	263.94	263.914	263.9	264.076	0.0809	0	0.1196
ED2	30	3029	3337.4	3171	3173.26	3097.21	3173	3231.053	66.922	0	87.941
ED3	30	6007	7335.8	6687	6650.93	6538.11	6651	6819.832	140.86	0	296.27
ED4	30	0.013	0.0148	0.013	0.01292	0.01283	0.013	0.01302	9.60E-05	3	0.0005
ED5	30	1.747	2.3849	1.955	1.89044	1.8471	1.89	2.02693	0.0899	0	0.1679
ED6	30	-84714	-72181	-82693	-82983	-83196	-82983	-82854.3	170.78	3	2025.4
ED7	30	0.39	0.4083	0.397	0.39562	0.39244	0.396	0.402676	0.0051	0	0.0061
ED8	30	0	0	0	0	-	0	-	-	0	0
ED10	30	1.305	1.31	1.306	1.30634	1.30526	1.306	1.306986	0.0009	0	0.0015
ED11	30	0.007	0.0066	0.007	0.00663	0.00663	0.007	0.006626	2.60E-17	1	6.00E-17

Table 3.11(c): Test observations using hHHO-RES algorithm for ED Problems

Engineering Design Problem	Wilcoxon Rank sum Test		T-Test	
	p-value	h-value	p-value	h-value
ED1	0.46427291	0	0.03871466	1
ED2	0.00100353	1	8.77E-05	1
ED3	0.00831461	1	0.01138375	1
ED4	0.06567126	0	0.03192848	1
ED5	0.11881734	0	0.11132064	0
ED6	1.4294E-08	1	0.00015831	1
ED7	0.00018916	1	0.00011055	1
ED8	NA	0	NA	0
ED10	0.02236015	1	0.00473252	1
ED11	0.82911289	0	0.26617394	0

The p and h values using the non-parametric tests (t-test and rank sum test) for proposed memetic algorithms are presented in Table 3.11(c) and 3.12 (c) with the execution time for the proposed methods tabulated in Table 3.11(d) and 3.11(d) . The stochastic or random nature of complexity for the proposed memetic hHHO-RES and hSMA-RES is examined and justified by running the procedure for 30 independent trial runs with 500 maximum iterations as represented in Fig. 3.22 and Fig. 3.23 respectively. The box plots representing the statistical analysis for the proposed methods are also shown in Fig. 3.24

Table 3.11(d): Execution time using hHHO-RES algorithm for ED Problems

Engineering Design Problem	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
ED1	0.1875	0.2734375	0.859375
ED2	0.296875	0.342708333	0.5
ED3	0.203125	0.221875	0.234375
ED4	0.21875	0.24375	0.296875
ED5	0.234375	0.259895833	0.3125
ED6	0.40625	0.472395833	0.6875
ED7	0.25	0.277083333	0.3125
ED8	0.140625	0.170833333	0.28125
ED10	0.234375	0.258854167	0.296875
ED11	0.21875	0.2421875	0.28125

Table 3.12(a): Results using hSMA-RES algorithm for ED problems

Engineering Design Problem	Index	Mean Fitness	Best Fitness	Worst Fitness	Median	SD
ED1	16	266.0720598	264.2695251	268.8317056	265.968348	1.275792634
ED2	17	2994.487888	2994.472329	2994.607727	2994.48251	0.025201959
ED3	7	6204.649745	5887.280247	7075.181214	6147.51688	275.8759839
ED4	17	0.012836026	0.012673456	0.013196529	0.01283343	0.000116132
ED5	9	1.773116743	1.724995128	2.164078109	1.72819176	0.120533444
ED6	4	-85536.784	-85539.1655	-85511.3841	-85538.5338	6.084668178
ED7	6	0.391191519	0.389653942	0.40465955	0.38992874	0.003013524
ED8	25	6.65E-12	4.38E-16	3.21E-11	1.96E-12	9.07E-12
ED10	12	1.303618154	1.303301215	1.304575225	1.30351025	0.000320697
ED11	17	0.00662596	0.006625958	0.006625967	0.00662596	1.93E-09

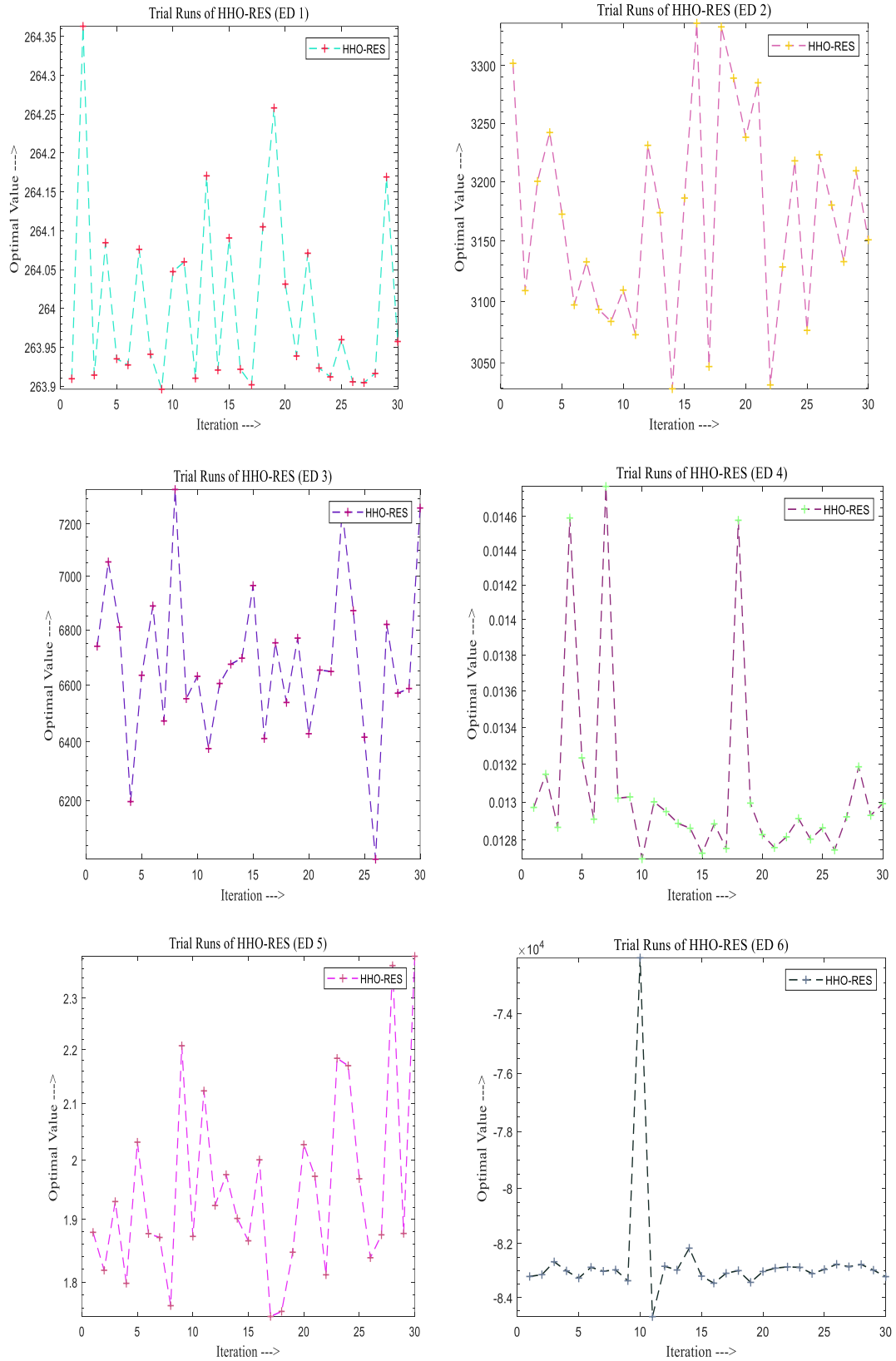


Fig 3.22(a): Trial runs using hHHO-RES for ED Problems (ED1 to ED6)

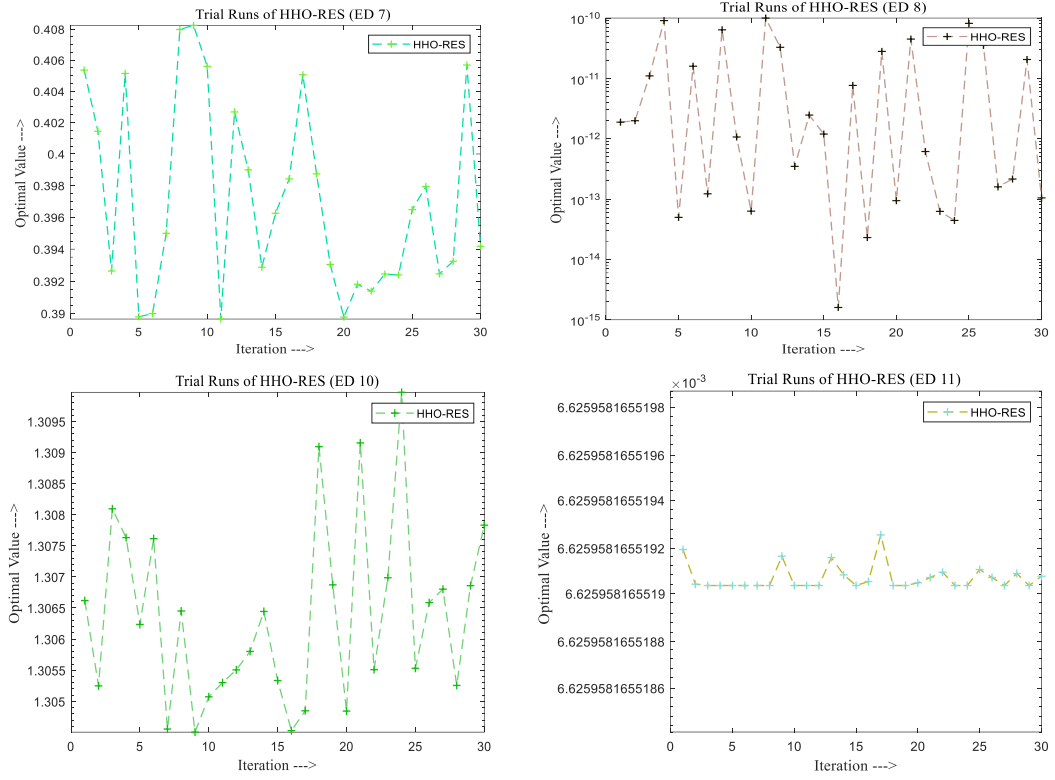


Fig 3.22 (b): Trial runs using hHHO-RES for ED problems (ED7 to ED11)

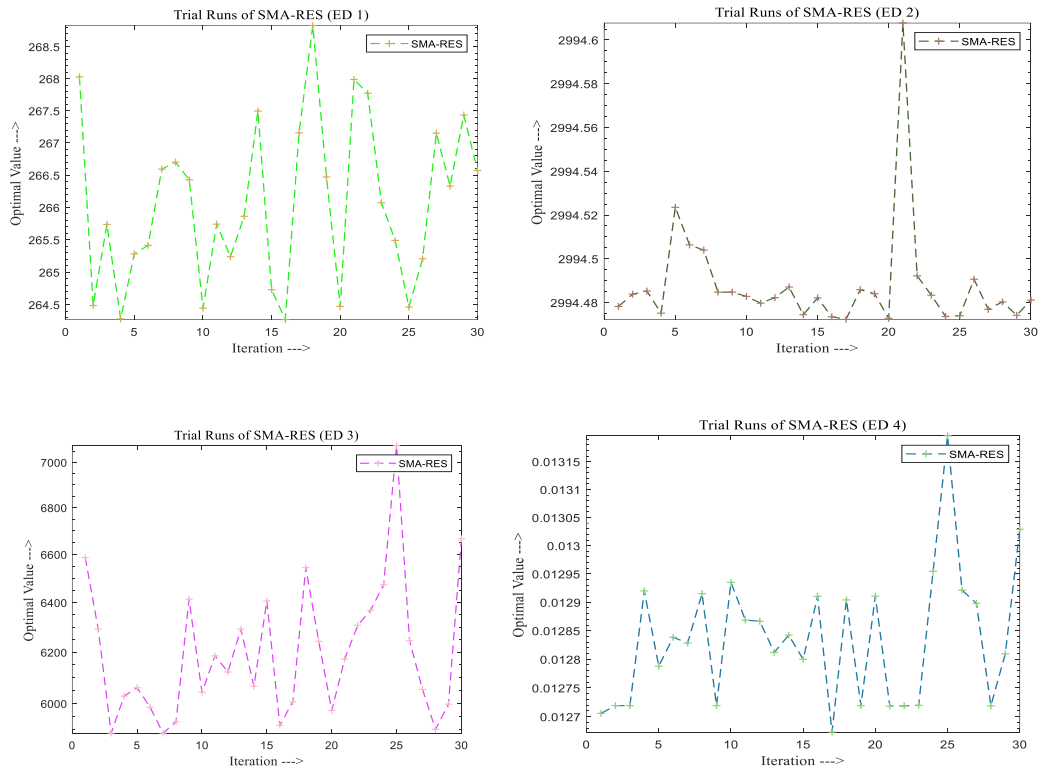


Fig 3.23(a): Trial runs using hSMA-RES for ED problems (ED1 to ED4)

Table 3.12(b): Statistical Analysis using hSMA-RES algorithm for ED problems

Engineering Design Problem	Minimum value	Maximum value	Mean Value	Median	1 st quartile (25th Percentile)	2 nd quartile (50th Percentile)	3 rd quartile (75th Percentile)	Semi Inter-quartile Dev.	No. of outliers	SD
ED1	264.27	268.832	266.072	265.968	265.207	265.968	267.1527	0.97281	0	1.27579
ED2	2994.47	2994.61	2994.49	2994.48	2994.48	2994.48	2994.486	0.00536	2	0.0252
ED3	5887.28	7075.18	6204.65	6147.52	5997.73	6147.52	6368.975	185.624	0	275.876
ED4	0.01267	0.0132	0.01284	0.01283	0.01272	0.01283	0.012911	9.57E-05	0	0.00012
ED5	1.725	2.16408	1.77312	1.72819	1.72607	1.72819	1.735677	0.0048	4	0.12053
ED6	-85539.2	-85511	-85537	-85539	-85539	-85539	-85538	0.51315	4	6.08467
ED7	0.38965	0.40466	0.39119	0.38993	0.38966	0.38993	0.390961	0.00065	3	0.00301
ED8	4.38E-16	3.21E-11	6.65E-12	1.96E-12	2.33E-13	1.96E-12	1.25E- 11	6.13E-12	0	9.07E-12
ED10	1.3033	1.30458	1.30362	1.30351	1.30339	1.30351	1.303713	0.00016	1	0.00032
ED11	0.00663	0.00663	0.00663	0.00663	0.00663	0.00663	0.006626	7.36E-10	2	1.93E-09

Table 3.12(c): Test observations using hSMA-RES algorithm for ED problems

Engineering Design Problem	Wilcoxon Rank sum Test		T-Test	
	p-value	h-value	p-value	h-value
ED1	2.3715E-10	1	1.4203E-08	1
ED2	3.0199E-11	1	1.0803E-06	1
ED3	4.998E-09	1	1.8018E-08	1
ED4	0.00023885	1	0.00185914	1
ED5	2.3897E-08	1	3.8431E-07	1
ED6	3.0199E-11	1	9.1624E-06	1
ED7	7.1186E-09	1	2.3661E-05	1
ED8	1.2118E-12	1	0.00038613	1
ED10	1.4643E-10	1	8.0997E-08	1
ED11	2.843E-11	1	0.00027632	1

Table 3.12(d): Execution time using hSMA-RES algorithm for ED problems

Engineering Design Problem	Best Time (Sec)	Average Time (Sec.)	Worst Time (Sec)
ED1	0.375	0.496354167	1.265625
ED2	0.515625	0.607291667	1.390625
ED3	0.40625	0.428645833	0.484375
ED4	0.390625	0.427083333	0.546875
ED5	0.4375	0.455208333	0.484375
ED6	0.578125	0.609895833	0.65625
ED7	0.453125	0.4703125	0.515625
ED8	0.390625	0.417708333	0.4375
ED10	0.453125	0.465104167	0.515625
ED11	0.40625	0.431770833	0.46875

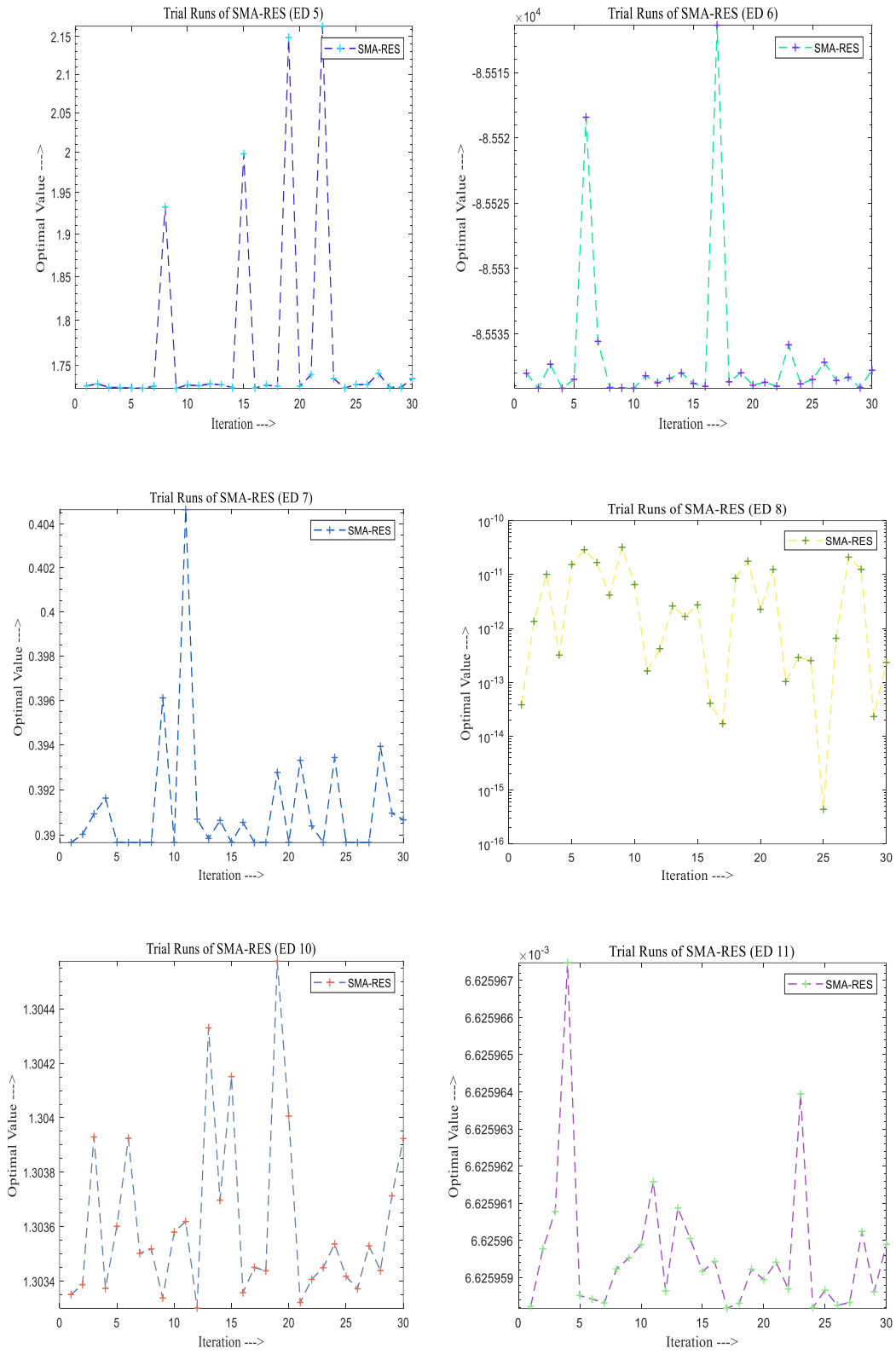


Fig 3.23(b): Trial runs using hHHO-RES for ED problems (ED5 to ED11)

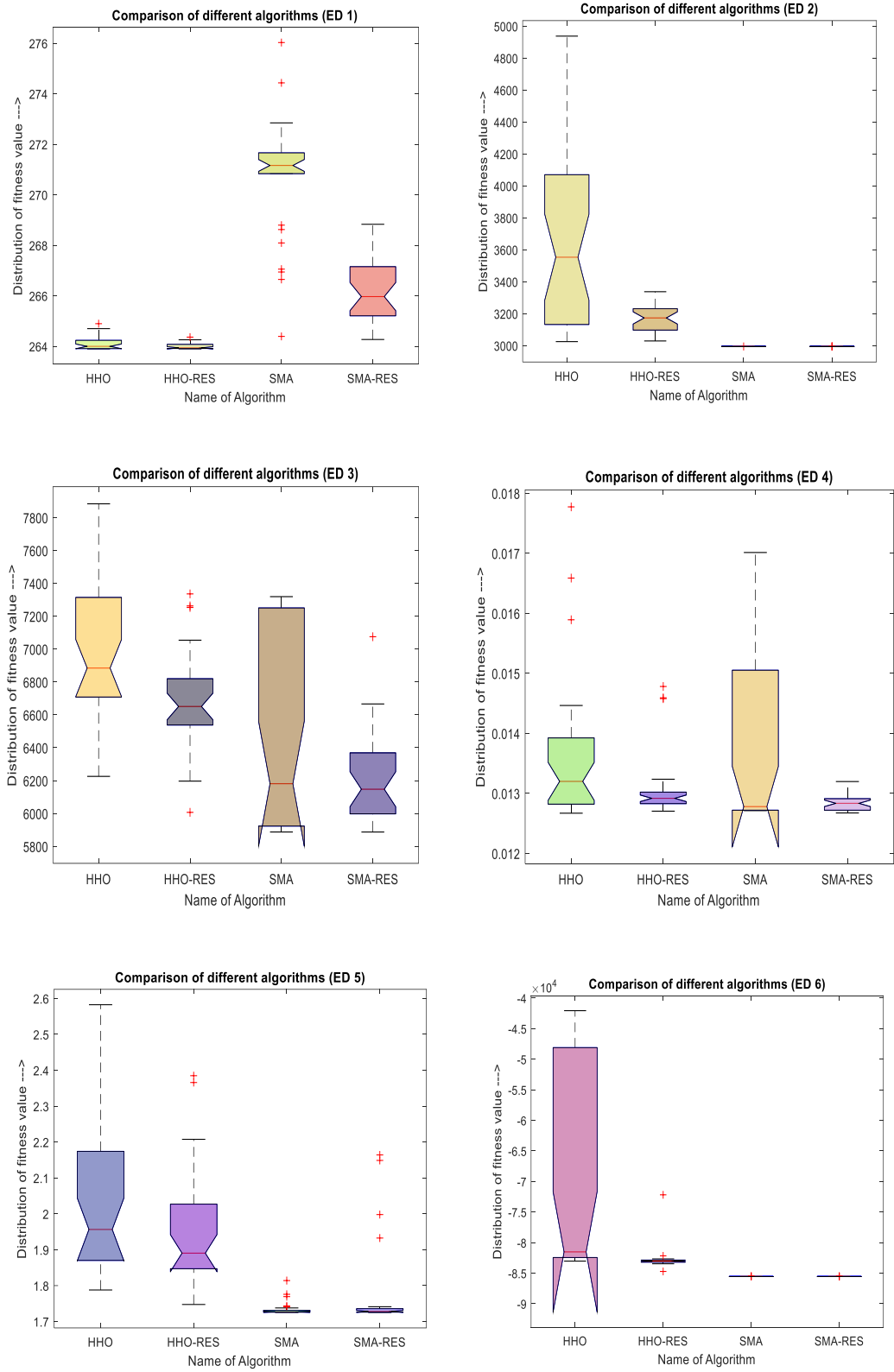


Fig 3.24(a): Box Plot using proposed methods for ED Problems (ED1 to ED6)

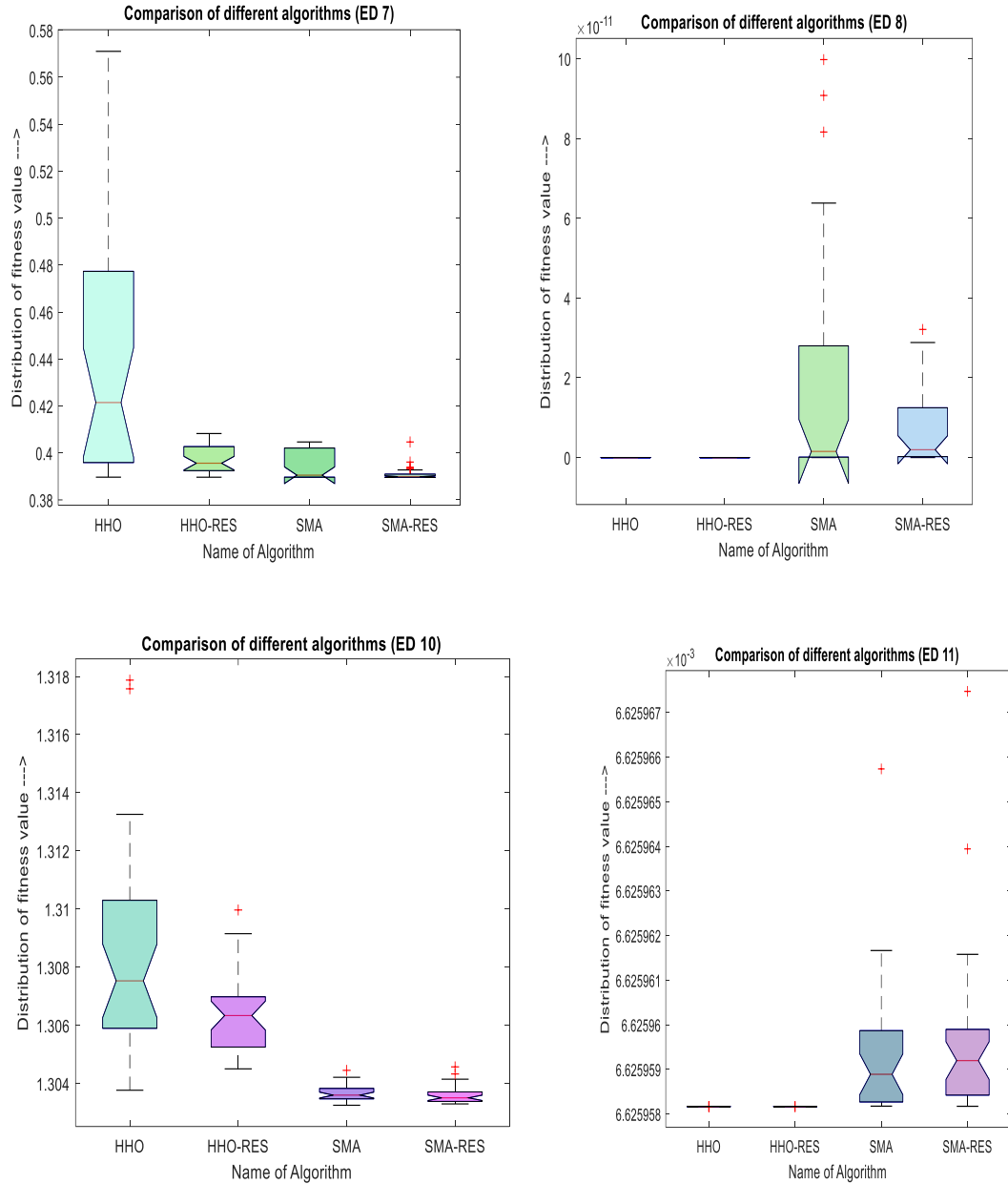


Fig 3.24(b): Box Plots using proposed methods for ED problems (ED7 to ED11)

The box plots showing the deviation, mean, median at different quartile levels using different proposed methods are presented in Fig. 3.24 for the ED problems considered. Fig. 3.25 shows the convergence curves for the different design problems (ED1 to ED11) using HHO, SMA, hHHO-RES and hSMA-RES methods proving superior or competitive performance of the proposed memetic methods in most of the design problems assumed.

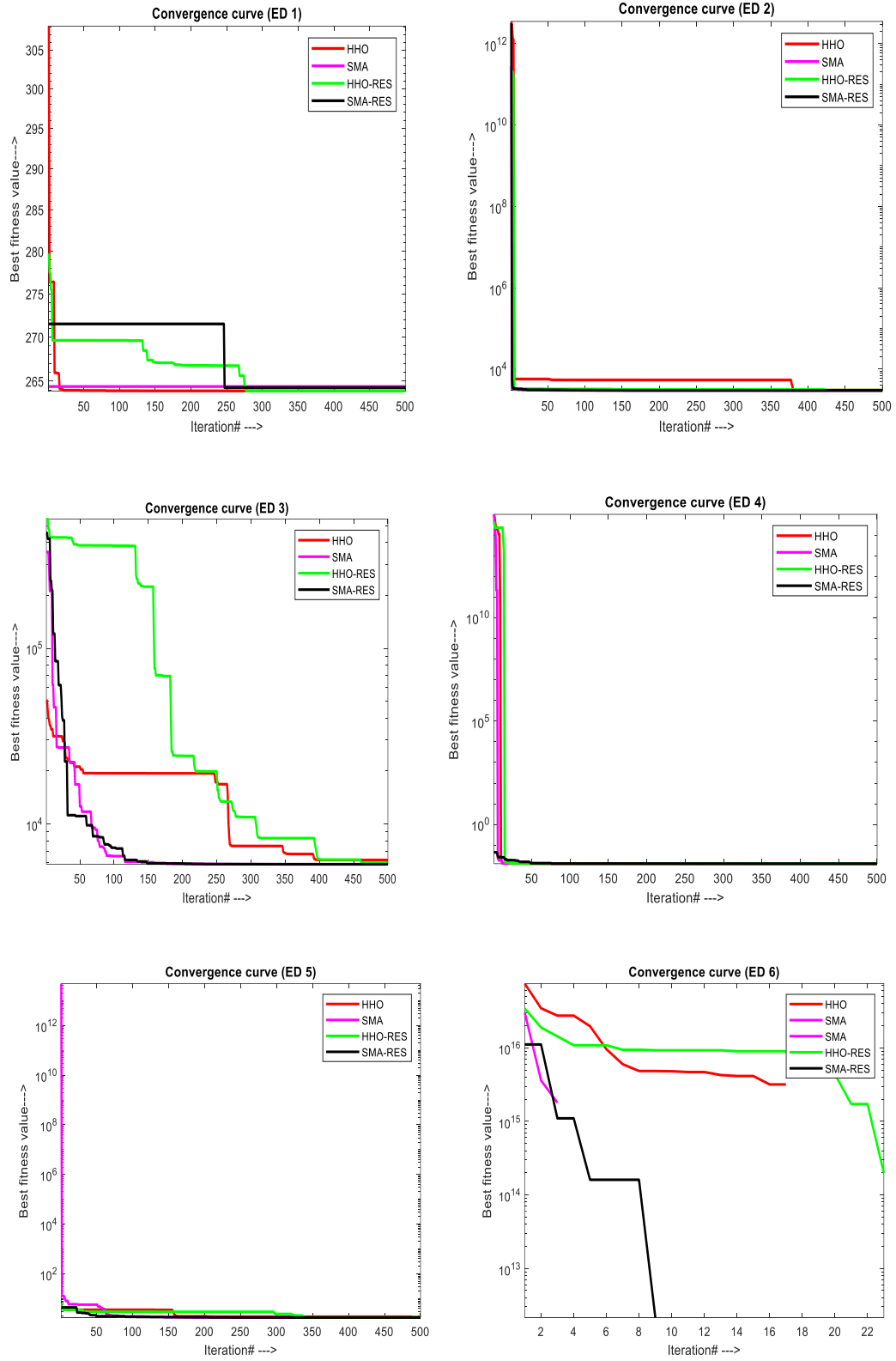


Fig 3.25(a): Convergence curves for ED Problems (ED1 to ED7)

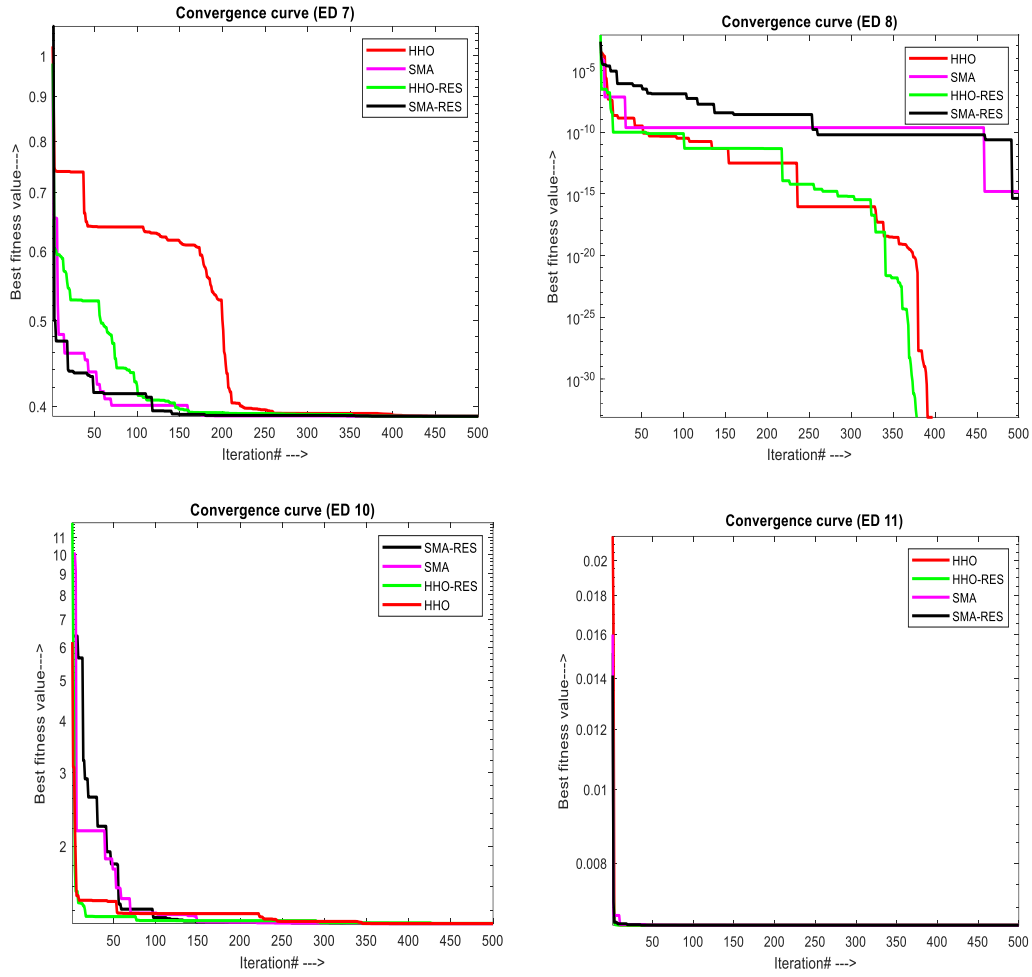


Fig 3.25(b): Convergence curves for ED Problems (ED8 to ED11)

The comparative analysis for different design problems (ED1 to ED11) are discussed as follows and the optimal values are tabulated in respective tables.

The proposed memetic algorithms are applied to find the optimum weight of three bar truss design problem (ED1). The results of the proposed hHHO-RES and hSMA-RES are compared with other methods as shown in Table 3.13. It is evident that the results of hHHO-RES is in competition to other algorithms and HHO but hSMA-RES gives better results than SMA. The proposed memetic HHO-RES can be used to achieve high quality solution with good efficacy in optimizing such problems.

Table 3.14 depicts the comparative results of speed reducer type of design problem (ED2). The proposed memetic approach hSMA-RES performed better in comparison to other algorithms – HEAA, MDE, PSO-DE, MBA, HHO, SMA and can be applied to achieve good quality solution for such problems.

The comparison of proposed memetic methods for pressure vessel design problem (ED3) has been tabulated in table 3.15 to attain the optimum cost value. The comparison results predicted that the proposed methods outperforms in comparison to ACO, GWO, PSO, GSA, ES, GA, etc.

Table 3.13: Comparative analysis of ED1 (3-bar truss problem)

Algorithm	Parameters		
	Optimal values (variables)		Optimal weight
	y1	y2	
hSMA-RES	0.785874754	0.419906	264.2695251
hHHO-RES	0.789334108	0.406388	263.896
SMA	0.80378755	0.370465	264.3919913
HHO	0.788662816	0.408283	263.896
CS[158]	0.789	0.409	263.972
Ray and Sain [184]	0.795	0.395	264.3
MFO [184]	0.788244771	0.409467	263.896
SSA[196]	0.788665414	0.408276	263.896
DEDS [184]	0.78867513	0.408248	263.896
MVO[185]	0.78860276	0.408453	263.896
GOA[170]	0.788897556	0.40762	263.896
MBA [179]	0.788565	0.40856	263.896
PSO-DE [179]	0.7886751	0.408248	263.896

Table 3.14: Comparative analysis of ED2 (Speed Reducer Design)

Method	Parameter							
	Variables (Optimal values)							Optimum fitness value
	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	
hSMA-RES	3.5	0.7	17	7.3	7.7153567	3.3502	5.287	2994.4723
hHHO-RES	3.5	0.7	17	7.569	8.1224229	3.3507	5.222	3024.109
SMA	3.5	0.7	17	7.3	7.7153629	3.35022	5.287	2994.4738
HHO	3.557	0.7	17	7.63	7.8496048	3.35874	5.287	3025.0037
MBA[205]	3.5	0.7	17	7.300033	7.715772	3.350218	5.286654	2994.4825
HEAA[205]	3.5	0.7	17	7.300427	7.715377	3.35023	5.287	2994.4991
PSO-DE[205]	3.5	0.7	17	7.3	7.8	3.350214	5.287	2996.3482
MDE[205]	3.5	0.7	17	7.300156	7.800027	3.350221	5.287	2996.3567
GJO [102]	3.5	0.7	17	7.321686	7.72122	3.35025	5.2866	2994.80
SSA [275]	3.5044	0.7	17	7.3018	7.8773	3.3531	5.2867	3000.4
SCO [275]	3.5	0.7	17	7.3018	7.7153	3.3505	5.2867	2994.80
GSA [275]	3.5266	0.7052	18	8.2	7.89	3.56	5.39	3384.4

Table 3.15: Comparative analysis of ED3 (Pressure Vessel Engineering Design)

Algorithm	Parameters				
	Optimum Value				Optimum cost
	T_s	T_h	R	L_h	
hSMA-RES	0.77930211	0.3852115	40.37833865	199.184192	5887.280247
hHHO-RES	0.811547924	0.4157450	41.92051511	178.853984	6006.919807
SMA	0.779397808	0.3852579	40.38328807	199.115581	5887.443029
HHO	0.81758383	0.4072927	42.09174576	176.719635	6000.46259
GWO [172]	0.8125	0.4345	42.0892	176.7587	6051.564
GSA [276]	1.125	0.625	55.9887	84.4542	8538.84
PSO [185]	0.8125	0.4375	42.0913	176.7465	6061.078
GA [185]	0.8125	0.4345	40.3239	200	6288.745
GA (C&M) [272]	0.8125	0.4375	42.0974	176.6541	6059.946
GA(Deb,Gene) [185]	0.9375	0.5	48.329	112.679	6410.381
ES (Coello) [185]	0.8125	0.4375	42.0981	176.641	6059.75
DE [185]	0.8125	0.4375	42.0984	176.6377	6059.734
ACO [146]	0.8125	0.4375	42.1036	176.5727	6059.089
LM[185]	1.125	0.625	58.291	43.69	7198.043
B&B [185]	1.125	0.625	47.7	117.701	8129.1
MFO[184]	0.8125	0.4375	42.0984	176.6366	6059.7143
BA[277]	0.8125	0.4375	42.0984	176.6366	6059.7143
HPSO [272]	0.8125	0.4375	42.0984	176.6366	6059.7143
CSS [272]	0.8125	0.4375	42.1036	176.5727	6059.0888
CPSO [272]	0.8125	0.4375	42.0912	176.7465	6061.0777
WOA[269]	0.8125	0.4375	42.0983	176.639	6059.741
MDDE [272]	0.8125	0.4375	42.0984	176.636	6059.7017
G-QPSO [272]	0.8125	0.4375	42.0984	176.6372	6059.7208
WEO [272]	0.8125	0.4375	42.098444	176.636622	6059.71
DELC [272]	0.8125	0.4375	42.0984456	176.636596	6059.7143
IACO [272]	0.8125	0.4375	42.098353	176.637751	6059.7258
MVO[185]	0.8125	0.4375	42.0907382	176.738690	6060.8066

The performance of multidisciplinary mechanical engineering problem of tension/compression spring design (ED4) is charted in Table 3.16 to achieve the optimum weight using the proposed memetic approaches. The comparative results of welded beam type of engineering design problem (ED5) is tabulated in Table 3.17 to attain the minimum making cost of the welded beam. The data reveals that hSMA-RES can achieve outstanding optimum value and attains good quality solution for this type of problems.

Table 3.18 displays the comparative findings for rolling bearing design problem (ED6) with an aim to achieve optimum/maximum dynamic load carrying capacity using

the proposed memetic algorithms. It is marked that hHHO-RES and hSMA-RES performs better in comparison to Passing vehicle search PVS [279], Spotted Hyena Optimiser SHO [280], Water cycle algorithm WCA [200], TLBO [281] and GA [282].

The comparative analysis of multi-plate disc clutch brake design (ED7) is shown in table 3.19 with an aim to optimize the overall weight. The optimum values of different variables are also depicted in this table with the optimized weight using the proposed methods. The comparative study reveals the competitive performance of hSMA-RES and hHHO-RES in attaining the optimum value and can further be utilized to tackle this type of problem with significant progress.

Table 3.16: Comparative analysis of ED4 (Tension/ Compression Spring Design)

Algorithm	Parameter			
	Optimum Variables			Optimum weight
	d_r	D_m	N_c	
hSMA-RES	0.0523643	0.3731806	10.38527	0.0126635
hHHO-RES	0.0502736	0.32361	13.530937	0.0127028
SMA	0.0501221	0.3201774	13.803212	0.0127115
HHO	0.0517964	0.3593054	11.138859	0.0127
GWO[172]	0.0516	0.3567	11.2889	0.01267
GSA[276]	0.0503	0.3237	13.5254	0.0127
PSO [172](Ha and Wang)	0.0517	0.3576	11.2445	0.01267
ES (C&M) [172]	0.052	0.364	10.8905	0.01268
GA(Coello) [172]	0.0515	0.3517	11.6322	0.0127
HS [172] (Mahdavi et al.)	0.0512	0.3499	12.0764	0.01267
DE [172] (Huang et al.)	0.0516	0.3547	11.4108	0.01267
MO [172]	0.0534	0.3992	9.1854	0.01273
Constraint correction[172]	0.05	0.3159	14.25	0.01283
SSA[278]	0.051207	0.345215	12.004032	0.01268
Belegundu [172]	0.05	0.3159	14.25	0.01283
GJO [102]	0.0515	0.354	11.448	0.01267
SCO [275]	0.0530	0.3885	9.6450	0.0127

Table 3.20 shows the performance of proposed memetic methods to achieve the optimal fitness for gear train engineering design problem (ED8). From table 3.20, it is recognized that the proposed hHHO-RES and hSMA-RES ranks best in comparison to other methods and provide superior solution quality. The proposed approaches can successfully be utilized to tackle such type of problems.

Cantilever beam design (ED10) is a civil engineering problem with main focus on beam weight minimization is compared in table 3.21 and reveals the superiority of the proposed hHHO-RES and hSMA-RES algorithms in attaining the optimum weight. The optimum values of five variables are also tabulated in table 3.21 to achieve the optimum beam weight. The proposed memetic methods outperforms the recent metaheuristic methods- ALO, SOS, CS, MMA, MFO and can tackle such civil engineering beam design problems.

The aim of I-beam structure design (ED11) problem is to minimize the vertical deviation by optimizing the variables. Table 3.22 depicts the optimum values of variables and optimum fitness of ED11 design problem. It is evident that the proposed memetic methods shows superior performance in comparison to SOS, CS, ARSM and IARSM. This validates the efficacy of the proposed methods in attaining high quality solution for this kind of problem.

Table 3.17: Comparative analysis of ED5 (Welded Beam Design Problem)

Algorithm	Parameters				
	Optimum Variables				Optimal cost
	h	l	t	b	
hSMA-RES	0.205748	3.470389	9.035889	0.205763	1.724995128
hHHO-RES	0.207281	3.481138	8.930168	0.210664	1.747405686
SMA	0.205767	3.470283	9.036066	0.205768	1.725080755
HHO	0.204039	3.531061	9.027463	0.206147	1.73199057
CDE [204]	0.203137	3.542998	9.033498	0.206179	1.733462
GSA[276]	0.1821	3.857	10	0.2024	1.88
WOA[269]	0.2054	3.4843	9.0374	0.2063	1.73050
Simplex[172]	0.2792	5.6256	7.7512	0.2796	2.5307
GWO[172]	0.2057	3.4784	9.0368	0.2058	1.7262
David[172]	0.2434	6.2552	8.2915	0.2444	2.3841
Random[172]	0.4575	4.7313	5.0853	0.66	4.1185
HS (Lee and Geem) [172]	0.2442	6.2231	8.2915	0.2443	2.3807
ESs [204]	0.199742	3.61206	9.0375	0.206082	1.7373
APPROX[172]	0.2444	6.2189	8.2915	0.2444	2.3815
GA (Deb) [172]	N/A	N/A	N/A	N/A	2.38
GA (Deb) [172]	0.2489	6.173	8.1789	0.2533	2.4331
GA (Coello) [172]	N/A	N/A	N/A	N/A	1.8245
GJO [102]	0.20562	3.4719	9.03681	0.20572	1.725

Table 3.18: Comparative analysis of ED6 (Rolling Bearing Design Problem)

Variables	Algorithm				
	hSMA-RES	hHHO-RES	SMA	HHO	GA [282]
DIM_m	125.72269	126.01901	125.723	125	125.7171
DIM_b	21.423301	21.238121	21.4233	21	21.423
N	11.001154	11.093733	11.0012	11.0921	11
f_i	0.515	0.515	0.515	0.515	0.515
f_o	0.515	0.515	0.515	0.515	0.515
$K_a (min)$	0.498034	0.4066071	0.4	0.4	0.4159
$K_a (max)$	0.6162431	0.6073125	0.63692	0.6	0.651
ϵ	0.3000001	0.3	0.3	0.3	0.300043
re	0.02	0.0616534	0.054862	0.05047	0.0223
β	0.6	0.6146148	0.62151	0.6	0.751
Optimum/ Maximum value	85539.186	84714.499	85539.17	83011.88	81843.3
Variables	TLBO [281]	PVS [279]	WCA [200]	SHO [280]	GA[282]
DIM_m	125.7191	125.7191	125.72117	125	125.7171
DIM_b	21.42559	21.42559	21.423	21.40732	21.423
N	11	11	1.00103	10.93268	11
f_i	0.515	0.515	0.515	0.515	0.515
f_o	0.515	0.515	0.515	0.515	0.515
$K_a (min)$	0.424266	0.40043	0.401514	0.4	0.4159
$K_a (max)$	0.633948	0.68016	0.659047	0.7	0.651
ϵ	0.3	0.3	0.300032	0.3	0.300043
re	0.068858	0.07999	0.040045	0.2	0.0223
β	0.799498	0.7	0.6	0.6	0.751
Optimum/ Maximum value	81859.74	81859.74	85538.48	85054.53	81843.3

Table 3.19: Comparative analysis of ED7 (Multidisc clutch break design)

Parameter		Algorithm				
		hSMA-RES	hHHO-RES	SMA	HHO	NSGA-II[283]
Optimal values for variables	x_1	69.999987	69.999966	69.999954	70	70
	x_2	90	90	90	90	90
	x_3	2.3127839	2.312788	2.3127831	2.312785	3
	x_4	1.5	1.5	1.5	1.5	1.5
	x_5	1000	1000	1000	1000	1000
Optimum fitness		0.3896536	0.3896538	0.3896544	0.3896538	0.4704

Table 3.20: Comparative analysis of ED8 (Gear Train Design Problem)

Algorithm	Parameter				Optimum Fitness
	Optimal values for variables				
	x1	x2	x3	x4	
hSMA-RES	16.6344	60	12	12	4.38E-16
hHHO-RES	57.1846	51.0233	20.51756	20.5176	0
SMA	39.6908	47.2399	22.54355	12	1.60E-15
HHO	56.0672	56.0661	35.33883	12.834	0
Sandgren [279]	60	45	22	18	0.14667
Kannan [279]	41	33	15	13	0.14412
GeneAS [279]	50	33	14	17	0.14424
MBA[176]	43	49	19	16	2.70E-12
ABC[184]	43	49	19	16	2.70E-12
MFO[184]	43	49	19	16	2.70E-12

Table 3.21: Comparative analysis of ED10 (Cantilever Beam Design)

Algorithm	Parameters					Optimum weight
	Optimal values for variables					
	X1	X2	X3	X4	X5	
hSMA-RES	5.9853018	4.8706494	4.460106	3.4809751	2.142157	1.3032551
hHHO-RES	6.0561995	4.8869003	4.3533938	3.4964195	2.1545746	1.3037716
SMA	5.9751949	4.8492422	4.4758054	3.4938439	2.1458431	1.3033012
HHO	5.8000715	4.9192151	4.6030936	3.4813118	2.1556017	1.3045064
ALO[148]	6.0181	5.3114	4.4884	3.4975	2.1583	1.33995
SOS[4]	6.0188	5.3034	4.4959	3.499	2.1556	1.33996
CS[284]	6.0089	5.3049	4.5023	3.5077	2.1504	1.33999
MMA [285]	6.01	5.3	4.49	3.49	2.15	1.34
GCA_I [285]	6.01	5.304	4.49	3.498	2.15	1.34
MFO [184]	5.983	5.3167	4.4973	3.5136	2.1616	1.339957
GCA [285]	6.01	5.3	4.49	3.49	2.15	1.34

Table-3.22: Comparative analysis of ED11 (I-Beam Structural Design)

Algorithm	Optimum values for variables				Optimum Cost
	b	h	T _w	T _f	
hSMA-RES	50	80	1.76471	5	0.00663
hHHO-RES	50	80	1.76471	5	0.00663
SMA	50	80	1.76471	5	0.00663
HHO	50	80	1.76471	5	0.00663
SOS[4]	50	80	0.9	2.3218	0.0131
CS[284]	50	80	0.9	2.3217	0.0131
ARSM[286]	37.05	80	1.71	2.31	0.0157
IARSM[286]	48.42	79.99	0.9	2.4	0.131

3.7 CONCLUSION

In this chapter, the memetic variants of SMA and HHO are developed and successfully tested for the optimum solution of 23 standard benchmark sets comprising of unimodal, multi-modal and fixed-dimension functions. Further, the proposed memetic methods are implemented and tested to attain optimum fitness of 10 engineering design problems. Local search technique based on random exploratory search is used to improve the classical HHO and SMA algorithms. The proposed memetic algorithms hHHO-RES and hSMA-RES proved to have better search capabilities. The mean fitness, best fitness, worst fitness, median, standard deviation and convergence curves are evaluated for qualitative investigation. The p-values are estimated using the non-parametric tests to validate the competence of the proposed memetic algorithm scientifically. The experimental results revealed that the proposed memetic algorithms can assure the exploration behaviour with superior exploitation. An excellent balance between explorations and exploitations has proved this to be a proficient method for most of the standard benchmark functions and general engineering design (ED) tasks. As a result, the resulting hHHO-RES and hSMA-RES algorithms are more capable of producing more convergent and better findings proving it as a viable option for tackling numerical optimization and real-world engineering design challenges.

SCALAR ECONOMIC LOAD DISPATCH

4.1 INTRODUCTION

Amongst the most complex and challenging problems of electric industry market are the problems related to electric power system. The main aim of ELD in electric power system planning, operation & control is to content the energy requirement at the most minimized charge while fulfilling the entire equality and inequality constraints. Nowadays, the electric power industry is considered to be the most stimulating and complex due to the continuous growth in electric power demand and lack of limited availability of energy resources thus necessitates the load dispatch of power generated at the most economic rates. With the development and modernization of societies, industrial, commercial, transport and urban sectors the growth in the demand of energy is also increased, thus forces the exact use and utilization of various energy sources along with the conventional energy sources through proper generation. In near future, use of electric vehicles is encouraged and so the energy demand. The main purpose of the economic (optimal) load dispatch (ELD) problem of an electrical energy generation system is to attain the system load requirement at the most reduced (minimum) fuel operating cost by scheduling the committed generating units, while satisfying the system constraints i.e. equality and inequality constraints[1][82]. So, the unceasingly budding demand for energy has inspired the researchers to consider the load dispatch problem for economic analysis. The current scenario in optimization and computing [4], [5] is to efficiently use the modern algorithms to obtain the most optimum solutions.

In the past, a single quadratic function was used to simulate the load dispatch problem and gradient-methods like lambda iteration, lagrangian were used to solve the problem. These methods typically struggle to identify a global optimum and typically only provide local optimal solutions. Traditional methods also demand a prior knowledge of the continuity and differentiability of the objective function associated with the provided optimization model. Numerous nature-inspired optimization

strategies are developed and put into use to address these drawbacks. Some of the modern metaheuristic methods used to solve the ELD problems successfully are evolutionary programming [129], tabu search [287] differential evolution [288], artificial bee colony algorithm [289], intelligent water drop algorithm [37], harmony search [54], gravitational search algorithm [41], etc. Nowadays, researchers are implementing hybrid methods of optimization to overcome the drawbacks of classical algorithms. Some of the hybrid methods implemented to ELD problems are PSO-SQP [98], hybrid GA-BF [99], PSO-GSA [100], improved DE [290], hybrid harmony search, differential HS [50], [54], emended salp swarm optimization [226], ameliorated grey wolf optimizer [110], Improved grasshopper algorithm [107], etc.

The remaining chapter is structured as follows: detailed explanation of the economic load dispatch (ELD) problem with its mathematical modelling and problem formulation is described in section 4.2 and section 4.3 respectively. Section 4.4 describes the proposed methodologies for solving the scalar and dynamic ELD problem. The test systems considered are presented in section 4.5 with results and discussions in section 4.6. The chapter is concluded in section 4.7.

4.2 SCALAR ECONOMIC LOAD DISPATCH

The scalar economic (optimal) load dispatch (ELD) problem stated as optimal scheduling of generators in power systems is explained as the distribution of load among the various thermal generating units of an existing power system in such a way that the total operational/ fuel cost of energy generation is reduced to a minimum possible value while taking into account the power balance (demand/generation) and power generation ability constraints, also known as equality- inequality constraints [1]. This problem is also classified in terms of convex problem or non-convex problem where linear constraints contribute to convex problem and non-linear constraints along with the linear constraints develops the non-convex nature of the ELD problem. The generation capacity and power balance constraints are categorized as linear constraints and provides the simplified approximate results and a more specific and accurate problem is modelled by considering the impact of non-linear constraints like valve point loading effects (VPLE), boundary restrictions known as RRLs- ramp rate limits and

non-operational regions known as prohibited operating zones (POZs) [6]. This chapter includes the entire mathematical formulation of classical economic load dispatch problem and has been validated using HHO, SMA and the proposed hHHO-RES, hSMA-RES optimizer to improve the system's efficacy and uniqueness.

4.3 ELD PROBLEM FORMULATION

The key purpose of the ELDP in conventional fossil-based plants is to curtail the total fuel/operational cost of the power generating stations whilst fulfilling the various equality/ inequality restrictions. This can be considered by neglecting the transmission losses or by taking the transmission losses. Also, the different non-linear constraints like VPLE, RRL and POZs can be considered for a realistic power system. The mathematical modelling of ELD problem [248] has been framed with the following notations :

Classical ELD Problem. The mathematical formulation of classical economic load dispatch problem for an hour is characterized as:

$$F(P^G) = \sum_{n=1}^{NG} [a_n (P_n^G)^2 + b_n P_n^G + c_n] \quad (4.1)$$

The equation of economic load dispatch for NG number of thermal generating units for H number of hours is characterized as:

$$F(P^G) = \sum_{h=1}^H \left(\sum_{n=1}^{NG} [a_n (P_n^G)^2 + b_n P_n^G + c_n] \right) \quad (4.2)$$

Cubical ELD Problem. To establish the output power of online generating units the ELD problem intends to congregate the system load at least cost whilst fulfilling the system constraints. So, as to attain correct dispatch outcomes, a cubical function is used for modelling the unit cost.

$$F(P^G) = \sum_{n=1}^{NG} [a_n (P_n^G)^3 + b_n (P_n^G)^2 + c_n P_n^G + d_n] \quad (4.3a)$$

The cubical ELD with Valve Point effect can be represented as:

$$F(P^G) = \sum_{n=1}^{NG} [a_n (P_n^G)^3 + b_n (P_n^G)^2 + c_n P_n^G + d_n] + |\varphi_n \sin(\gamma_n (P_{n(\min)}^G - P_n^G))| \quad (4.3b)$$

Heat and Power ELD Problem. The heat and power ELD problem of a system aims

to resolve the unit heat and power production of the generating units [291]. The mathematical formulation for heat and power ELD may be described as:

$$F_{Power}(P_n^G) = \sum_{n=1}^{NG} \left(c_n + b_n \times P_n^G + a_n \times (P_n^G)^2 \right) \quad (4.4a)$$

$$F_{Heat}(P_n^G) = \sum_{n=1}^{NG} \left(g_n + h_n \times P_n^G + q_n \times (P_n^G)^2 \right) \quad (4.4b)$$

$$F_{Overall}(P_n^G) = \sum_{n=1}^{NG} \left(c_n + b_n \times P_n^G + a_n \times (P_n^G)^2 + g_n \times P_n^G + h_n \times (P_n^G)^2 + q_n \times (P_n^G)^2 \right) \quad (4.4c)$$

The objective function for heat and power ELD considering valve point loading effects can be reframed as:

$$F_{Power}(P_n^G) = \sum_{n=1}^{NG} \left(c_n + b_n \times P_n^G + a_n \times (P_n^G)^2 + \left| \varphi_n \sin(\gamma_n (P_{n(\min)}^G - P_n^G)) \right| \right) \quad (4.5a)$$

$$F_{Heat}(P_n^G) = \sum_{n=1}^{NG} \left(g_n + h_n \times P_n^G + q_n \times (P_n^G)^2 + \left| \varphi_n \sin(\gamma_n (P_{n(\min)}^G - P_n^G)) \right| \right) \quad (4.5b)$$

$$F_{Overall}(P_n^G) = \sum_{n=1}^{NG} \left(c_n + b_n \times P_n^G + a_n \times (P_n^G)^2 + g_n \times P_n^G + h_n \times (P_n^G)^2 + q_n \times (P_n^G)^2 + \left| \varphi_n \sin(\gamma_n (P_{n(\min)}^G - P_n^G)) \right| \right) \quad (4.6)$$

All the objective functions of ELD problem as mentioned above are subjected to equality and inequality constraints as follows:

Power Balance Constraints/Equality Constraints. The overall power produced by all the power generating units in a power plant must be equal to the total load requirement and real power loss. Mathematically it is represented as

$$\sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} \quad (4.7)$$

Where, P^{Loss} is the power transmission loss and may be represented as:

$$P^{Loss} = \sum_{n=1}^{NG} \sum_{m=1}^{NG} P_n^G B_{nm} P_m^G \quad (4.8)$$

and if B_{i0} , B_{00} are loss coefficients, then the loss equation can be changed as:

$$P^{Loss} = P_n^G B_{nm} P_m^G + \sum_{n=1}^{NG} P_n^G \times B_{i0} + B_{00} \quad (4.9)$$

The expanded version of the above equation may be represented as:

$$P^{Loss} =$$

$$[P_1 \ P_2 \ \dots \ P_{NG}] \begin{bmatrix} B_{11} & B_{12} & \dots & B_{1n} \\ B_{21} & B_{22} & \dots & B_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ B_{n1} & B_{n2} & \dots & B_{nn} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_{NG} \end{bmatrix} + [P_1 \ P_2 \ \dots \ P_{NG}] \begin{bmatrix} B_{01} \\ B_{02} \\ \vdots \\ B_{0NG} \end{bmatrix} + B_{00} \quad (4.10)$$

Generator limit constraints (Inequality constraints). The power produced by each generating unit must lie within the maximum and minimum values of operating power.

$$P_{n(\min)}^G \leq P_n^G \leq P_{n(\max)}^G \quad n = 1, 2, 3, \dots, NG \quad (4.11)$$

Ramp rate limits. In order to maintain the rate of change of output power within a specified range as to keep the thermal shifts in the turbine within its safe boundaries and to increase the life, the operating range for online generators is controlled by their ramp rate limits (RRLs) as follows. Mathematically,

$$P_n^G - P_0^G \leq UR_n \quad n = 1, 2, 3, \dots, NG \quad (4.12)$$

$$P_n^G - P_n^G \leq DR_n \quad n = 1, 2, 3, \dots, NG \quad (4.13)$$

$$\max[P_{n(\max)}^G, (UR_n - P_n^G)] \leq P_n^G \leq \min[P_{n(\max)}^G, (P_n^G - DR_n)] \quad n = 1, 2, 3, \dots, NG \quad (4.14)$$

Prohibited Operating Zones. Thermal power producing units may fall within a limited operating range where operation is difficult owing to physical limits such as shaft vibration, steam valve, and other machine components. Such constrained or restricted regions are acknowledged as prohibited operating zones (POZ). Under such constraints, the operational region splits into isolated sub-regions, thus forming a non-convex problem.

$$\begin{cases} P_{n(\min)} \leq P_n \leq P_{n(\min),1}^{POZ} \\ P_{n(\max),m-1}^{POZ} \leq P_n \leq P_{min,m}^{POZ} ; \quad m = 2, 3, \dots, N_{POZ} \\ P_{n(\max),m}^{POZ} \leq P_n \leq P_{n(\max)} \quad ; m = N_{POZ} \end{cases} \quad (4.15)$$

4.4 SOLUTION METHODOLOGIES

ELDP has been affirmed by taking into account the system's equality and inequality constraints of thermal generating units. The present study have used HHO, SMA,

hHHO-RES and hSMA-RES to tackle the load dispatch issue of electric power system. The solution can be attained by optimum combination of all generating units in order to reduce the fuel/operating price while satisfying load demand and losses, maintaining equality/inequality constraints. Metaheuristic (MH) methods are used to handle different physical and operational constraints of scalar economic load dispatch problem. The proposed algorithms are described for scalar economic load dispatch problem in below sections.

4.4.1 Harris Hawks Optimizer (HHO) for ELD Problem

Harris Hawks optimizer – (HHO) discussed in section 3.3.1 is designed by Heidari et al. [204] is a MH search algorithm based on the chasing strategy of Hawks to seizure the evading prey, most probably a rabbit. Harris Hawks are the clever hunting birds that used to chase in groups. The primary feature of HHO is based on the combined hunting behavior using different steps - encircling, surprise pounce, soft and hard besiege. It is an efficient and less time-consuming approach to solve complex optimization issues comprising discrete or continuous, constraint or unconstrained problems. The key benefits of HHO are simple and easy methodology, flexibility, improved performance and easily applicable to variety of problems. The mathematical formulation of HHO is based on the different strategies of hawks and the escaping energy of the target, rabbit. The detailed mathematical modelling and steps, flowchart and pseudocode of HHO algorithm is explained in chapter 3.

The various steps of HHO algorithm for tackling ELD problems by attaining the optimal power generated by different units while considering all the constraints are illustrated below:

Step 1: Initialize the search agents/population size, dimension and maximum iterations.

Step 2: Initialize the active power generation of all the units randomly between the upper and lower limits (maximum and minimum power limits) excluding the last generating unit. The power generated from last unit is evaluated from the power balance equation stated in equation 4.7 and checked if the inequality constraints are satisfied or not.

Step 3: Reinitialize the infeasible solutions. Based on the population size many solution sets are generated and the position of search agents (hawks) are represented by control variables i.e. number of generators. Based on initial search agent's/hawk's position matrix is formed as below:

$$X = \begin{pmatrix} P_1^1 & P_2^1 & \cdots & P_{Ng}^1 \\ P_1^2 & & \ddots & \vdots \\ \vdots & & & \\ P_1^{sa} & P_2^{sa} & \cdots & P_{Ng}^{sa} \end{pmatrix} \quad (4.16)$$

Step 4: Evaluate the fitness of each solution set using equation 4.1 to 4.6. The distance of individual hawk from the prey (rabbit) is represented by each fitness value.

Step 5: Update the position of each search agent by updating the initial energy E_0 and E for phase of exploration and exploitation using equations 3.3 to 3.16 depending upon the values of E and r . The position of each search agent depicts the power generated by each unit/generator in the system.

Step 6: Check the violation of inequality constraints i.e whether the generated power of each unit is within the operating range except for the last generating unit.

$$P_n^G = P_{n(\min)}^G \quad \text{if} \quad P_n^G \leq P_{n(\min)}^G \quad n = 1, 2, 3, \dots, NG$$

$$P_n^G = P_{n(\max)}^G \quad \text{if} \quad P_n^G \geq P_{n(\max)}^G \quad n = 1, 2, 3, \dots, NG$$

Step 7: Evaluate the power generated by the last unit using equation 4.7 and check whether all the inequality constraints are satisfied. The infeasible results are replaced by best feasible values.

Step 8: Evaluate fuel cost using suitable equations from (4.1) to (4.6).

Step 9: Repeat the process from step 2 until termination criteria is met i.e. maximum iterations are reached.

4.4.2. Slime Mould Algorithm (SMA) for ELD Problem

Slime mould algorithm is a newly constructed stochastic algorithm based on the organism slime mould's oscillation method developed by Chen et al. [292] for solving stochastic optimization problems. The contraction phase in slime mould behaves like: (i) Thick vein progress and radius are seen when contraction moves from the outside to the inside. (ii) Anisotropy becomes apparent during the unstable period of contraction

mode. (iii) The venous arrangement appears only when the slime mould contraction mode is no longer controlled by time and space. SMA is a very simple and easily adoptable algorithm. The algorithm is formatted by mimicking the behaviour of slime moulds and ability of searching, approaching, wrapping and grabbing food. Some other algorithms designed by other researchers which sounds similar to SMA but have adopted different designing strategies and also their mathematical approach was also different. The foraging behaviour of *pysarum polycephalum* commonly known as ‘slime mould’ to search food sites have been efficiently adopted by researchers to develop new algorithms with different objectives. The detailed steps and mathematical modelling of approaching food, wrapping the food and grabble the food is already described in chapter-3.

The various steps of SMA algorithm for undertaking ELD problems by attaining the optimal power generated by different units while considering all the constraints are illustrated below:

Step 1: Initialization of the search agents/population size and maximum iterations.

Step 2: Initialize the active power generation of all the units randomly between the upper/lower limits (maximum and minimum power limits) excluding the last generating unit. The power generated from last unit is evaluated from the power balance equation stated in equation 4.7 and checked if the inequality constraints are satisfied.

Step 3: Reinitialize the infeasible solutions. Based on the population size many solution sets are generated and the position of search agents (slime moulds) are represented through control variables i.e. number of generators. Based on initial search agents position matrix is formed as stated in equation 4.16 and given below

$$X = \begin{pmatrix} p_1^1 & p_2^1 \cdots & p_{Ng}^1 \\ p_1^2 & \ddots & \vdots \\ \vdots & & \\ p_1^{sa} & p_2^{sa} \cdots & p_{Ng}^{sa} \end{pmatrix}$$

Step 4: Evaluate the fitness of each slime mould using equation 4.1 to 4.6.

Step 5: Sort the fitness and update the best and worst fitness value based on smell index.

Step 6: Calculate weight W_s using equation 3.23.

Step 7: Update the position of each search agent by updating the values of p , v_b , v_c and returns the best fitness value. The position of each search agent depicts the solution of power generated by each unit.

Step 8: Check the violation of inequality constraints i.e. whether the generated power of each unit is within the operating range except for the last generating unit.

$$P_n^G = P_{n(\min)}^G \quad \text{if} \quad P_n^G \leq P_{n(\min)}^G \quad n = 1, 2, 3, \dots, NG$$

$$P_n^G = P_{n(\max)}^G \quad \text{if} \quad P_n^G \geq P_{n(\max)}^G \quad n = 1, 2, 3, \dots, NG$$

Step 9: Evaluate the power generated by the last unit using equation 4.7 and check whether all the inequality constraints are satisfied. The infeasible results are replaced by best feasible values.

Step 10: Evaluate fuel cost using suitable equations from (4.1) to (4.6).

Step 11: Repeat the process from step 2 until termination criteria is met i.e. maximum iterations are reached.

4.4.3. Hybrid HHO-RES Method for ELD Problem

Major problem in almost all evolutionary, heuristic and MH algorithms is their possibility of premature convergence or getting trapped in a local minimum point. To overcome this problem, memetic or hybrid algorithms are preferred by combining these algorithms with other optimization methods. This improves the performance and local search capability of many researchers have developed new hybrid algorithms by combining them with other algorithms that improve the performance and local search method of prevailing algorithms. Conventional Harris Hawks Optimizer has a tendency to improve exploration search capability and to explore local search space [293], this can be obtained by combining the traditional HHO with RES. The hybrid variation of HHO is established by RES algorithm namely *Hybrid Harris Hawks-Random Exploratory Search Algorithm (hHHO-RES)* with an aim to improve the exploration phase and to avoid local optima. The methodological steps for solution of economic load dispatch problem using hHHO-RES is explained as follows:

Step 1: Initialize the search agents/population size, dimension and maximum iterations.

Step 2: Initialize the active power generation of all the units randomly between the upper/lower limits (maximum and minimum power limits) excluding the last generating unit. The power generated from last unit is evaluated from the power balance equation stated in equation 4.7 and checked if the inequality constraints are satisfied.

Step 3: Reinitialize the infeasible solutions. Based on the population size many solution sets are generated and the position of search agents (hawks) are represented by control variables i.e. number of generators. Based on initial search agents (hawks) position matrix is formed as below:

$$X = \begin{pmatrix} P_1^1 & P_2^1 \cdots & P_{Ng}^1 \\ P_1^2 & \ddots & \vdots \\ \vdots & & \\ P_1^{sa} & P_2^{sa} \cdots & P_{Ng}^{sa} \end{pmatrix} \quad (4.16)$$

Step 4: Evaluate the fitness of each solution set using equation 4.1 to 4.6. The distance of individual hawk from the prey (rabbit) is represented by each fitness value.

Step 5: Update the position/generated power of each search agent by updating the initial energy E_0 and E for phase of exploration and exploitation using equations 3.3 to 3.16 depending upon the values of E and r .

Step 6: Check the violation of inequality constraints i.e. whether the generated power of each unit is within the operating range except for the last generating unit.

$$P_n^G = P_{n(\min)}^G \quad \text{if} \quad P_n^G \leq P_{n(\min)}^G \quad n = 1, 2, 3, \dots, NG$$

$$P_n^G = P_{n(\max)}^G \quad \text{if} \quad P_n^G \geq P_{n(\max)}^G \quad n = 1, 2, 3, \dots, NG$$

Step 7: Assess the power generated by the last unit using equation 4.7 and check whether all the inequality constraints are satisfied. The infeasible results are replaced by best feasible values.

Step 8: Update the best position attained using random exploratory search. RES improves the best fitness by performing the neighboring search around the best position. The minimum value among f , f^+ and f^- is regarded as the best fitness value.

$$f_{final} \leftarrow \min(f^+, f^-, f)$$

Step 9: Evaluate fuel cost using suitable equations from (4.1) to (4.6).

Step 10: Repeat the process from step 2 until termination criteria is met i.e. maximum iterations are reached.

4.4.4. Hybrid SMA-RES Method for ELD Problem

Memetic SMA (hSMA-RES) is an extension of slime mould algorithm based on the organism slime mould's oscillation method. The classical slime mould algorithm can be improved in terms of exploration search capability and local search space. To improve the exploration capability of original SMA, it is combined with the local search algorithm –Random exploratory search and a novel memetic algorithm is developed named hSMA-RES. The main objective of the suggested algorithm is to improve the exploration phase and to avoid local optima with fast convergence rate. The complete steps and mathematical modelling is discussed in chapter 3 for approaching the food, wrapping the food and grabble the food. The steps for solution of ELD problem using hSMA-RES is explained through the given algorithm:

Step 1: Initialize the search agents/population size, dimension and maximum iterations.

Step 2: Initialize the active power generation of all the units randomly between the upper and lower limits (maximum and minimum power limits) excluding the last generating unit. The power generated from last unit is evaluated from the power balance equation stated in equation 4.7 and checked if the inequality constraints are satisfied.

Step 3: Reinitialize the infeasible solutions. Based on the population size many solution sets are generated and the position of search agents (slime moulds) are represented through control variables i.e number of generators. Based on initial search agents position matrix is formed as stated in equation 4.16 and given below

$$X = \begin{pmatrix} p_1^1 & p_2^1 \cdots & p_{Ng}^1 \\ p_1^2 & \ddots & \vdots \\ \vdots & & \\ p_1^{sa} & p_2^{sa} \cdots & p_{Ng}^{sa} \end{pmatrix}$$

Step 4: Evaluate the fitness of each slime mould using equation 4.1 to 4.6.

Step 5: Sort the fitness and update the best and worst fitness value based on smell index.

Step 6: Calculate weight W_s using equation 3.23.

Step 7: Update the position of each search agent/generated power by updating the values of p , v_b and v_c . returning the best fitness value. The position of each search agent depicts the solution of power generated by each unit.

Step 8: Check the violation of inequality constraints i.e whether the generated power of each unit is within the operating range except for the last generating unit.

$$P_n^G = P_{n(\min)}^G \quad \text{if} \quad P_n^G \leq P_{n(\min)}^G \quad n = 1, 2, 3, \dots, NG$$

$$P_n^G = P_{n(\max)}^G \quad \text{if} \quad P_n^G \geq P_{n(\max)}^G \quad n = 1, 2, 3, \dots, NG$$

Step 9: Evaluate the power generated by the last unit using equation 4.7 and check whether all the inequality constraints are satisfied. The infeasible results are replaced by best feasible values.

Step 10: Update the best position attained using random exploratory search. RES improves the best fitness by performing the neighboring search around the best position. The minimum value among f , f^+ and f^- is regarded as the best fitness value.

$$f_{final} \leftarrow \min (f^+, f^-, f)$$

Step 11: Evaluate fuel cost using suitable equations from (4.1) to (4.6).

Step 12: Repeat the process from step 2 until termination criteria is met i.e. maximum iterations are reached.

4.5 TEST SYSTEMS –ELD PROBLEMS

The economic load dispatch problem has been described, taking into account the system and physical limits of thermal generating units. The non-smooth, non-convex, and constrained ELD problem has been solved and tested in regard to small, medium and large scale power systems for static ELD cases and 5-unit, 6-unit, 7-unit and 10-unit for DELD cases to validate the proposed memetic algorithms. These are considered with and without valve point loading effect for various test systems. The transmission losses are also considered in some test systems. The following are the characteristics of the generating units, fuel cost coefficients, and load demand for the various IEEE test systems considered in this research study.

4.5.1 Static Economic Load Dispatch Problem

4.5.1.1 Test System A (TS-A) - Small Scale Power System

In TS-A four cases are categorized under small power systems is considered. Among these two different test cases are examined with no VPLE and other two with the effects of valves.

Case 1 (C-1) -Three- Unit System:

The input test data for C-1 is taken from [284], with a load demand of 150 MW without VPLE. The cost co-efficients, power capacity range and B-matrix is shown in Table 4.1.

Table 4.1: Input test data for C-1 (TS-A)

Generator/ Unit	P _{min} (MW)	P _{max} (MW)	a _i (\$/MW ² hr)	b _i (\$/MWhr)	c _i (\$/hr)
1	10	85	0.008	7	200
2	10	80	0.009	6.3	180
3	10	70	0.007	6.8	140

Loss Coefficients/ B-Coefficients

$$B = 10^{-3} \begin{bmatrix} 0.0218 & 0.0093 & 0.0028 \\ 0.0093 & 0.0228 & 0.0017 \\ 0.0028 & 0.0017 & 0.0179 \end{bmatrix}$$

$$B_0 = [0.0003 \quad 0.0031 \quad 0.0015]$$

$$B_{00} = [0.0003 \quad 0.0052 \quad 3]$$

Case 2 (C-2) - Six Unit System:

The input test data for C-2 (TS-A) with 6- generating units without VPLE and losses with demand of 1263 MW considered from [45] is given in Table-4.2.

Case 3 (C-3)-Three Unit System with VPLE:

The input test data for C-3 (TS-A) with 3- three generating units with VPLE having a demand of 850 is referred from [294] is displayed in Table-4.3.

Table 4.2: Input test data for C-2 (TS-A)

Generator/Unit	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	P_{min} (MW)	P_{max} (MW)
1	0.0070	7.0	240	100	500
2	0.0095	10.0	200	50	200
3	0.0090	8.5	220	80	300
4	0.0090	11.0	200	50	150
5	0.0080	10.5	220	50	200
6	0.0075	12.0	190	50	120

Table 4.3: Input test data for C-3 (TS-A)

Generator/Unit	P_{min} (MW)	P_{max} (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	d_i (\$/hr)	e_i (1/MW)
1	100	600	0.001562	7.92	561	300	0.0315
2	100	400	0.00194	7.85	310	200	0.042
3	50	200	0.00482	7.97	78	150	0.063

Table 4.4: Input test data for C-4 (TS-A)

Generator/Unit	P_{min} (MW)	P_{max} (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	d_i (\$/hr)	e_i (1/MW)
1	50	300	0.0015	1.8	40	200	0.035
2	20	125	0.0035	1.8	60	140	0.04
3	30	175	0.0012	2.1	100	160	0.038
4	10	75	0.008	2	25	100	0.042
5	40	250	0.001	2	120	180	0.037

Case 4 (C-4) - Five Unit System with VPLE:

The input test data for C-4 (TS-A) having 5-generating units with VPLE and a requirement of 730 MW considered from [295] is displayed in Table-4.4. The data comprises of cost coefficients including valve effect co-efficients.

4.5.1.2 Test System B (TS-B) - Medium Scale Power System

In TS-B four cases are categorized under medium scale power systems is considered. These test cases are tested using the proposed memetic algorithms for better efficacy

and optimum cost. Among them 2 cases considered are without VPLE and other two cases with the rippling effect of valves.

Case-1 (C-1) -Fifteen Unit System without VPLE:

The input test data for C-1 (TS-B) having 15-generating units without VPLE and a load demand of 2630 MW is considered. The input test information/data is taken from [27] and displayed in Table-4.5.

Case-2 (C-2) - Twenty Unit System without VPLE:

The input test data for C-2 (TS-B) having 20-generating units without VPLE and load demand of 2500 MW and the input test information/data with loss coefficients is considered from [27] and displayed in Table-4.6.

Table 4.5: Input test data for C-1 (TS-B)

Generator/Unit	$P_{\min}$ (MW)	$P_{\max}$ (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)
1	150	455	0.000299	10.1	671
2	150	455	0.000183	10.2	574
3	20	130	0.001126	8.8	374
4	20	130	0.001126	8.8	374
5	150	470	0.000205	10.4	461
6	135	460	0.000301	10.1	630
7	135	465	0.000364	9.8	548
8	60	300	0.000338	11.2	227
9	25	162	0.000807	11.2	173
10	25	160	0.001203	10.7	175
11	20	80	0.003586	10.2	186
12	20	80	0.005513	9.9	230
13	25	85	0.000371	13.1	225
14	15	55	0.001929	12.1	309
15	15	55	0.004447	12.4	323

Loss Coefficient/B Coefficient Matrix for C-1 (TS-B)

$$B=10^{-3} \begin{bmatrix} 1.4 & 1.2 & 0.7 & -0.1 & -0.3 & -0.1 & -0.1 & -0.1 & -0.3 & -0.5 & -0.3 & -0.2 & 0.4 & 0.3 & -0.1 \\ 1.2 & 1.5 & 1.3 & 0.0 & -0.5 & -0.2 & 0.0 & 0.1 & -0.2 & -0.4 & -0.4 & 0.0 & 0.4 & 1.0 & -0.2 \\ 0.7 & 1.3 & 7.6 & -0.1 & -1.3 & -0.9 & -0.1 & 0.0 & -0.8 & -1.2 & -1.7 & 0.0 & -2.6 & 11.1 & -2.8 \\ -0.1 & 0.0 & -0.1 & 3.4 & -0.7 & -0.4 & 1.1 & 5.0 & 2.9 & 3.2 & -1.1 & 0.0 & 0.1 & 0.1 & -2.6 \\ -0.3 & -0.5 & -1.3 & -0.7 & 9.0 & 1.4 & -0.3 & -1.2 & -1.0 & -1.3 & 0.7 & -0.2 & -0.2 & -2.4 & -0.3 \\ -0.1 & -0.2 & -0.9 & -0.4 & 1.4 & 1.6 & 0.0 & -0.6 & -0.5 & -0.8 & 1.1 & -0.1 & -0.2 & -1.7 & 0.3 \\ -0.1 & 0.0 & -0.1 & 1.1 & -0.3 & 0.0 & 1.5 & 1.7 & 1.5 & 0.9 & -0.5 & 0.7 & 0.0 & -0.2 & -0.8 \\ -0.1 & 0.1 & 0.0 & 5.0 & -1.2 & -0.6 & 1.7 & 16.8 & 8.2 & 7.9 & -2.3 & -3.6 & 0.0 & 0.5 & -7.8 \\ -0.3 & -0.2 & -0.8 & 2.9 & -1.0 & -0.5 & 1.5 & 8.2 & 12.9 & 11.6 & -2.1 & -2.5 & 0.7 & -1.2 & -7.2 \\ -0.5 & -0.4 & -1.2 & 3.2 & -1.3 & -0.8 & 0.9 & 7.9 & 11.6 & 20.0 & -2.7 & -3.4 & 0.9 & -1.1 & -8.8 \\ -0.3 & -0.4 & -1.7 & -1.1 & 0.1 & 1.1 & -0.5 & -2.3 & -2.1 & -2.7 & 14.0 & 0.1 & 0.4 & -3.8 & 16.8 \\ -0.2 & 0.0 & 0.0 & 0.0 & -0.2 & -0.1 & 0.7 & -3.6 & -2.5 & -3.4 & 0.1 & 5.4 & -0.1 & -0.4 & 2.8 \\ 0.4 & 0.4 & -2.6 & 0.1 & -0.2 & -0.2 & 0.0 & 0.0 & 0.7 & 0.9 & 0.4 & -0.1 & 10.3 & -10.1 & 2.8 \\ -0.1 & -0.2 & -2.8 & -2.6 & -0.3 & 0.3 & -0.8 & -7.8 & -7.2 & -8.8 & 16.8 & 2.8 & 2.8 & -9.4 & 128.3 \\ -0.1 & -0.2 & -2.8 & -2.6 & -0.3 & 0.3 & -0.8 & -7.8 & -7.2 & -8.8 & 16.8 & 2.8 & 2.8 & -9.4 & 128.3 \end{bmatrix}$$

Loss Coefficient/B Coefficient Matrix for C-2 (TS-B)

$$B=10^{-3} \begin{bmatrix} 8.70 & 0.43 & -4.61 & 0.36 & 0.32 & -0.66 & 0.96 & -1.60 & 0.80 & -0.10 & 3.60 & 0.64 & 0.79 & 2.10 & 1.70 & 0.80 & -3.20 & 0.70 & 0.48 & -0.70 \\ 0.43 & 8.30 & -0.97 & 0.22 & 0.75 & -0.28 & 5.04 & 1.70 & 0.54 & 7.20 & -0.28 & 0.98 & -0.46 & 1.30 & 0.80 & -0.20 & 0.52 & -1.70 & 0.80 & 0.20 \\ -4.61 & -0.97 & 9.00 & -2.00 & 0.63 & 3.00 & 1.70 & -4.30 & 3.10 & -2.00 & 0.70 & -0.77 & 0.93 & 4.60 & -0.30 & 4.20 & 0.38 & 0.70 & -2.00 & 3.60 \\ 0.36 & 0.22 & -2.00 & 5.30 & 0.47 & 2.62 & -1.96 & 2.10 & 0.67 & 1.80 & -0.45 & 0.92 & 2.40 & 7.60 & -0.20 & 0.70 & -1.00 & 0.86 & 1.60 & 0.87 \\ 0.32 & 0.75 & 0.63 & 0.47 & 8.60 & -0.80 & 0.37 & 0.72 & -0.90 & 0.69 & 1.80 & 4.30 & -2.80 & -0.70 & 2.30 & 3.60 & 0.80 & 0.20 & -3.00 & 0.50 \\ -0.66 & -0.28 & 3.00 & 2.62 & -0.80 & 11.8 & -4.90 & 0.30 & 3.00 & -3.00 & 0.40 & 0.78 & 6.40 & 2.60 & -0.20 & 2.10 & -0.40 & 2.30 & 1.60 & -2.10 \\ 0.96 & 5.04 & 1.70 & -1.96 & 0.37 & -4.90 & 8.24 & -0.90 & 5.90 & -0.60 & 8.50 & -0.83 & 7.20 & 4.80 & -0.90 & -0.10 & 1.30 & 0.76 & 1.90 & 1.30 \\ -1.60 & 1.70 & -4.30 & 2.10 & 0.72 & 0.30 & -0.90 & 1.20 & -0.96 & 0.56 & 1.60 & 0.80 & -0.40 & 0.23 & 0.75 & -0.56 & 0.80 & -0.30 & 5.30 & 0.80 \\ 0.80 & 0.54 & 3.10 & 0.67 & -0.90 & 3.00 & 5.90 & -0.96 & 0.93 & -0.30 & 6.50 & 2.30 & 2.60 & 0.58 & -0.10 & 0.23 & -0.30 & 1.50 & 0.74 & 0.70 \\ -0.10 & 7.20 & -2.00 & 1.80 & 0.69 & -3.00 & -0.60 & 0.56 & -0.30 & 0.99 & -6.60 & 3.90 & 2.30 & -0.30 & 2.80 & -0.80 & 0.38 & 1.90 & 0.47 & -0.26 \\ 3.60 & -0.28 & 0.70 & -0.45 & 1.80 & 0.40 & 8.50 & 1.60 & 6.50 & -6.60 & 10.7 & 5.30 & -0.60 & 0.70 & 1.90 & -2.60 & 0.93 & -0.60 & 3.80 & -1.50 \\ 0.64 & 0.98 & -0.77 & 0.92 & 4.30 & 0.78 & -0.83 & 0.80 & 2.30 & 3.90 & 5.30 & 8.00 & 0.90 & 2.10 & -0.70 & 5.70 & 5.40 & 1.50 & 0.70 & 0.10 \\ 0.79 & -0.46 & 0.93 & 2.40 & -2.80 & 6.40 & 7.20 & -0.40 & 2.60 & 2.30 & -0.60 & 0.90 & 11.0 & 0.87 & -1.00 & 3.60 & 0.46 & -0.90 & 0.60 & 1.50 \\ 2.10 & 1.30 & 4.60 & 7.60 & -0.70 & 2.60 & 4.80 & 0.23 & 0.58 & -0.30 & 0.70 & 2.10 & 0.87 & 3.80 & 0.50 & -0.70 & 1.90 & 2.30 & -0.97 & 0.90 \\ 1.70 & 0.80 & -0.30 & -0.20 & 2.30 & -0.20 & -0.90 & 0.75 & -0.10 & 2.80 & 1.90 & -0.70 & -1.00 & 0.50 & 11.0 & 1.90 & -0.80 & 2.60 & 2.30 & -0.10 \\ 0.80 & -0.20 & 4.20 & 0.70 & 3.60 & 2.10 & -0.10 & -0.56 & 0.23 & -0.80 & -2.60 & 5.70 & 3.60 & -0.70 & 1.90 & 10.8 & 2.50 & -1.80 & 0.90 & -2.60 \\ -3.20 & 0.52 & 0.38 & -1.00 & 0.80 & -0.40 & 1.30 & 0.80 & -0.30 & 0.38 & 0.93 & 5.40 & 0.46 & 1.90 & -0.80 & 2.50 & 8.70 & 4.20 & -0.30 & 0.68 \\ 0.70 & -1.70 & 0.70 & 0.86 & 0.20 & 2.30 & 0.76 & -0.30 & 1.50 & 1.90 & -0.60 & 1.50 & -0.90 & 2.30 & 2.60 & -1.80 & 4.20 & 2.20 & 0.16 & -0.30 \\ 0.48 & 0.80 & -2.00 & 1.60 & -3.00 & 1.60 & 1.90 & 5.30 & 0.74 & 0.47 & 3.80 & 0.70 & 0.60 & -0.97 & 2.30 & 0.90 & -0.30 & 0.16 & 7.60 & 0.69 \\ -0.70 & 0.20 & 3.60 & 0.87 & 0.50 & -2.10 & 1.30 & 0.80 & 0.70 & -0.26 & -1.50 & 0.10 & 1.50 & 0.90 & -0.10 & -2.60 & 0.68 & -0.30 & 0.69 & 7.00 \end{bmatrix}$$

$$B_0 = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]; \quad B_{00} = 0$$

Table 4.6: Input test data for C-2 (TS-B)

Generator/Unit	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	P_{min} (MW)	P_{max} (MW)
1	0.00068	18.19	1000	150	600
2	0.00071	19.26	970	50	200
3	0.0065	19.8	600	50	200
4	0.005	19.1	700	50	200
5	0.00738	18.1	420	50	160
6	0.00612	19.26	360	20	100
7	0.0079	17.14	490	25	125
8	0.00813	18.92	660	50	150
9	0.00522	18.27	765	50	200
10	0.00573	18.92	770	30	150
11	0.0048	16.69	800	100	300
12	0.0031	16.76	970	150	500
13	0.0085	17.36	900	40	160
14	0.00511	18.7	700	20	130
15	0.00398	18.7	450	25	185
16	0.0712	14.26	370	20	80
17	0.0089	19.14	480	30	85
18	0.00713	18.92	680	30	120
19	0.00622	18.47	700	40	120
20	0.00773	19.79	850	30	100

Case-3 (C-3) -Ten Unit Test System with VPLe:

The input test data for C-3 (TS-B) having 10-generating units with VPLe and a power demand of 2000 MW and the input test data with loss coefficients is considered from [296] and displayed in Table 4.7.

Case-4 (C-4)-Thirteen Unit System with VPLe:

The input data for C-4 (TS-B) 13-generator test system with VPLe is considered with a required power of 2520 MW. The test system information is referred from [297] with

no loss coefficient matrix . Table 4.8 displays the input test data with lower and upper power limits as well as the generator cost coefficients.

Table 4.7: Input test data for C-3 (TS-B) with VPLE

Generator/ Unit	$P_{\min}$ (MW)	$P_{\max}$ (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	d_i (\$/hr)	e_i (1/MW)
1	10	55	0.12951	40.5407	1000.403	33	0.0174
2	20	80	0.10908	39.5804	950.606	25	0.0178
3	47	120	0.12511	36.5104	900.705	32	0.0162
4	20	130	0.12111	39.5104	800.705	30	0.0168
5	50	160	0.15247	38.539	756.799	30	0.0148
6	70	240	0.10587	46.1592	451.325	20	0.0163
7	60	300	0.03546	38.3055	1243.531	20	0.0152
8	70	340	0.02803	40.3965	1049.998	30	0.0128
9	135	470	0.02111	36.3278	1658.569	60	0.0136
10	150	470	0.01799	38.2704	1356.659	40	0.0141

Table 4.8: Input data for C-4 (TS-B) with VPLE

Generator/ Unit	$P_{\min}$ (MW)	$P_{\max}$ (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	d_i (\$/hr)	e_i (1/MW)
1	0	680	0.00028	8.1	550	300	0.035
2	0	360	0.00056	8.1	309	200	0.042
3	0	360	0.00056	8.1	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

4.5.1.3 Test System C (TS-C) - Large Scale Power System

In TS-C two cases are categorized under large scale power system problems. These cases are tested using the proposed memetic algorithms. Among them one case considered is without valve point loading effect and other is with valve point loading effect.

Case-1 (C-1) – Thirty- Eight Unit System without VPLE:

The input test data for C-1 (TS-C) having 38-generating units without VPLE and a required load of 6000 MW and the input test information/data is considered from [70] along with the upper and lower bounds of each power generator and displayed in Table 4.9.

Case-2 (C-2) - Forty Unit Test System with VPLE:

The input test data for C-2 (TS-C) having 40-generator test system with VPLE is employed with a load of 10500 MW and the input data is considered from [297] with loss coefficient matrix as zero. Table 4.10 displays the input test data which consists of lower and upper power limits with cost coefficients of thermal generating units.

4.5.2 Dynamic Economic Load Dispatch Problem

This section includes the test system data considered for different DELD problems with a variable load demand for 24 hours a day. The four different test cases with five, six, seven and ten generators are considered and tested using the proposed memetic approaches. The input data with cost coefficients, load demand and generating capacity limits are elaborated in the following subsections.

4.5.2.1 Five generator test system (Dynamic TS-1)

The input test data for 5-generating units (Dynamic TS-1) for dynamic load dispatch with VPLE is referred from [38] for a load demand of 24 hours with the loss coefficient matrix. The cost coefficients and power generating capacity limits are given in Table 4.11. The B-matrix is also given with the variable load demand for 24 hours and is shown in Table 4.12.

Table 4.9: Input test data for C-1 (TS-C)

Generator/Unit	$P_{\min}$ (MW)	$P_{\max}$ (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)
1	220	550	0.3133	796.9	64782
2	220	550	0.3133	796.9	64782
3	220	550	0.3127	795.5	64670
4	220	550	0.3127	795.5	64670
5	220	550	0.3127	795.5	64670
6	220	550	0.3127	795.5	64670
7	220	550	0.3127	795.5	64670
8	220	550	0.3127	795.5	64670
9	114	500	0.7075	915.7	172832
10	114	500	0.7075	915.7	172832
11	114	500	0.7515	884.2	176003
12	114	500	0.7083	884.2	173028
13	110	500	0.4211	1250.1	91340
14	90	365	0.5145	1298.6	63440
15	82	365	0.5691	1298.6	65468
16	120	325	0.5691	1290.8	77282
17	65	315	2.5881	238.1	190928
18	65	315	3.8734	1149.5	285372
19	65	315	3.6842	1269.1	271676
20	120	272	0.4921	696.1	39197
21	120	272	0.5728	660.2	45576
22	110	260	0.3572	803.2	28770
23	80	190	0.9415	818.2	36902
24	10	150	52.123	33.5	105510
25	60	125	1.1421	805.4	22233
26	55	110	2.0275	707.1	30953
27	35	75	3.0744	833.6	17044
28	20	70	16.765	2188.7	81079
29	20	70	26.355	1024.4	124767
30	20	70	30.575	837.1	121915
31	20	70	25.098	1305.2	120780
32	20	60	33.722	716.6	104441
33	25	60	23.915	1633.9	83224
34	18	60	32.562	969.6	111281
35	8	60	18.360	2625.8	64142
36	25	60	23.915	1633.9	103519
37	20	38	8.482	694.7	13547
38	20	38	9.693	655.9	13518

Table 4.10: Input test data for C-2 (TS-C) with VPLe

Generator/ Unit	P _{min} (MW)	P _{max} (MW)	a _i (\$/MW ² hr)	b _i (\$/MWhr)	c _i (\$/hr)	d _i (\$/hr)	e _i (1/MW)
1	36	114	0.0069	6.73	94.705	100	0.084
2	36	114	0.0069	6.73	94.705	100	0.084
3	60	120	0.02028	7.07	309.54	100	0.084
4	80	190	0.00942	8.18	369.03	150	0.063
5	46	97	0.0114	5.35	148.89	120	0.077
6	68	140	0.01142	8.05	222.33	100	0.084
7	110	300	0.00357	8.03	287.71	200	0.042
8	135	300	0.00492	6.99	391.98	200	0.042
9	135	300	0.00573	6.6	455.76	200	0.042
10	130	300	0.00606	12.9	722.82	200	0.042
11	94	375	0.00515	12.9	635.2	200	0.042
12	94	375	0.00569	12.8	654.69	200	0.042
13	125	500	0.00421	12.5	913.4	300	0.035
14	125	500	0.00752	8.84	1760.4	300	0.035
15	125	500	0.00708	9.15	1728.3	300	0.035
16	125	500	0.00708	9.15	1728.3	300	0.035
17	220	500	0.00313	7.97	647.85	300	0.035
18	220	500	0.00313	7.95	649.69	300	0.035
19	242	550	0.00313	7.97	647.83	300	0.035
20	242	550	0.00313	7.97	647.81	300	0.035
21	254	550	0.00298	6.63	785.96	300	0.035
22	254	550	0.00298	6.63	785.96	300	0.035
23	254	550	0.00284	6.66	794.53	300	0.035
24	254	550	0.00284	6.66	794.53	300	0.035
25	254	550	0.00277	7.1	801.32	300	0.035
26	254	550	0.00277	7.1	801.32	300	0.035
27	10	150	0.52124	3.33	1055.1	120	0.077
28	10	150	0.52124	3.33	1055.1	120	0.077
29	10	150	0.52124	3.33	1055.1	120	0.077
30	47	97	0.0114	5.35	148.89	120	0.077
31	60	190	0.0016	6.43	222.92	150	0.063
32	60	190	0.0016	6.43	222.92	150	0.063
33	60	190	0.0016	6.43	222.92	150	0.063
34	90	200	0.0001	8.95	107.87	200	0.042
35	90	200	0.0001	8.62	116.58	200	0.042
36	90	200	0.0001	8.62	116.58	200	0.042
37	25	110	0.0161	5.88	307.45	80	0.098
38	25	110	0.0161	5.88	307.45	80	0.098
39	25	110	0.0161	5.88	307.45	80	0.098
40	242	550	0.00313	7.97	647.83	300	0.035

Table 4.11: Input test data for (Dynamic TS-1) with VPLE

Generator/Units	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	d_i (\$/hr)	e_i (1/MW)	P_{min} (MW)	P_{max} (MW)
1	0.008	2	25	100	0.042	10	75
2	0.003	1.8	60	140	0.04	20	125
3	0.0012	2.1	100	160	0.038	30	175
4	0.001	2	120	180	0.037	40	250
5	0.0015	1.8	40	200	0.035	50	300

Table-4.12: Load Demand (Dynamic TS-1)

Time (hr)	Load (MW)	Time (hr)	Load (MW)	Time (hr)	Load (MW)
1	410	9	690	17	558
2	435	10	704	18	608
3	475	11	720	19	654
4	530	12	740	20	704
5	558	13	704	21	680
6	608	14	690	22	605
7	626	15	654	23	527
8	654	16	580	24	463

4.5.2.2 Six Generator Test System (Dynamic TS-2)

The input test data for 6-generating units (Dynamic TS-2) for dynamic load dispatch without VPLE is referred from [298] for a load demand of 24 hours and loss coefficient matrix is considered. The fuel cost coefficients and power generating capacity limits are tabulated in Table 4.13 and Table 4.14 represents the variable load demand for a day or 24 hours. The proposed memetic algorithms are implemented to find the optimum fuel cost for six generating unit system.

Table 4.13: Input test data for (Dynamic TS-2) without VPLe

Generator/ Unit	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	P_{min} (MW)	P_{max} (MW)
1	0.0070	7.0	240	100	500
2	0.0095	10.0	200	50	200
3	0.0090	8.5	220	80	300
4	0.0090	11.0	200	50	150
5	0.0080	10.5	220	50	200
6	0.0075	12.0	190	50	120

Table 4.14: Load Demand for 24 hours (Dynamic TS-2)

Time (hr)	Load (MW)	Time (hr)	Load (MW)	Time (hr)	Load (MW)
1	700	9	1300	17	1000
2	750	10	1400	18	1100
3	850	11	1450	19	1200
4	950	12	1500	20	1400
5	1000	13	1400	21	1300
6	1100	14	1300	22	1100
7	1150	15	1200	23	900
8	1200	16	1050	24	800

4.5.2.3 Seven Generator Test System (Dynamic TS-3)

The input test data for 7-generating units (Dynamic TS-3) for DELD problem without taking the effect of valves and is referred from [145] for a load demand of 24 hours. The cost coefficients and power capacity limits of generators are given in Table 4.15 and the variable load demand for 24 hours is shown in Table 4.16.

4.5.2.4 Ten Generator Test System (Dynamic TS-4)

The input test data for 10-generating units (Dynamic TS-4) for DELD problem without VPLe is referred from [145] for a load demand of 24 hours. The variable load demand for 24 hours is given in Table 4.17 and Table 4.18 gives the cost coefficients and power capacity limits of generators.

Table 4.15 Input test data for (Dynamic TS-3) without VPLe

Generator/ Units	$P_{\min}$ (MW)	$P_{\max}$ (MW)	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)
1	100	575	0.007	7	400
2	50	100	0.0095	10	200
3	50	140	0.009	8.5	220
4	50	100	0.009	11	200
5	100	550	0.008	10.5	240
6	50	100	0.0075	12	200
7	100	410	0.0068	10	180

Table 4.16: Power demand for 24 hours (Dynamic TS-3)

Time (hr)	Load (MW)	Time (hr)	Load (MW)	Time (hr)	Load (MW)
1	800	9	800	17	1500
2	780	10	900	18	900
3	750	11	1000	19	850
4	750	12	1200	20	800
5	720	13	1400	21	780
6	700	14	1500	22	750
7	700	15	1750	23	700
8	700	16	1800	24	800

Table 4.17: Power demand for 24 hours (Dynamic TS-4)

Time (hrs)	1	2	3	4	5	6	7	8
Load (MW)	700	750	850	950	1000	1100	1150	1200
Time (hrs)	9	10	11	12	13	14	15	16
Load (MW)	1300	1400	1450	1500	1400	1300	1200	1050
Time (hrs)	17	18	19	20	21	22	23	24
Load (MW)	1000	1100	1200	1400	1300	1100	900	800

Table 4.18: Input test data for (Dynamic TS-4) without VPLE

Generators/Units	a_i (\$/MW ² hr)	b_i (\$/MWhr)	c_i (\$/hr)	P_{min} (MW)	P_{max} (MW)
1	0.00048	16.19	1000	150	455
2	0.00031	17.26	970	150	455
3	0.002	16.6	700	20	130
4	0.00211	16.5	680	20	130
5	0.00398	19.7	450	25	162
6	0.00712	22.26	370	20	80
7	0.0079	27.74	480	25	85
8	0.00416	25.92	660	10	55
9	0.002222	27.27	665	10	55
10	0.00173	27.79	670	10	55

4.6 RESULTS AND DISCUSSIONS

4.6.1 Static Economic Load Dispatch

Proposed algorithms such as HHO, SMA, hHHO-RES and hSMA-RES are successfully implemented to the static ELD problems of power system. This part covers the solution and discussion of different cases considered with different number of units and demand. Different cases with and without consideration of losses and valve point loading effects are considered and tested using the MATLAB 2018a environment on a computer having Windows 10, 4GB RAM core i5 processor. The efficacy of proposed algorithms is proved by comparing with other well-known existing algorithms.

4.6.1.1 Test System A (TS-A) -Small Scale Power Systems

In this section the outcomes of test cases categorized under small power system load dispatch problems are discussed. Table-4.19, 4.20 and 4.21 shows the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods; statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed

methods respectively for case 1 (3 generating units without VPL effect). The results reveals that the cost achieved with proposed memetic approach hSMA-RES is 1590.643733 \$/hr and hHHO-RES is 1590.684891\$/hr. The optimum fuel cost using SMA is 1590.65412 \$/hr and HHO is 1590.80054 \$/hr. The simulation time required is less in memetic HHO-RES algorithm (hHHO-RES) of 3.78125 seconds as compared to hSMA-RES. The best, mean and worst time for C-1, test system A has also been recorded in table -4.21.

Table 4.19: Load dispatch and comparison C-1(TS-A)
(3 generating units without VPLe)

Algorithm	Power Demand (MW)	Dispatch of Power Generating Units (MW)			P _{Loss} (MW)	Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃		
hSMA-RES	150	10	75.39071	65.27916	0.33493	1590.643733
SMA	150	10	75.04464	65.62413	0.33438	1590.656412
hHHO-RES	150	10	74.492599	66.174389	0.33349	1590.684891
HHO	150	10	73.099333	67.563183	0.33125	1590.80054
GWO [70]	150	30.4998	64.6208	54.8994	0.23	1597.4815
LM [70]	150	33.4701	64.0974	55.1011	2.6686	1599.98
GA [299]	150	34.4895	64.0299	54.1534	2.6728	1600
QP [299]	150	32.8116	64.5973	54.9329	2.3419	1596
PSO [70]	150	32.8101	64.595	54.9369	2.342	1597.48

Table 4.20: Statistical results: C-1 (TS-A) (3 generating units without VPLe)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	1590.643733	1590.887151	1591.1536	0.172547331	1590.834265
SMA	1590.656412	1604.692514	1797.714085	52.46936299	1590.834299
hHHO-RES	1590.684891	1777.018801	1797.714085	63.14722797	1797.714085
HHO	1590.80054	1790.816967	1797.714085	37.77707209	1797.714085

Table 4.22, table 4.23 and table 4.24 shows the statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods; load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods respectively for case 2 (6 generating units without VPL effect). The results reveals that the cost achieved with SMA and proposed memetic approach hSMA-RES is 15275.9304\$/hr and with HHO and hHHO-RES is 15275.9305 \$/hr and 15276.01066 \$/hr respectively. The simulation time required is less in memetic HHO-RES algorithm (hHHO-RES) of 4.1875 seconds as compared to memetic SMA-RES. The best, mean and worst time has also been depicted in table 4.23.

Table 4.21: Simulation time: C-1 (TS-A) (3 generating units without VPLe)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	5.859375	6.1703125	7.9375
SMA	3.390625	3.697916667	5.578125
hHHO-RES	3.78125	4.18125	6.453125
HHO	3.265625	3.746354167	7.1875

Table 4.22: Statistical results: C-2 (TS-A) (6 generating units without VPLe)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	15275.9304	15275.93055	15275.93103	0.000120069	15275.93053
SMA	15275.9304	15275.9305	15275.93075	7.31929E-05	15275.93048
hHHO-RES	15276.01066	15276.32821	15278.40188	0.45003795	15276.17977
HHO	15275.93051	15275.93131	15275.93245	0.000548928	15275.93116

Table 4.23: Simulation time: C-2 (TS-A) (6 generating units without VPLe)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.015625	6.242708333	8.046875
SMA	3.5	3.990625	7.71875
hHHO-RES	4.1875	4.893229167	6.125
HHO	3.484375	3.751041667	5.453125

Table 4.24: Load Dispatch and comparison - C-2 (TS-A) (6 generating units without VPLe)

Algorithm	Power Demand (MW)	Dispatch of power generating Units (MW)						Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	
hSMA-RES	1263	446.7368	171.2628	264.1154	125.2112	172.1238122	83.54989	15275.93041
SMA	1263	446.6894	171.2582	264.089	125.2351	172.1235047	83.60477	15275.9304
hHHO-RES	1263	446.395	170.394	263.3982	123.6596	173.6368421	85.51645	15276.01066
HHO	1263	446.6973	171.3117	264.0242	125.2657	172.0923175	83.60882	15275.93051
FA[42]	1263	445.08	173.08	264.42	139.59	166.02	87.21	15443
BBO[300]	1263	447.3997	173.2392	263.3163	138.0006	165.4104	87.07979	15443.0963
N-MPSO [301]	1263	446.71	173.01	265.00	139.00	165.23	86.78	15447
PSO [302]	1263	447.50	173.32	263.47	139.06	165.48	87.13	15450
New PSO [303]	1263	447.4734	173.1012	262.6804	139.4156	165.3002	87.9761	15450
SOHPSO[304]	1263	438.21	172.58	257.42	141.09	179.37	86.88	15446.02
PSO–LRS[303]	1263	447.4440	173.3430	263.3646	139.1279	165.5076	87.1698	15450
GA [305]	1263	474.81	178.64	262.21	134.28	151.90	74.18	15459
NPSOLRS[303]	1263	446.96	173.3944	262.3436	139.5120	164.7089	89.0162	15450
ABCO[306]	1263	438.65	167.90	262.82	136.77	171.76	97.67	15445.90
DE[307]	1263	400.00	186.55	289.00	150.00	200.00	50.00	15445.90
SA [45]	1263	447.08	173.18	263.92	139.06	165.58	86.63	15466.00
CPSO1 [308]	1263	434.4236	173.4385	274.2247	128.0183	179.7042	85.9082	15447
CPSO2 [308]	1263	434.4295	173.3231	274.4735	128.0598	179.4759	85.9281	15446
IPSO [308]	1263	440.5711	179.8365	261.3798	131.9134	170.9823	90.8241	15444

Table 4.25 - 4.27 shows the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods; statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods respectively for case III (3 generating units with VPL effect).

Table-4.25: Load Dispatch and comparison– C-3 (TS-A) (3 generating units with VPLe)

Algorithm	Power Demand (MW)	Dispatch of Power Generating Units (MW)			Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	
hSMA-RES	850	300.2669	400	149.7331	8234.07173
SMA	850	300.2669	400	149.7331	8234.07173
hHHO-RES	850	300.2669	400	149.7331	8234.07173
HHO	850	300.2669	400	149.7331	8234.07173
EP[294]	850	300.264	400	149.736	8234..07
EP-SQP[294]	850	300.264	400	149.733	8234..07
PSO[294]	850	300.267	400	149.732	8234.07
PSO-SQP[294]	850	300.268	400	149.733	8234.07
CPSO[294]	850	300.267	400	149.733	8234.07
DE[290]	850	300.2668999	400	149.7331001	8234.07173
Lambda[295]	850	382.258	340.323	127.419	8575.68
GA[295]	850	382.2552	340.3202	127.4184	8575.64
ABC[295]	850	300.266	400	149.733	8253.10

Table-4.26: Statistical results -C-3 (TS-A) (3 generating units with VPLe)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	8234.07173	8234.82331	8241.587522	2.293282735	8234.071731
SMA	8234.07173	8234.572783	8241.587522	1.906817457	8234.07173
hHHO-RES	8234.07173	8238.800496	8250.663753	6.207209294	8234.07173
HHO	8234.07173	8246.279841	8366.66926	33.13821679	8234.07173

Table-4.27: Simulation time: C-3 (TS-A) (3 generating units with VPLe)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.59375	6.908854167	9.140625
SMA	3.953125	4.50677083	7.71875
hHHO-RES	4.28125	5.235416667	8.484375
HHO	3.78125	4.1390625	7.828125

Table-4.28: Load Dispatch and comparison: C-4 (TS-A) (5 generating units with VPLe)

Algorithm	Power Demand (MW)	Dispatch of Power Generating Units (MW)					Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	
hSMA-RES	730	229.5197	102.9863	112.6781	75	209.8159417	2034.971052
SMA	730	229.5197	102.9865	112.678	75	209.8158108	2034.971073
hHHO-RES	730	229.5196	99.1153	111.5679	75	214.7972415	2052.84509
HHO	730	229.5196	102.6988	112.9897	75	209.7919643	2035.392558
LM[295]	730	218.028	109.014	147.535	28.38	272.042	2412.709
GA[295]	730	218.018	109.0092	147.5229	28.37844	227.0275	2412.538
PSO [295]	730	229.52	125	175	75	125.4804	2252.572
APSO[295]	730	225.385	113.02	109.4146	73.11176	209.0692	2140.97

The results reveals that the cost achieved with SMA, HHO, proposed memetic approach hSMA-RES and hHHO-RES is 8234.07173 \$/hr, this proves the competency of the suggested approaches. The simulation time using the proposed memetic methodologies is shown in Table-4.27 with best performance among memetic algorithms stated by hHHO-RES with elapsed time of 4.28125 seconds. The outcomes of case 4 (5 generating units with VPL effect) using proposed methods has been presented in tables- 4.28 through table-4.30 showing load dispatch and attained fuel cost by HHO, SMA, hHHO-RES, hSMA-RES and compared with other approaches; statistical analysis in regard to median, mean and standard deviation (SD); simulation time for different approaches.

The results exposes the competence of proposed memetic approaches in regard to other stochastic approaches with optimum fuel cost of 2034.971052 \$/hr, 2034.971073 \$/hr, 2035.392558 \$/hr and 2052.84509 \$/hr using hSMA-RES, SMA, HHO and hHHO-RES respectively. The best simulation time for proposed memetic methods is recorded as 4.578125 secs with hHHO-RES. The convergence curves for four test cases categorized under test system A are shown in fig. 4.1.

Table 4.29: Statistical results: – C-4 (TS-A) (5 generating units with VPLe)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	2034.971052	2076.472945	2094.28	27.6211316	2094.242619
SMA	2034.971073	2068.572266	2094.296327	29.86529483	2094.239042
hHHO-RES	2052.84509	2181.228937	2314.217881	71.27002961	2181.60043
HHO	2035.392558	2084.148841	2230.691761	54.60200061	2095.429237

Table 4.30: Simulation time: C-4 (TS-A) (5 generating units with VPLe)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.671875	6.866666667	9.0625
SMA	4.4375	4.818229167	7.046875
hHHO-RES	4.578125	5.854166667	9.5625
HHO	3.890625	4.414583333	7.28125

4.6.1.2 Test System-B (Medium Scale Power System)

In this section four diverse test systems are tested using the proposed algorithms for better efficacy and optimum cost and compared with other existing algorithms in literature. Two test cases considered are without VPLe and other two cases studied are with the non-linear effect of valves.

Table 4.31 to table 4.33 shows the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods; statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods respectively for case 1 (15 generating units without VPL effect). The results reveals that the cost achieved with proposed memetic approach hSMA-RES is 32259.93241 \$/hr and hHHO-RES is

32300.36778 \$/hr. The optimum fuel cost using SMA is 32262.06825 \$/hr and HHO is 32463.34041 \$/hr. The simulation time required is less in memetic HHO-RES algorithm (hHHO-RES) as compared to hSMA-RES. The best, mean and worst time has also been recorded in Table-4.33. It is evident to conclude that the proposed memetic SMA performs better than other algorithms.

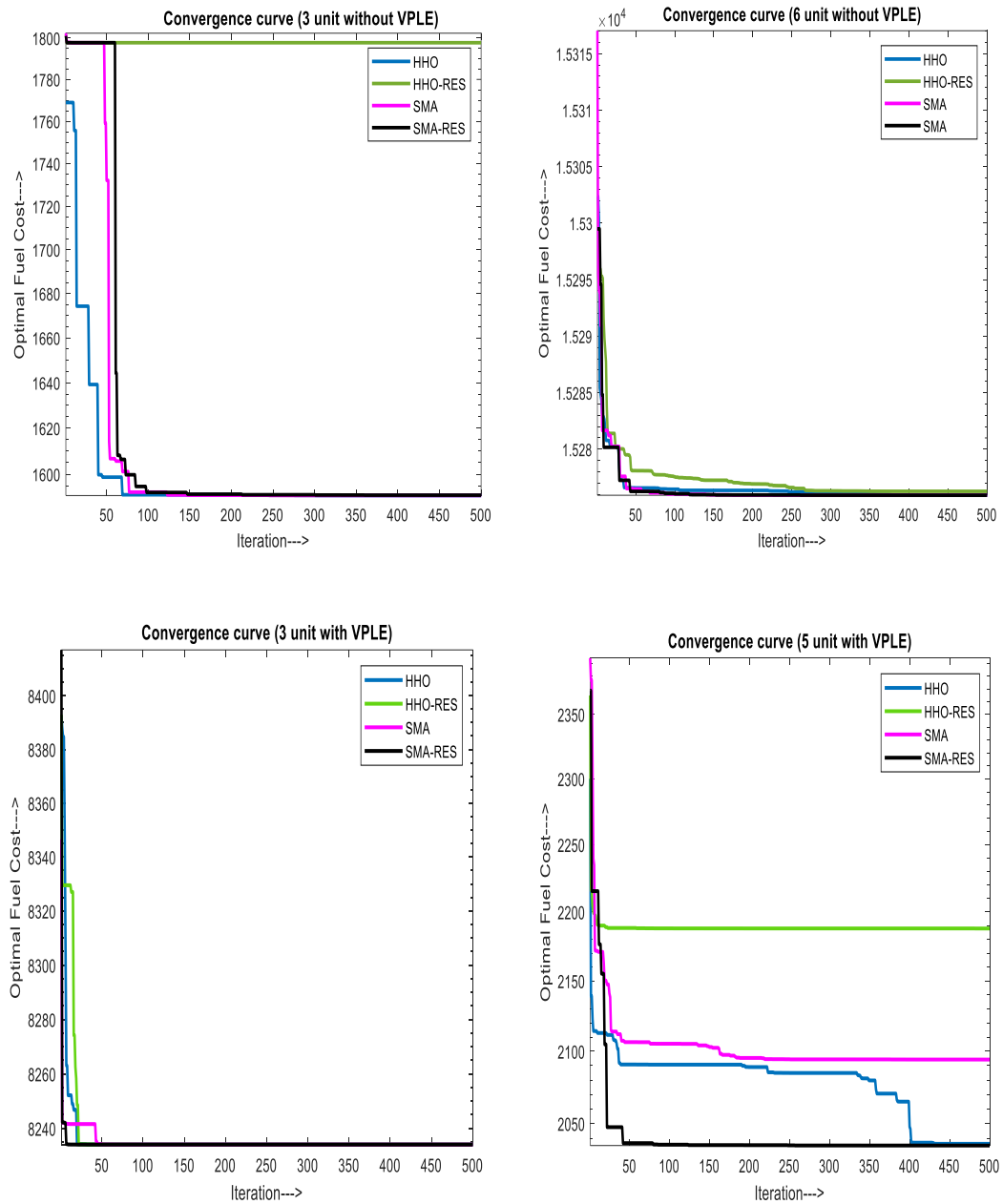


Fig 4.1: Convergence graphs-TS- A (*Small Scale Systems*) using proposed methods

Table 4.34 to Table- 4.36 shows the statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods and load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods respectively for case II (20 generating units without VPL effect). The results reveals that the cost achieved with SMA and proposed memetic approach hSMA-RES is 60152.62515 \$/hr, with SMA is 60152.67179 \$/hr; with HHO and hHHO-RES is 60178.69777 \$/hr and 60248.46507 \$/hr respectively. The simulation time required is less in memetic HHO-RES algorithm (hHHO-RES) in comparison to proposed hSMA-RES. The best, mean and worst time has also been depicted in table-4.35.

Table 4.31: Statistical results: C-1 (TS-B) (15 generating units without VPLE)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	32259.93241	32262.52086	32266.93874	1.023541908	32262.33248
SMA	32262.06825	32262.99814	32267.3062	1.341190498	32262.53617
hHHO-RES	32300.36778	32542.36282	32705.50642	92.66091162	32545.87381
HHO	32463.34041	32692.5102	32912.1402	105.4386429	32676.84685

Table 4.32: Simulation time: C-1 (TS-B) (15 generating units without VPLE)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.03125	6.478645833	8.09375
SMA	3.765625	4.218229167	7.390625
hHHO-RES	5.453125	5.931770833	7.96875
HHO	3.71875	4	5.65625

Table 4.37 to Table 4.39 shows the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods; statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods respectively for case III (10 generating units with VPL effect).

Table 4.33: Load Dispatch and comparison– C-1 (TS-B) (15 generating units without VPLE)

Method	hSMA-RES	SMA	hHHO-RES	HHO	PSO(4) [21]	ES [21]	PSO [21]	GA [21]	ETQ [21]	ESO [21]	ABC [300]	HGAPSO [298]	CPSO1 [298]	CPSO2 [298]	SOHPSO [298]	IPSO [298]
Load (MW)	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630	2630
PG₁	455	455	455	455	440.499	455	439.12	415.31	450	456	455	436.8482	450.05	450.02	455	455
PG2	454.9268	454.427	454.9849	350.499	179.5947	380	407.97	359.72	450	456	380	409.6974	454.04	454.06	380	380
PG3	129.9864	129.949	130	130	21.0524	130	119.63	104.42	130	130	130	117.0074	124.82	124.81	130	129.97
PG4	129.9941	129.903	130	130	87.1376	150	129.99	74.98	130	130	130	128.2705	124.82	124.81	130	130
PG5	289.9622	289.936	253.2689	416.788	360.7675	168.92	151.07	380.28	335	304.24	169.99	153.3361	151.03	151.06	170	169.93
PG6	459.594	457.123	460	404.076	395.833	459.34	459.99	426.79	455	460	460	457.4078	460	460	459.96	459.88
PG7	464.8024	464.915	465	314.866	432.0085	430	425.56	341.32	465	465	430	424.44	434.53	434.57	430	429.25
PG8	60.30779	60.0293	60.65076	60	168.9198	97.42	98.56	124.79	60	60	71.969	101.1949	148.41	148.46	117.53	60.43
PG9	25.04644	25.0682	71.38539	96.2879	162	30.61	113.49	133.14	25	25	59.179	116.1186	63.61	63.59	77.9	74.78
PG10	28.98414	31.7226	26.51806	57.5592	138.4343	142.56	101.11	89.26	20	20	159.8	102.2243	101.13	101.12	119.54	158.02
PG11	25.12235	20.0244	26.67509	70.3856	52.6294	80	33.91	60.06	20	29.15	80	35.0317	28.656	28.655	54.5	80
PG12	51.2817	56.9739	39.44499	69.5476	66.8875	85	79.96	50	55	59.24	80	78.8482	20.912	20.914	80	78.57
PG13	25.0011	25	25.36495	25	62.7471	15	25	38.77	25	25	25.002	27.1292	25.001	25.002	25	25
PG14	15.02272	15.0002	16.38525	15	47.5574	15	41.41	41.94	15	17.28	15.006	37.1594	54.418	54.414	17.86	15
PG15	15.00008	15	15.38808	35.0803	27.6065	15	35.61	22.64	15	15	15.0014	37.039	20.625	20.624	15	15
P_{Loss}	0.016079	0.03607	0.03323	0.0451	13.6745	23.85	32.42	38.28	15.8	13.79	13	31.75	32.1302	32.1303	32.28	30.858
Fuel Cost (\$/hr)	32259.93	32262.068	32300.368	32463.34	32508.12	32568.54	32858	33113	32507.5	32506.6	32707.85	32724	32835	32834	32751.39	32709

Table 4.34: Load Dispatch and comparison: C-2(TS-B) (20 generating units without VPLe)

Algorithm	hSMA-RES	SMA	hHHO-RES	HHO	LIM [27]	HNN [17]
Power demand (MW)	2500	2500	2500	2500	2500	2500
PG₁	599.99758	599.98301	600	599.4109	512.7805	512.7804
PG₂	133.01243	129.50178	125.42053	130.7248	169.1033	169.1035
PG₃	50	50	50	50	126.8898	126.8897
PG₄	50.000032	50.000019	75.133574	50	102.8657	102.8656
PG₅	88.928146	91.461209	119.08886	89.92467	113.6836	113.6836
PG₆	20.000863	20.000002	32.640766	22.81068	73.571	73.5709
PG₇	125	124.99084	100.31754	123.4074	115.2878	115.2876
PG₈	50	50	50	50.1876	116.3994	116.3994
PG₉	114.33587	112.34627	70.012003	134.6384	100.4062	100.4063
PG₁₀	46.093364	48.252947	58.178861	64.53020	106.0267	106.0267
PG₁₁	286.2771	286.17074	246.61417	277.0663	150.2394	150.2395
PG₁₂	434.0149	434.67282	414.12884	455.7015	292.7648	292.7647
PG₁₃	123.45237	122.55604	124.9094	144.4634	119.1154	119.1155
PG₁₄	74.193356	74.755041	24.961049	23.48230	30.834	30.8342
PG₁₅	90.348979	95.121001	102.31225	91.65221	115.8057	115.8056
PG₁₆	36.717156	35.972417	37.716981	35.22087	36.2545	36.2545
PG₁₇	30.000011	30.000021	59.946995	30.05477	66.859	66.859
PG₁₈	37.846971	36.167207	91.956855	35.30991	87.972	87.972
PG₁₉	79.778957	78.048611	86.661319	61.39860	100.8033	100.8033
PG₂₀	30.001914	30.000008	30	30.01568	54.305	54.305
Fuel Cost (\$/hr)	60152.672	60152.625	60248.465	60178.69	62456.64	62456.63

The results reveals that the cost achieved with the proposed memetic approach hSMA-RES and hHHO-RES is 106170.4501 \$/hr and 106257.4271 \$/hr while SMA and HHO yields 106170.4692 \$/hr and 106249.6724 \$/hr respectively showing hSMA- RES as

the best performing algorithm. The simulation time using the proposed methodologies is shown in Table-4.39 with best performance stated by hHHO-RES among the memetic algorithms with elapsed time of 5.265625 seconds.

Table-4.35: Statistical results: C-2 (TS-B) (20 generating units without VPLe)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	60152.67179	60153.06924	60154.44709	0.428323487	60152.94815
SMA	60152.62515	60152.93835	60153.36404	0.205645003	60152.91275
hHHO-RES	60248.46507	60405.71163	60561.91321	66.31521784	60398.56158
HHO	60178.69777	60246.03903	60312.29888	30.8526545	60240.73149

Table 4.36: Simulation time: C-2 (TS-B) (20 generating units without VPLe)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.3125	6.8609375	7.953125
SMA	3.890625	4.286979167	5.78125
hHHO-RES	6.15625	6.524479167	8.265625
HHO	3.78125	4.3375	7.671875

The outcomes of case IV (13 generating units with VPL effect) using proposed methods has been presented in Tables- 4.40 through Table-4.42 showing load dispatch and attained fuel cost by HHO, SMA, hHHO-RES, hSMA-RES and compared with other approaches; statistical analysis in terms of median and standard deviation(SD); simulation time for different approaches. The results exposes the competence of proposed memetic approaches in regard to other stochastic approaches with optimum fuel cost of 24176.81302 \$/hr, 24180.80315 \$/hr, 24291.59188\$/hr and 24461.82642\$/hr using hSMA-RES, SMA, HHO and hHHO-RES respectively. The best simulation time among the proposed memetic algorithms is recorded as 5.65625 seconds with hHHO-RES.

Table-4.37: Load Dispatch and comparison- C-3 (TS-B) (10 generating units with VPLe)

Method	hSMA-RES	SMA	hHHO-RES	HHO	GSA [302]	FPA [302]	MODE [302]	NSGAI [302]	ABC_PSO [302]	PSO [301]	PDE [302]	PSO- TVAC [301]	EMOCA [302]	MSCO [302]	SPEA-2 [302]
Power Demand = 2000 MW															
PG₁	54.99987	54.9998	55	54.9237	54.9992	53.188	54.9487	51.9515	55	53.1	54.9853	53.8	55	52.8995	52.9761
PG₂	80	80	78.7461	78.99998	79.9586	79.975	74.5821	67.2584	80	79.2	79.3803	78.9	80	74.9428	72.813
PG₃	89.18157	88.4723	94.44013	83.18582	79.4341	78.105	79.4294	73.6879	81.14	112	83.9842	109	83.5594	97.4068	78.1128
PG₄	80.27976	80.1411	93.18499	100.5875	85	97.119	80.6875	91.3554	84.216	121	86.5942	125	84.6031	95.9554	83.6088
PG₅	66.21202	66.4891	50	58.33947	142.1063	152.74	136.8551	134.0522	138.34	98.8	144.4386	98.8	146.563	131.87	137.2432
PG₆	70	70	70	70.15425	166.567	163.08	172.6393	174.9504	167.508	100	165.7756	90.4	169.248	200.512	172.9188
PG₇	291.6651	290.789	292.7048	284.6714	292.8749	258.61	283.8233	289.435	296.834	299	283.2122	298	300	227.922	287.2033
PG₈	327.6623	329.109	332.078	332.7524	313.2387	302.22	316.3407	314.0556	311.582	320	312.7709	330	317.349	303.651	326.4023
PG₉	469.9993	470	465.6396	467.8887	441.1775	433.21	448.5923	455.6978	420.336	467	440.1135	468	412.918	366.319	448.8814
PG₁₀	470	470	468.2064	468.4968	428.6306	466.07	436.4287	431.8054	449.159	356	432.6783	351	434.313	470	423.9025
Fuel Cost (\$/hr)	106170.5	106170.5	106257.4	106249.7	113490	11337	113484	113539	113420	10762	113510	10738	113445	110870	113520

Table 4.38: Statistical results: C-3 (TS-B) (*10 generating units with VPLe*)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	106170.4501	106170.6384	106171.0458	0.158898692	106170.6083
SMA	106170.4692	106170.7196	106171.1715	0.191771142	106170.6273
hHHO-RES	106257.4271	109009.3455	110605.4699	1293.605822	109585.2618
HHO	106249.6724	107348.3544	108531.7967	809.2517545	107462.5166

Table 4.39: Simulation time: C-3 (TS-B) (*10 generating units with VPLe*)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	6.984375	7.380208333	9.625
SMA	5.234375	5.443229167	7.296875
hHHO-RES	5.265625	5.660416667	7.765625
HHO	4.140625	4.585416667	7.625

Table 4.40: Statistical results: C-4 (TS-B) (*13 generating units with VPLe*)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	24176.81302	24256.1735	24398.56943	57.08310894	24275.07379
SMA	24180.80315	24285.41797	24557.06644	78.95261898	24276.83253
hHHO-RES	24291.59188	24568.96821	24934.44945	174.3602055	24516.86349
HHO	24461.82642	24801.13624	25071.48658	167.8840155	24803.59115

Table 4.41: Simulation time: C-4 (TS-B) (*13 generating units with VPLe*)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	7.015625	7.2515625	9.046875
SMA	4.15625	4.5390625	6.328125
hHHO-RES	5.65625	6.264583333	8.875
HHO	4.046875	4.589583333	8.59375

Table 4.42a: Load Dispatch and comparison:C-4 (TS-B) (13 *generating units with VP*LE)

Algorithm	hSMA-RES	SMA	hHHO-RES	HHO	GA [287]	CPSO [284]	CJAYA [303]	JAYA [303]
Load = 2520 (MW)								
PG₁	628.318	628.318	628.269	628.319	627.05	682.32	628.319	628.319
PG₂	298.932	299.014	298.35	359.879	359.4	299.83	299.199	299.201
PG₃	298.988	299.011	299.841	359.879	358.95	299.17	299.199	306.911
PG₄	159.715	159.725	160.336	155.92	158.93	159.7	159.733	159.734
PG₅	159.26	159.56	111.332	155.802	159.73	159.64	159.733	159.734
PG₆	159.719	159.589	161.785	153.045	159.68	159.67	159.733	159.734
PG₇	159.71	159.45	159.734	160.114	159.53	159.64	159.733	109.867
PG₈	159.684	159.721	159.976	159.778	158.89	159.65	159.733	159.734
PG₉	159.722	159.646	159.665	161.42	110.15	159.78	159.733	159.734
PG₁₀	114.356	111.311	74.378	75.843	77.27	112.46	110.04	114.801
PG₁₁	74.888	114.655	115.776	40	75	74	114.799	114.8
PG₁₂	91.707	55	93.201	55	60	56.5	55	92.402
PG₁₃	55	55	97.357	55	55.41	91.64	55	55.003
Fuel Cost (\$/hr)	24176.81	24180.80	24291.59	24461.83	24419	24211.56	24178.8	24220.75

The convergence graphs for test system B are shown in Fig. 4.2 comprises of 4 cases under medium scale power systems.

4.6.1.3 Test System-C (Large Scale Power System)

This section elaborates the results of two large scale test systems. One test case is investigated without VPLE and other with VPLE to validate the effectiveness of the proposed algorithms. Table 4.43 to Table- 4.45 shows the statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median; simulation time taken by different proposed methods and the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods respectively for case 1 (38 generating units without VPL effect). The results reveal that the cost achieved with proposed memetic approach hSMA-RES is 9402607.969 \$/hr and hHHO-RES is 9452053.175 \$/hr. The optimum fuel cost using SMA is 9402608.352 \$/hr and HHO is 9425015.415 \$/hr. The simulation time required

is less in memetic HHO algorithm as compared to hSMA-RES. The best, mean and worst time has also been recorded in Table 4.44. It is evident to conclude that the proposed memetic SMA works better in achieving the optimum cost than other algorithms while hHHO-RES take less running time.

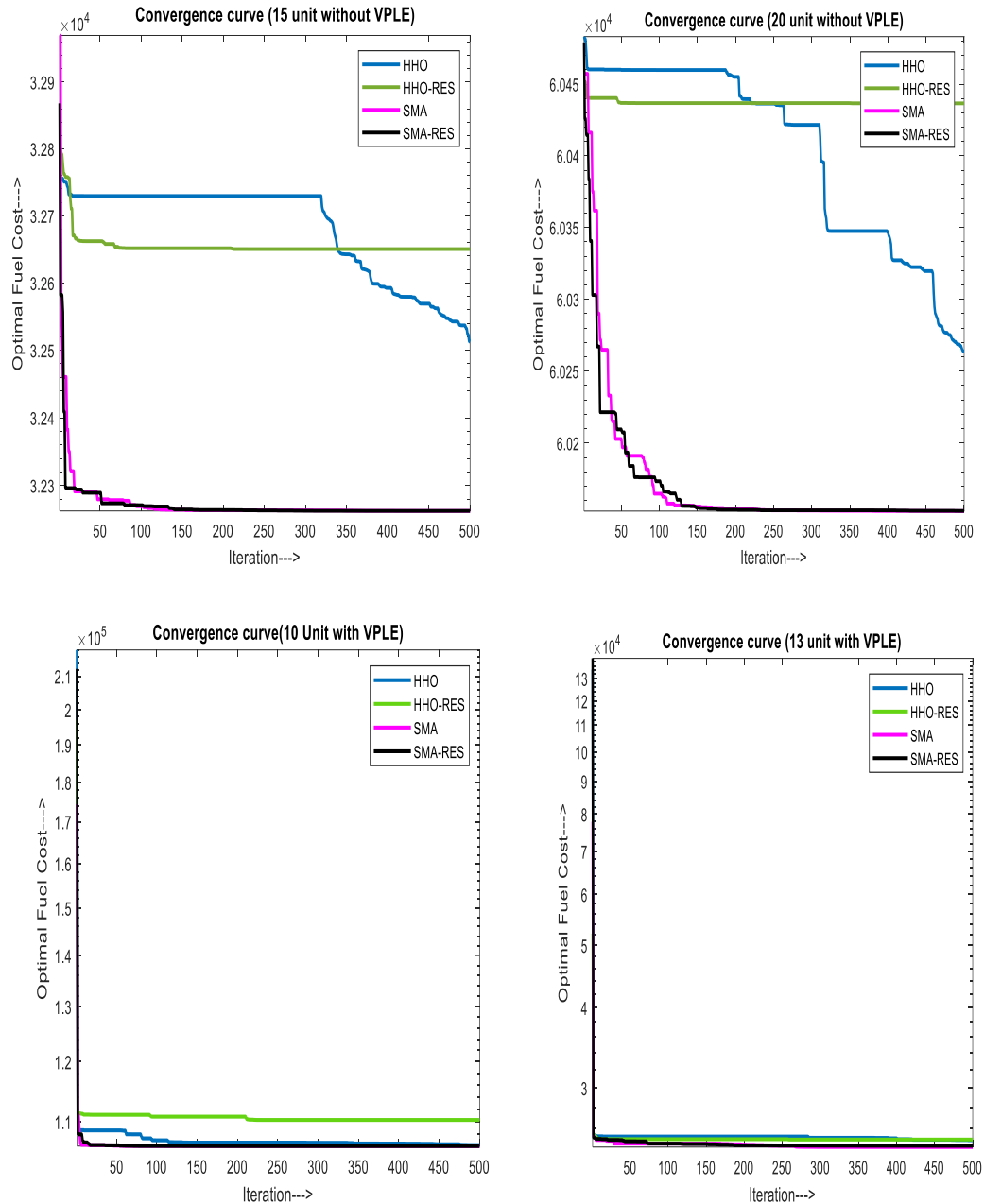


Fig 4.2: Convergence graphs-TS-B (Medium Scale Systems) using proposed methods

Table 4.42(b): Load Dispatch and comparison: C-4 (TS-B) (13 generating units with VPLe)
(Continued....)

Algorithms	SA [287]	GWO [303]	GWOI [303]	GWOII [303]	NGWO [303]	EP-SQP [287]	GA-SA [287]	PSO-SQP [287]
Power Demand = 2520 MW								
PG₁	668.4	647.384	645.557	630.981	630.995	628.314	628.23	628.321
PG₂	359.78	306.4	306.954	300.804	297.936	299.172	299.22	299.052
PG₃	358.2	309.612	306.536	302.748	299.925	299.047	299.17	298.968
PG₄	104.28	175.14	169.688	160.17	157.927	159.64	159.12	159.468
PG₅	60.36	66.879	168.492	161.025	159.643	159.656	159.95	159.143
PG₆	110.64	162.747	174.972	160.985	159.234	158.483	158.85	159.272
PG₇	162.12	174.311	167.139	159.123	159.763	159.675	157.26	159.537
PG₈	163.03	61.225	116.88	110.428	159.662	159.727	159.93	158.852
PG₉	161.52	175.14	116.88	159.772	159.427	159.665	159.86	159.785
PG₁₀	117.09	116.76	116.88	116.858	76.879	114.033	110.78	110.962
PG₁₁	75	116.76	109.91	77.042	79.504	75	75	75
PG₁₂	60	99.917	59.035	91.499	86.804	60	60	60
PG₁₃	119.58	108.56	66.513	88.692	94.194	87.588	92.62	91.64
Fuel Cost (\$/hr)	24970.91	24231.18	24244.69	24198.47	24185.45	24266.44	24275.71	24261.05

Table 4.43: Statistical results: C-1 (TS-C) (38 generating units without VPL effect)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	9402607.969	9402610.994	9402617.205	2.027741567	9402610.896
SMA	9402608.352	9402612.998	9402633.523	5.03012152	9402611.342
hHHO-RES	9452053.175	9484252.99	9490636.907	10012.04861	9490636.907
HHO	9425015.415	9455082.359	9473152.541	14577.58777	9458770.215

Table 4.44: Simulation time: C-1 (TS-C) (38 generating units without VPL effect)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	8.515625	8.971354167	10.96875
SMA	4.375	4.700520833	6.390625
hHHO-RES	6.03125	6.613020833	8.265625
HHO	3.75	4.195833333	7.515625

Table 4.45: Load Dispatch and comparison: C-1 (TS-C) (38 generating units without VPLE)

Algorit hm	hSMA- RES	SMA	hHHO- RES	HHO	BBO [97]	λ -logic [97]	GWO [97]	SPSO [31]	(PS) [97]	PSO_Cr azy [31]	PSO_TV AC [31]	NPSO [31]
Power Demand =6000 MW												
PG₁	550.000	550.000	550.000	550.000	550.000	426.606	429.706	519.097	258.34	366.631	443.659	550.000
PG₂	324.288	323.931	220.000	331.007	550.000	426.606	416.244	437.920	258.34	550.000	342.956	512.263
PG₃	327.164	327.407	220.000	329.286	500.000	429.663	408.405	374.789	238.34	467.129	433.117	485.733
PG₄	326.465	326.690	220.000	341.588	500.000	429.663	412.453	394.877	238.34	370.471	500.000	391.083
PG₅	327.251	326.702	220.000	340.848	375.622	429.663	433.642	356.603	238.34	425.712	410.539	443.846
PG₆	326.328	327.641	220.000	337.849	200.000	429.663	425.652	380.358	238.34	415.226	482.864	358.398
PG₇	326.590	327.341	220.000	337.674	200.000	429.663	435.621	300.234	238.34	339.872	409.483	415.729
PG₈	327.166	327.049	326.995	338.337	200.000	429.663	437.654	335.871	238.34	289.777	446.079	320.816
PG₉	114.000	114.000	114.000	114.000	114.000	114.000	115.275	238.171	196.235	195.965	119.566	115.347
PG₁₀	114.000	114.000	114.000	114.000	114.649	114.000	116.883	218.563	196.235	170.608	137.274	204.422
PG₁₁	114.000	114.000	114.000	114.000	162.162	119.768	130.794	196.630	196.235	138.984	138.933	114.000
PG₁₂	114.000	114.015	114.000	114.000	114.000	127.073	153.239	234.500	196.235	262.350	155.401	249.197
PG₁₃	110.000	110.000	110.000	110.000	129.243	110.000	110.000	111.529	196.235	114.008	121.719	118.886
PG₁₄	90.000	90.000	90.000	90.000	90.000	90.000	90.028	100.731	196.235	92.393	90.924	102.802
PG₁₅	82.000	82.000	82.000	82.000	153.243	82.000	82.011	122.464	196.235	89.044	97.941	89.039
PG₁₆	120.000	120.000	120.000	120.000	120.000	120.000	120.000	125.310	196.235	130.555	128.106	120.000
PG₁₇	147.155	147.110	147.192	151.148	204.324	159.598	157.168	155.981	196.235	167.850	189.108	156.562
PG₁₈	65.000	65.000	65.000	65.000	65.000	65.000	65.000	65.000	196.235	65.754	65.000	84.265
PG₁₉	65.000	65.000	65.000	65.000	65.000	65.000	65.033	70.071	196.235	65.000	65.000	65.041

PG₂₀	271.996	272.000	120.000	189.334	120.000	272.000	271.952	263.950	196.235	199.594	267.422	151.104
PG₂₁	272.000	272.000	272.000	186.703	182.432	272.000	271.959	245.065	196.235	272.000	221.383	226.344
PG₂₂	260.000	260.000	110.000	169.810	110.000	160.000	259.810	191.702	196.235	130.379	130.804	209.298
PG₂₃	96.439	96.409	80.000	120.229	187.297	130.649	120.883	99.123	190.000	173.544	124.269	85.719
PG₂₄	10.000	10.000	10.000	14.530	27.027	10.000	12.357	15.058	150.000	13.263	11.535	10.000
PG₂₅	85.141	85.089	60.000	90.435	125.000	113.305	107.634	60.060	125.000	112.161	77.103	60.000
PG₂₆	72.370	72.268	55.000	82.935	110.000	88.067	92.412	91.140	110.000	105.898	55.018	90.489
PG₂₇	35.000	35.000	35.000	52.734	75.000	37.505	39.667	41.006	75.000	35.995	75.000	39.670
PG₂₈	20.000	20.000	20.000	20.000	70.000	20.000	20.005	20.399	70.000	22.335	21.682	20.000
PG₂₉	20.000	20.000	20.000	20.000	70.000	20.000	20.001	34.650	70.000	30.045	29.829	20.995
PG₃₀	20.000	20.000	20.000	20.000	70.000	20.000	20.030	20.957	70.000	24.112	20.326	22.810
PG₃₁	20.000	20.000	20.000	20.000	70.000	20.000	20.013	20.219	70.000	20.494	20.000	20.000
PG₃₂	20.000	20.000	20.000	20.000	60.000	20.000	20.007	25.424	60.000	20.011	21.840	20.416
PG₃₃	25.000	25.000	25.000	25.000	60.000	35.000	25.003	26.517	60.000	27.440	25.620	25.000
PG₃₄	18.000	18.000	18.000	18.000	60.000	18.000	18.008	18.822	60.000	18.000	24.261	21.319
PG₃₅	8.000	8.000	8.000	8.000	60.000	8.000	8.006	9.173	60.000	8.024	9.667	9.122
PG₃₆	25.000	25.000	25.000	25.000	60.000	25.000	25.002	26.507	60.000	25.000	25.000	25.184
PG₃₇	20.005	20.001	20.000	28.748	38.000	21.000	22.438	24.344	38.000	20.000	31.642	20.000
PG₃₈	20.000	20.000	20.000	23.728	38.000	21.000	20.005	27.181	38.000	24.371	29.935	25.104
Fuel Cost (\$/hr)	9402607.969	9402608.352	9452053.175	9425015.415	9417633.600	9417235.800	9417226.000	9543984.777	9543984.800	9520024.601	9500448.307	9516448.312

Table 4.46: Load Dispatch and comparison: C-2 (TS-C) (40 generating units with VPL effect)

Algorithm m	hSMA- RES	SMA	hHHO- RES	HHO	NGWO [309]	NPSO [309]	PSO- LRS [309]	MPSO [309]	CJAYA [309]	IGA [309]	GWO [309]	GWOI [309]	GWOII [309]
Power Demand = 10500 MW													
PG₁	113.980	113.787	110.800	110.690	111.318	113.989	111.986	114.000	114.000	110.970	109.095	109.727	107.654
PG₂	113.806	111.596	113.609	97.710	112.755	113.633	110.527	114.000	111.665	110.880	112.047	111.734	109.216
PG₃	97.940	98.605	107.498	118.716	118.638	97.550	98.556	120.000	119.988	98.170	115.458	119.220	94.787
PG₄	179.877	179.883	190.000	181.081	183.365	180.006	182.962	182.222	188.261	178.850	179.833	181.604	182.344
PG₅	95.242	96.997	97.000	96.155	91.810	97.000	87.725	97.000	96.976	87.780	46.165	89.884	86.973
PG₆	139.993	140.000	140.000	140.000	104.370	140.000	139.993	140.000	139.949	140.000	83.157	125.182	109.191
PG₇	261.082	259.601	300.000	265.006	297.653	300.000	259.663	300.000	264.095	260.370	261.635	265.078	259.491
PG₈	289.352	298.767	300.000	293.104	289.435	300.000	297.791	299.021	299.981	286.830	292.403	290.222	284.180
PG₉	297.067	286.028	300.000	281.594	298.404	284.580	284.846	300.000	284.904	285.140	284.715	285.259	285.153
PG₁₀	130.000	130.029	300.000	275.086	129.350	130.052	130.000	130.000	130.091	204.860	132.905	134.923	129.350
PG₁₁	168.788	243.603	164.886	242.674	241.970	243.713	94.674	94.000	94.001	165.980	101.673	167.998	317.479
PG₁₂	94.007	94.000	164.997	225.016	166.911	169.010	94.373	94.000	94.000	167.750	319.817	183.631	157.356
PG₁₃	125.000	214.817	214.903	302.115	214.849	125.000	214.737	125.000	125.103	214.310	215.075	219.540	300.610
PG₁₄	394.289	304.500	213.950	305.055	215.669	393.966	394.137	304.485	394.253	305.650	394.926	394.926	305.085
PG₁₅	394.273	394.337	215.027	303.858	305.690	304.759	483.182	394.607	484.126	393.660	398.183	212.715	395.310
PG₁₆	394.297	304.526	215.027	300.919	394.648	304.512	304.538	305.323	304.595	394.600	304.155	484.557	203.954
PG₁₇	489.545	489.875	500.000	489.172	494.762	489.602	489.214	490.272	490.827	489.220	490.084	494.348	489.672
PG₁₈	489.671	489.564	500.000	490.877	493.156	489.609	489.615	500.000	489.344	489.250	493.252	491.237	492.349
PG₁₉	511.373	511.298	550.000	423.595	512.742	511.790	511.178	511.404	51.378	511.230	511.423	514.376	514.388
PG₂₀	511.476	511.455	550.000	512.937	520.893	511.262	511.734	512.174	512.140	510.690	511.942	514.376	511.732

PG₂₁	525.829	523.178	550.000	527.006	526.114	523.327	523.407	550.000	523.662	524.740	532.376	522.602	532.205
PG₂₂	524.062	523.465	550.000	523.792	532.144	523.220	523.460	523.655	523.353	525.520	532.248	523.699	527.319
PG₂₃	523.285	523.302	550.000	531.667	536.842	523.471	523.476	534.661	524.968	522.980	530.773	523.699	527.319
PG₂₄	523.314	523.549	550.000	535.340	524.467	523.066	523.703	550.000	524.285	522.220	526.111	536.139	539.934
PG₂₅	523.457	523.603	550.000	534.252	525.246	523.398	523.785	525.057	522.928	523.260	524.455	523.545	526.631
PG₂₆	523.298	523.336	550.000	525.732	529.329	523.290	523.276	549.155	523.230	523.320	523.493	524.078	524.866
PG₂₇	10.014	10.016	10.000	12.410	9.950	10.021	10.000	10.000	10.000	10.000	11.503	14.857	9.950
PG₂₈	10.141	10.000	10.000	16.605	9.950	10.093	10.625	10.000	10.005	10.000	9.954	21.096	9.950
PG₂₉	10.000	10.000	10.000	19.687	9.950	10.062	10.073	10.000	10.000	10.000	10.327	13.129	9.950
PG₃₀	96.923	96.980	47.000	89.729	88.411	88.946	51.332	97.000	97.000	88.860	91.602	88.509	90.339
PG₃₁	189.999	189.976	189.349	172.559	188.909	189.995	189.805	190.000	190.000	162.300	188.848	188.018	159.688
PG₃₂	190.000	190.000	190.000	162.596	188.813	190.000	189.739	190.000	189.950	177.940	165.253	166.297	188.992
PG₃₃	189.992	190.000	189.348	159.334	186.962	190.000	189.912	190.000	190.000	160.180	188.920	182.081	173.197
PG₃₄	165.642	183.355	200.000	178.851	195.090	165.983	199.326	200.000	169.886	166.540	189.297	164.964	189.681
PG₃₅	171.943	199.998	200.000	168.190	171.505	172.415	199.307	200.000	199.855	164.800	180.461	172.695	192.167
PG₃₆	199.987	165.927	200.000	181.113	176.109	191.298	192.898	200.000	199.990	170.680	184.270	191.077	157.503
PG₃₇	110.000	110.000	25.000	59.493	89.530	109.989	110.000	110.000	109.971	108.170	89.675	108.894	104.410
PG₃₈	99.489	109.992	106.605	57.724	89.359	109.952	109.863	110.000	109.998	100.680	90.149	100.880	86.741
PG₃₉	110.000	107.208	25.000	57.800	109.322	109.873	92.875	110.000	109.987	109.340	57.046	27.874	100.297
PG₄₀	511.568	512.849	550.000	530.756	512.541	511.567	511.688	512.964	511.225	511.280	514.362	511.772	512.439
Fuel Cost (\$./hr)	121648.14 5	121679.7 93	125238.05 3	124291.0 41	121881.8 10	121704.7 39	122035.7 95	122252.2 65	122581.8 50	121915.9 30	122602.3 70	122678.9 10	122430.7 40

Table 4.47: Statistical results: C-2 (TS-C) (40 generating units with VPL effect)

Algorithm	Fuel Cost (\$/hr)				
	Best	Mean	Worst	SD	Median
hSMA-RES	121648.1451	122219.34	123147.6091	417.3691432	122133.6567
SMA	121679.7935	122258.122	123235.1643	372.7027271	122217.4313
hHHO-RES	125238.0535	131937.4203	153858.1176	6570.469923	129302.7882
HHO	124291.0406	126819.3633	131753.1414	1784.578232	126576.7165

Table 4.48: Simulation time: C-2 (TS-C) (40 generating units with VPL effect)

Algorithm	Best Time (Sec)	Average Time (Sec)	Worst Time (Sec)
hSMA-RES	19.9375	21.0734375	23.46875
SMA	10.625	12.478125	15.09375
hHHO-RES	17.171875	17.509375	20.203125
HHO	10.3125	11.090625	15.59375

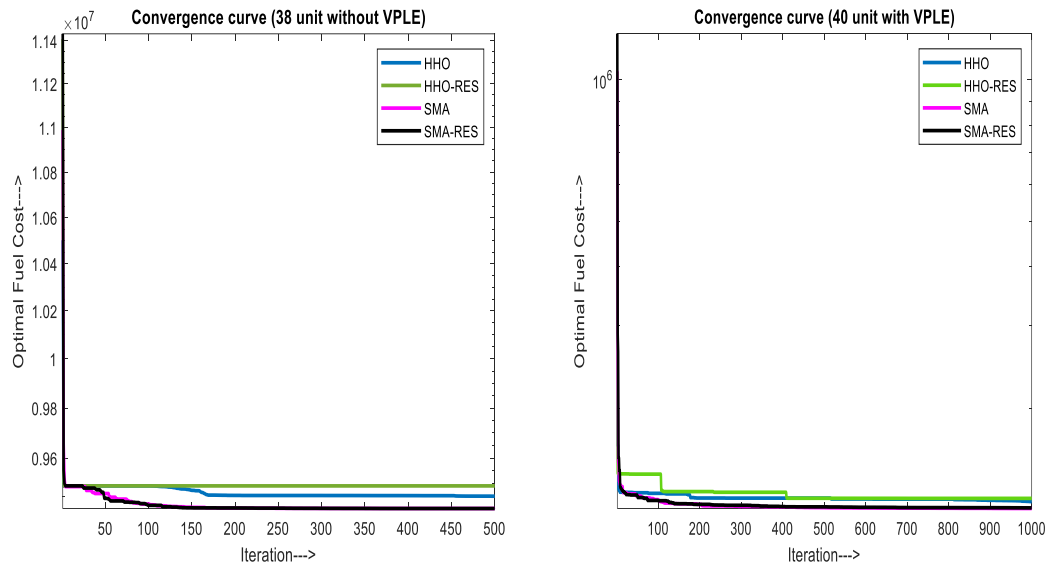
**Fig. 4.3:** Convergence graphs-TS-C (Large Scale Systems) using proposed methods

Table 4.46 to Table 4.48 shows the load dispatch and optimized fuel cost obtained using proposed approaches and comparison with other methods; statistical analysis including best, mean, worst values of fuel cost, their standard deviation (SD) and median and simulation time taken by different proposed methods respectively for case 2 (40 generating units with VPL effect).

The results reveal that the cost achieved with proposed memetic approach hSMA-RES and SMA is 121648.1451 \$/hr and 121679.7935\$/hr respectively; with HHO and hHHO-RES is 124291.0406\$/hr and 125238.0535\$/hr respectively. The simulation time recorded by hHHO-RES approach is less as compared to hSMA-RES. The convergence curves for test system III (large scale power systems) using proposed approaches are shown in Fig. 4.3.

Table 4.49: Test observations for p-value using proposed algorithms: *Test System A*

Test System A	Algorithm	Wilcoxon Rank Sum Test		T-Test Parameters	
		P value	h value	P value	h value
Case I (3-Unit Test System without VPLE)	hSMA-RES	1.7344E-06	1	9.4691E-117	1
	SMA	1.73E-06	1	7.38E-45	1
	hHHO-RES	5.07E-07	1	8.23E-44	1
	HHO	5.94248E-07	1	2.24919E-50	1
Case II (6-Unit Test System without VPLE)	hSMA-RES	1.73E-06	1	8.33E-237	1
	SMA	1.7344E-06	1	4.8627E-243	1
	hHHO-RES	1.73E-06	1	3.64E-133	1
	HHO	1.7344E-06	1	1.1567E-217	1
Case III (3-Unit Test System with VPLE)	hSMA-RES	1.73E-06	1	7.13E-105	1
	SMA	1.7344E-06	1	3.3797E-107	1
	hHHO-RES	1.45E-06	1	2.44E-92	1
	HHO	1.40E-06	1	2.96E-71	1
Case IV (5-Unit Test System with VPLE)	hSMA-RES	1.73E-06	1	3.52E-56	1
	SMA	1.73E-06	1	3.78E-55	1
	hHHO-RES	1.73E-06	1	7.23E-45	1
	HHO	1.73E-06	1	1.20E-47	1

Non-parametric hypothesis tests (Wilcoxon rank sum test and t-test) are executed for all the test systems using the proposed HHO, SMA, memetic HHO and memetic SMA algorithms to check the validity of the results obtained in all cases. The h-value 0 represents the null hypothesis that signifies no substantial different between the results obtained and h-value 1 is taken as opposite to null hypothesis. In this study the tests are

Table 4.50: Test observations for p-value using proposed algorithms: *Test System B*

Test System B	Algorithm	Wilcoxon Rank Sum Test		T-Test Parameters	
		p value	h value	p value	h value
Case I (15-Unit Test System without VPLE)	hSMA-RES	1.73E-06	1	7.91E-129	1
	SMA	1.73E-06	1	3.12E-132	1
	hHHO-RES	1.73E-06	1	5.03E-74	1
	HHO	1.7344E-06	1	1.35656E-75	1
Case II (20-Unit Test System without VPLE)	hSMA-RES	1.73E-06	1	4.75E-151	1
	SMA	1.7344E-06	1	2.7258E-160	1
	hHHO-RES	1.7344E-06	1	1.34594E-87	1
	HHO	1.7344E-06	1	3.35016E-97	1
Case III (10-Unit Test System with VPLE)	hSMA-RES	1.73E-06	1	2.51E-168	1
	SMA	1.7344E-06	1	1.0761E-170	1
	hHHO-RES	1.73E-06	1	1.28E-57	1
	HHO	1.73E-06	1	2.48E-63	1
Case IV (13-Unit Test System with VPLE)	hSMA-RES	1.73E-06	1	6.34E-74	1
	SMA	1.73E-06	1	5.40E-78	1
	hHHO-RES	1.7344E-06	1	1.09354E-64	1
	HHO	1.73E-06	1	4.30E-64	1

Table 4.51: Test observations for p-value using proposed algorithms: *Test System C*

Test System C	Algorithm	Wilcoxon Rank Sum Test		T-Test Parameters	
		P value	h value	P value	h value
Case I (38-Unit Test System without VPLE)	hSMA-RES	1.73E-06	1	1.19E-183	1
	SMA	1.73E-06	1	4.29E-195	1
	hHHO-RES	1.00009E-06	1	4.32095E-88	1
	HHO	1.73331E-06	1	2.54734E-83	1
Case II (40-Unit Test System with VPLE)	hSMA-RES	1.73E-06	1	9.82E-75	1
	SMA	1.73E-06	1	2.64E-73	1
	hHHO-RES	1.73E-06	1	1.44E-39	1
	HHO	1.73E-06	1	1.80E-55	1

performed with assumed significance level of 0.05 for evaluating the p-value (expected probability of rejecting the null hypothesis). The results are validated with smaller p-

values, the values less than 0.05 are considered as better performing systems. The test results for all the test systems are shown in table-4.49 to table 4.51.

4.6.2 Dynamic Economic Load Dispatch

Proposed algorithms (HHO, slime mould, hHHO-RES and hSMA-RES) are successfully implemented to attain the optimum solution for the dynamic ELD problems of the electric power system. This part covers the results and discussions of dynamic cases using the proposed memetic algorithms when applied on the test systems with dynamic load demand. The test system data and the load demand is already stated in section 4.5. The suggested methods are implemented in MATLAB 2018a environment with a computer having Windows 10, 4GB RAM and Core i5 processor configuration.

4.6.2.1 Harris Hawks Optimizer-HHO

The Harris Hawks Optimizer (HHO) is studied on different test systems discussed in section 4.5.2 for 24 hr load demand. The ability of the said method is tested on four different systems comprising of 5- generating unit test system for 1000 iterations and 6, 7,10-generating unit test system for 500 iterations. The 50 search agents and 30 trial runs are considered to validate this algorithm for Dynamic ELD Problems. Following are the results and discussions of different test cases.

1. Dynamics TS-1: Five generator test system with VPL effect

The harris hawks optimizer is implemented to find minimum fuel cost for a 5-unit generating dynamic test system with VPL effect with a 24 hr load demand and its input test data is given in section 4.5.2. The best solutions have been stated among the 30 trial solutions for this DELD problem with 5 generators. Table 4.52 depicts the optimal fuel cost and power dispatch of 5 generating units using HHO.

2. Dynamics TS-2: Six generator test system without VPL effect

The harris hawks optimizer- HHO has been utilized to evaluate the minimum fuel/operating price for a 6-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best

solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table 4.53.

3. Dynamics TS-3: Seven generator test system without VPL effect

The harris hawks optimizer- HHO has been utilized to evaluate the minimum fuel/operating price for a 7-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table 4.54.

Table 4.52: Dynamic ELD using HHO (*Dynamic TS-1: Five generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)					Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	
1	410	10.24	20	30.35	209.34	140.07	1220.89
2	435	29.76	20	30	124.94	230.29	1351.92
3	475	73.59	20	30	210.39	141.01	1443.46
4	530	40.14	20	30	210.18	229.68	1595.47
5	558	69.36	20	30	209.64	229.00	1642.76
6	608	34.73	20	114.91	209.63	228.73	1778.38
7	626	58.09	99.15	30	209.91	228.84	1813.46
8	654	74.03	20	113.19	214.22	232.56	1898.57
9	690	30.42	102.15	110.81	214.88	231.73	2005.59
10	704	70.10	20	175	209.52	229.38	2093.30
11	720	66.25	102.27	109.49	210.21	231.76	2063.49
12	740	73.19	111.84	112.73	211.65	230.60	2125.91
13	704	66.14	97.69	100.69	210.30	229.18	2047.82
14	690	18.50	118.84	113.97	209.83	228.87	1999.17
15	654	74.32	20	112.76	214.93	231.99	1895.72
16	580	10.10	20.20	112.21	212.32	225.16	1656.81
17	558	68.91	20	30	209.41	229.68	1643.07
18	608	39.44	97.65	30	208.97	231.95	1786.65
19	654	74.71	20	113.60	209.59	236.09	1895.86
20	704	48.06	97.49	118.01	209.40	231.04	2038.16
21	680	45.13	20	175	209.46	230.41	2070.02
22	605	30.98	102.10	30	211.71	230.21	1770.36
23	527	36.56	20	30	210.86	229.58	1585.77
24	463	74.61	99.20	30	209.19	50.00	1416.17
Fuel Cost (\$/day)							42838.76

Table 4.53: Dynamic ELD using HHO (*Dynamics TS-2: Six generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)						Optimum Fuel Cost (\$)/hr
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	
1	700	312.70	72.86	159.52	50	54.92	50	8299.38
2	750	327.19	84.26	170.80	50	67.74	50	8873.45
3	850	354.02	108.39	192.10	52.83	92.66	50	10052.55
4	950	375.54	123.85	210.22	75.58	114.81	50	11267.31
5	1000	390.99	132.59	222.20	79.40	124.81	50	11887.15
6	1100	415.49	152.76	237.87	99.26	144.62	50	13152.39
7	1150	420.44	152.99	247.75	108.62	154.08	66.12	13796.02
8	1200	432.17	159.13	255.17	113.20	161.42	78.90	14446.91
9	1300	451.82	172.23	270.27	132.81	180.04	92.84	15768.52
10	1400	473.56	189.43	281.99	150	194.25	110.77	17117.76
11	1450	485.62	200	294.38	150	200	120	17802.79
12	1500	500	200	300	150	200	120	48080.5
13	1400	469.65	190.21	286.12	143.65	200	110.37	17117.83
14	1300	448.62	176.69	276.02	129.84	180.41	88.41	15768.83
15	1200	430.21	158.96	258.45	117.30	159.08	76.00	14446.92
16	1050	403.39	138.65	230.70	93.68	133.57	50	12515.43
17	1000	393.08	130.71	221.44	83.29	121.48	50	11887.09
18	1100	412.69	144.25	243.47	97.27	147.55	54.78	13152.50
19	1200	429.76	165.14	252.88	117.89	163.94	70.39	14446.76
20	1400	472.53	188.77	282.19	150	200	106.52	17117.92
21	1300	452.63	179.45	267.54	128.52	174.97	96.89	15768.80
22	1100	415.49	150.64	238.85	100.70	144.32	50	13152.20
23	900	365.78	114.00	204.37	66.24	99.61	50	10655.70
24	800	340.89	94.10	181.93	50	83.08	50	9457.89
		Fuel Cost (\$/day)						356032.59

Table 4.54: Dynamic ELD using HHO (*Dynamics TS-3: Seven generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)							Optimum Fuel Cost (\$)/hr
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	
1	800	298.18	61.82	140	50	100	50	100	9759.80
2	780	286.81	53.45	139.74	50	100	50	100	9537.92
3	750	271.88	50	128.12	50	100	50	100	9210.34
4	750	271.87	50	128.13	50	100	50	100	9210.34
5	720	255	50	115	50	100	50	100	8889.7
6	700	243.75	50	106.25	50	100	50	100	8679.88
7	700	243.75	50	106.25	50	100	50	100	8679.88
8	700	243.75	50	106.25	50	100	50	100	8679.88
9	800	298.18	61.82	140	50	100	50	100	9759.80
10	900	339.14	92.54	140	50	100	50	128.33	10908.67
11	1000	373.18	100	140	65.72	108.59	50	162.51	12108.26
12	1200	427.16	100	140	100	153.15	63.61	216.08	14626.46
13	1400	482.16	100	140	100	202.86	100	274.98	17292.09
14	1500	516.56	100	140	100	232.75	100	310.68	18690.71
15	1750	575	100	140	100	325	100	410	22406.36
16	1800	575.00	100	140	100	375.00	100	410	23211.36
17	1500	516.44	100	140	100	232.64	100	310.92	18690.71
18	900	339.10	92.11	140	50	100	50	128.79	10908.66
19	850	320.83	79.29	140	50	100	50	109.88	10327.51
20	800	298.18	61.82	140	50	100	50	100	9759.80
21	780	286.81	53.59	139.60	50	100	50	100	9537.92
22	750	271.88	50	128.12	50	100	50	100	9210.34
23	700	243.75	50	106.25	50	100	50	100	8679.88
24	800	298.18	61.82	140	50	100	50	100	9759.80
	Fuel Cost (\$/day)								288526.02

Table 4.55: Dynamic ELD using HHO (*Dynamics TS-4: Ten generator test system*)

Time (hr)	Load (MW)	Dispatch of Power Generating Units (MW)										Optimal Fuel cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	
1	700	410	150	20	20	25	20	25	10	10	10	19075
2	750	451	150	20	29	25	20	25	10	10	10	19905
3	850	455	150	62	83	25	20	25	10	10	10	21580
4	950	455	150	115	130	25	20	25	10	10	10	23275
5	1000	455	185	130	130	25	20	25	10	10	10	24139
6	1100	455	285	130	130	25	20	25	10	10	10	25880
7	1150	455	335	130	130	25	20	25	10	10	10	26752
8	1200	455	385	130	130	25	20	25	10	10	10	27627
9	1300	455	455	130	130	55	20	25	10	10	10	29453
10	1400	455	455	130	130	155	20	25	10	10	10	31507
11	1450	455	455	130	130	162	63	25	10	10	10	32636
12	1500	455	455	130	130	162	80	25	43	10	10	33896
13	1400	455	455	130	130	155	20	25	10	10	10	31508
14	1300	455	455	130	130	55	20	25	10	10	10	29453
15	1200	455	385	130	130	25	20	25	10	10	10	27627
16	1050	455	235	130	130	25	20	25	10	10	10	25009
17	1000	455	185	130	130	25	20	25	10	10	10	24139
18	1100	455	285	130	130	25	20	25	10	10	10	25880
19	1200	455	385	130	130	25	20	25	10	10	10	27627
20	1400	455	455	130	130	155	20	25	10	10	10	31507
21	1300	455	455	130	130	55	20	25	10	10	10	29453
22	1100	455	285	130	130	25	20	25	10	10	10	25880
23	900	455	150	91	104	25	20	25	10	10	10	22425
24	800	455	150	37	58	25	20	25	10	10	10	20740
Fuel Cost (\$/day)												636972.8

4. Dynamics TS-4: Ten generator test system (without VPL effect without losses)

The Harris Hawks Optimizer- HHO has been utilized to evaluate the minimum fuel/operating price for a 10-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table 4.55.

The simulation results using HHO approach for various DELD test systems are presented in Table 4.52 to Table 4.55. Table 4.52 gives the optimal power generated and total fuel cost of 42838.75994 \$/day for 5 generating unit test system for 24 hour demand. The overall cost of 356032.59 \$/day for 6 generating unit system for 24 hr load demand is depicted in table 4.53. Table 4.54 presents the total operating cost for 7 unit generating system for 24 hr period as 288526.02 \$/day and table 4.55 gives load dispatch and total optimum fuel cost of 636972.78 \$/day for 10 generating unit test system with hourly demand for 24 hours.

4.6.2.2 Slime Mould Algorithm-SMA

Slime Mould Algorithm (SMA) optimization approach is applied on various test systems discussed in section 4.5.2 for 24 hr load demand. The ability of the said method is confirmed on four test systems comprising of 5- generating unit for 1000 iterations; 6, 7 and 10-generating unit test system for 500 iterations. The 50 search agents and 30 trial runs are considered validate this algorithm for DELDP. Following are the results and discussions of different test cases.

1. Dynamics TS-1: Five generator test system (with VPL effect)

The Slime Mould Algorithm (SMA) optimizer to find minimum fuel cost for a 5-unit generating test system with VPLe is considered with a 24 hr load demand and the input test data is given in section 4.5.2. The best solutions have been stated among the 30 trial solutions for this DELD with 5 generators. Table 4.56 depicts the optimal fuel cost and power dispatch of 5 generating units using SMA.

2. Dynamics TS-2: Six generator test system (without VPL effect)

The slime mould algorithm has been utilized to evaluate the minimum fuel/operating price for a 6-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table-4.57.

Table 4.56: Dynamic ELD using SMA (*Dynamics TS-1: Five generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)					Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	
1	410	18.55	103.33	30.00	208.11	50.00	1293.44
2	435	10.02	38.75	30.09	125.56	230.58	1373.88
3	475	11.35	100.92	97.62	125.40	139.71	1453.81
4	530	34.76	20.00	30.00	210.78	234.46	1623.00
5	558	13.32	101.66	175	40	228.03	1714.83
6	608	18.51	29.31	122.08	210.32	227.79	1824.34
7	626	73.27	97.37	100.66	211.21	143.48	1876.87
8	654	11.79	101.57	101.68	212.16	226.79	1888.12
9	690	44.62	91.04	110.70	210.33	233.32	2035.21
10	704	55.43	98.69	116.26	209.29	224.33	2045.90
11	720	60.78	103.47	114.67	211.19	229.89	2067.07
12	740	74.31	103.61	122.14	208.49	231.46	2137.89
13	704	56.93	100.10	111.25	213.38	222.34	2073.09
14	690	27.27	108.57	112.08	208.62	233.45	2009.43
15	654	18.60	96.90	104.87	201.72	231.91	1924.26
16	580	14.32	90.20	30.67	212.45	232.36	1702.18
17	558	14.26	99.66	102.70	209.08	132.30	1678.67
18	608	32.82	104.32	113.94	127.32	229.60	1795.95
19	654	12.86	92.45	113.45	202.42	232.82	1886.17
20	704	49.19	95.45	119.54	209.00	230.82	2059.89
21	680	21.26	96.47	111.80	209.93	240.54	1964.55
22	605	13.24	21.67	131.21	210.60	228.28	1804.47
23	527	35.93	20.00	113.26	127.48	230.33	1597.97
24	463	10.84	70.19	30.13	210.22	141.63	1469.65
		Fuel Cost (\$/day)					43300.64

Table 4.57: Dynamic ELD using SMA (*Dynamics TS-2: Six generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)						Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	
1	700	321.023316	64.7244727	163.161551	50.9515498	50.1390935	50.0000167	8301.2198
2	750	323.438272	97.8501765	177.334451	50.0007953	51.3762755	50.0000298	8878.01243
3	850	347.980466	97.2937449	193.760492	64.605448	95.5925964	50.7672522	10054.801
4	950	378.009441	117.864878	217.777019	73.2965126	111.120862	51.9312884	11268.4409
5	1000	396.937669	121.753564	229.768889	84.0756879	117.464157	50.0000331	11888.9802
6	1100	411.869921	156.956254	233.481909	100.714543	140.954527	56.0228454	13153.2973
7	1150	417.893645	147.487353	254.616313	114.02434	156.932291	59.046058	13797.7212
8	1200	437.132348	168.090074	251.411022	108.990908	151.805133	82.5705161	14448.8006
9	1300	444.855535	180.379287	274.425821	128.629704	171.006934	100.702719	15770.4079
10	1400	473.266569	190.850471	286.20389	145.62291	194.400439	109.655722	17117.5082
11	1450	486.407178	199.287806	296.849482	149.999989	199.99999	117.455556	17802.9024
12	1500	500	200	300	150	200	120	48080.5
13	1400	472.736526	190.541474	284.110964	149.486271	190.845894	112.278871	17117.8702
14	1300	456.978382	174.894813	262.369249	130.490409	176.396259	98.87089	15769.3632
15	1200	433.969428	159.722008	261.562113	126.088101	156.181434	62.4769169	14448.776
16	1050	397.626345	139.216557	232.350184	96.4170434	129.288285	55.1015859	12516.7696
17	1000	405.443839	133.696829	222.251895	78.3088753	103.851795	56.4467671	11893.8549
18	1100	403.777783	145.199303	247.464829	96.8544415	149.783196	56.9204478	13153.955
19	1200	433.816483	159.052577	248.215021	129.340144	167.054165	62.5216106	14449.474
20	1400	472.844096	190.686066	286.339564	143.790711	190.686066	115.653498	17118.1035
21	1300	450.974056	173.127388	277.834594	126.57765	180.840994	90.6453178	15769.18
22	1100	409.499049	156.773037	227.689199	100.252517	142.600464	63.1857345	13154.8674
23	900	368.82577	119.248248	192.768904	57.1166248	112.04045	50.0000028	10657.7986
24	800	350.101234	93.7456037	187.856483	50	68.2966791	50	9459.72031
		Fuel Cost (\$/ day)						356072.32

3. Dynamics TS-3: Seven generator test system (without VPL effect)

Slime Mould Algorithm (SMA) has been utilized to evaluate the minimum fuel/operating price for a 7-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best

solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table 4.58.

4. *Dynamics TS-4: Ten generator test system (without VPL effect)*

Slime Mould Algorithm (SMA) has been utilized to evaluate the minimum fuel/operating price for a 10-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solution have been tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost has been tabulated in Table 4.59.

Table 4.58: Dynamic ELD using SMA (*Dynamics TS-3: Seven generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)							Optimum Fuel Cost (\$)/hr
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	
1	800	291.49	68.50195	140	50	100	50	100	9760.533
2	780	290	50	140	50	100	50	100	9538.1
3	750	272.48391	61.2518	116.2643	50	100	50	100	9214.433
4	750	281.12329	50	111.6122	55.62915	100.1202	50.86374	100.6514	9222.042
5	720	254.19734	50	115.8027	50	100	50	100	8889.71
6	700	261.02892	50	88.97108	50	100	50	100	8684.652
7	700	258.14829	50	91.85171	50	100	50	100	8683.192
8	700	237.70232	50	112.2977	50	100	50	100	8680.46
9	800	304.16148	55.83853	140	50	100	50	100	9760.385
10	900	333.84031	91.08912	140	62.93976	103.0794	51.01121	118.0402	10915.27
11	1000	371.30675	95.21553	140	58.14945	118.2029	53.9583	163.1671	12113.94
12	1200	434.42512	100	140	100	157.2442	50	218.3307	14628.52
13	1400	481.79693	100	140	100	202.8232	100	275.3799	17292.09
14	1500	521.79959	99.14464	137.4624	93.28221	238.9976	95.48208	313.8315	18714.9
15	1750	561.50469	99.99974	132.9526	99.99868	351.2188	98.04955	406.2759	22460.21
16	1800	550.80018	99.25472	139.8488	91.41202	415.4065	93.28836	409.9894	23320.79
17	1500	520.06223	97.77989	137.5545	99.856	215.5191	87.02266	342.2056	18723.95
18	900	351.2461	96.15518	138.7225	55.3342	100	50.76471	107.7772	10915.56
19	850	316.0142	93.98578	140	50	100	50	100	10330.58
20	800	309.9646	50	140	50	100	50.03534	100	9762.15
21	780	279.7096	60.29036	140	50	100	50	100	9538.715
22	750	268.5117	50	131.4838	50	100	50	100	9210.524
23	700	259.0302	50	90.96498	50	100	50	100	8683.613
24	800	294.4333	64.35987	140	50.21084	100.0006	50.80375	100.1916	9761.416
Fuel Cost (\$/ day)									288805.7

Table 4.59: Dynamic ELD using SMA (*Dynamics TS-4: Ten generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)										Optimum Fuel Cost (\$)/hr
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	
1	700	410	150	20	20	25	20	25	10	10	10	19075.288
2	750	451	150	20	29	25	20	25	10	10	10	19905.453
3	850	455	150	56	89	25	20	25	10	10	10	21579.9607
4	950	455	150	115	130	25	20	25	10	10	10	23274.9871
5	1000	455	185	130	130	25	20	25	10	10	10	24139.0753
6	1100	455	285	130	130	25	20	25	10	10	10	25879.642
7	1150	455	335	130	130	25	20	25	10	10	10	26752.252
8	1200	455	385	130	130	25	20	25	10	10	10	27626.4119
9	1300	455	455	130	130	55	20	25	10	10	10	29453.393
10	1400	455	455	130	130	155	20	25	10	10	10	31506.9725
11	1450	455	455	130	130	162	63	25	10	10	10	32636.2949
12	1500	455	455	130	130	162	80	25	43	10	10	33894.6068
13	1400	455	455	130	130	155	20	25	10	10	10	31506.9731
14	1300	455	455	130	130	55	20	25	10	10	10	29453.3918
15	1200	455	385	130	130	25	20	25	10	10	10	27626.4122
16	1050	455	235	130	130	25	20	25	10	10	10	25008.582
17	1000	455	185	130	130	25	20	25	10	10	10	24139.073
18	1100	455	285	130	130	25	20	25	10	10	10	25879.6419
19	1200	455	385	130	130	25	20	25	10	10	10	27626.4119
20	1400	455	455	130	130	155	20	25	10	10	10	31506.9743
21	1300	455	455	130	130	55	20	25	10	10	10	29453.392
22	1100	455	285	130	130	25	20	25	10	10	10	25879.6418
23	900	455	150	92	103	25	20	25	10	10	10	22424.8996
24	800	455	150	37	58	25	20	25	10	10	10	20739.9164
	Fuel Cost (\$/ day)											636969.65

The simulation results for SMA optimizer for various test systems are shown in Table 4.56 to Table 4.59. The power generated in 5 generating unit test case and the overall operating cost has been tabulated in table 4.56. The minimum fuel cost evaluated by SMA approach is 43300.64034 \$/day. Table 4.57 gives dispatching of power generating units for hourly demand for 24 hours and overall fuel cost for 6-unit generating system with the optimum cost of 356072.32 \$/day. The power generated in 7 generating unit test case and the overall operating cost has been tabulated in table 4.58. The optimum fuel cost evaluated by SMA approach is 288805.7 \$/day. Table 4.59 depicts the optimal power generation of 10 generating units for hourly demand for 24 hours and overall fuel cost for this system is 636969.65 \$/day.

4.6.2.3 Memetic Harris Hawk Optimizer

The proposed memetic approach hHHO-RES has been applied on various test systems discussed in section 4.5.2 for 24 hr load demand. The capability of the said method is implemented on different generating systems comprising of 5- generating unit for 1000 iterations; 6, 7 and 10-generating unit test system for 500 iterations. The 50 search agents and 30 trial runs are considered validate this algorithm for DELDP. Following are the results and discussions of different test cases.

1. Dynamic TS-2: Five generator test system (with VPL effect)

The hHHO-RES optimizer to find minimum fuel cost for a 5-unit generating test system with VPL effect is considered with a 24 hr load demand and its input test data is given in section 4.5.2. The best solutions have been stated among the 30 trial solutions for this DELDP with 5 generators. Table 4.60 depicts the optimal fuel cost and power dispatch of 5 generating units using hHHO-RES.

2. Dynamic TS-2: Six generator test system (without VPL effect)

The hHHO-RES algorithm has been utilized to evaluate the minimum fuel/operating price for a 6-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solution is tabulated

among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is tabulated in table 4.61.

Table 4.60: Dynamic ELD using hHHO-RES(*Dynamic TS-1:5 generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)					Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	
1	410	10.42	20	30.00	209.82	139.76	1214.30
2	435	30.57	20	30	124.91	229.52	1348.52
3	475	10.00	93.72	111.81	209.45	50.01	1401.81
4	530	54.12	98.54	112.67	124.91	139.76	1577.35
5	558	75.00	98.55	30.01	124.92	229.52	1608.46
6	608	42.36	98.54	112.67	124.91	229.52	1757.76
7	626	65.21	98.54	112.67	209.82	139.76	1785.62
8	654	10.01	92.41	112.36	209.71	229.50	1801.09
9	690	39.45	98.54	112.67	209.82	229.52	1944.99
10	704	53.45	98.54	112.67	209.82	229.52	1985.71
11	720	69.45	98.54	112.67	209.82	229.52	1996.74
12	740	74.99	112.31	113.10	209.88	229.72	2107.06
13	704	53.45	98.54	112.67	209.82	229.52	1985.71
14	690	39.45	98.54	112.67	209.82	229.52	1944.99
15	654	10.02	92.25	112.46	209.76	229.51	1801.05
16	580	12.12	98.54	30.00	209.82	229.52	1605.73
17	558	75.00	98.57	30.00	124.91	229.52	1608.42
18	608	42.36	98.54	112.67	124.91	229.52	1757.76
19	654	10.00	92.67	112.10	209.74	229.49	1801.22
20	704	53.45	98.54	112.67	209.82	229.52	1985.71
21	680	29.45	98.54	112.67	209.82	229.52	1897.91
22	605	39.36	98.54	112.67	124.91	229.52	1746.40
23	527	51.12	98.54	112.67	124.91	139.76	1571.57
24	463	69.79	98.54	30.00	124.91	139.76	1399.36
		Fuel Cost (\$/day)					41635.24

3. *Dynamic TS-3: Seven generator test system (without VPL effects)*

The hHHO-RES algorithm has been utilized to evaluate the minimum fuel/operating price for a 7-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solutions are tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is tabulated in Table 4.62.

Table 4.61: Dynamic ELD using hHHO-RES (*Dynamic TS-2:6 generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)						Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	
1	700	312.71	72.53	159.89	50	54.87	50	8299.38
2	750	327.46	83.39	171.36	50	67.78	50	8873.44
3	850	355.67	104.17	193.30	54.41	92.46	50	10052.33
4	950	379.66	121.86	211.96	73.07	113.45	50	11267.05
5	1000	391.66	130.70	221.29	82.40	123.95	50	11887.02
6	1100	414.75	147.71	239.25	100.36	144.16	53.77	13152.01
7	1150	424.55	154.93	246.88	107.99	152.73	62.92	13795.76
8	1200	434.36	162.16	254.50	115.61	161.31	72.07	14446.38
9	1300	453.96	176.60	269.75	130.86	178.47	90.36	15768.20
10	1400	473.57	191.05	285.00	146.11	195.62	108.66	17117.47
11	1450	485.67	199.97	294.41	150	200	119.96	17802.79
12	1500	500	200	300	150	200	120	48080.50
13	1400	473.57	191.05	285.00	146.11	195.62	108.66	17117.47
14	1300	453.96	176.60	269.75	130.86	178.47	90.36	15768.20
15	1200	434.36	162.16	254.50	115.61	161.31	72.07	14446.38
16	1050	403.66	139.54	230.62	91.73	134.45	50	12515.38
17	1000	391.66	130.70	221.29	82.40	123.95	50	11887.02
18	1100	414.75	147.71	239.25	100.36	144.16	53.77	13152.01
19	1200	434.36	162.16	254.50	115.61	161.31	72.07	14446.38
20	1400	473.57	191.05	285.00	146.11	195.62	108.66	17117.47
21	1300	453.96	176.60	269.75	130.86	178.47	90.36	15768.20
22	1100	414.75	147.71	239.25	100.36	144.16	53.77	13152.01
23	900	367.66	113.02	202.63	63.74	102.96	50	10655.49
24	800	342.21	94.26	182.83	50	80.69	50	9457.83
Fuel Cost (\$/ day)								356026.17

4. Dynamic TS-4: Ten generator test system (without VPL effect)

The hHHO-RES algorithm has been utilized to evaluate the minimum fuel/operating price for a 10-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solutions are tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is computed in Table 4.63.

Table 4.62: Dynamic ELD using hHHO-RES(Dynamic TS-3:7 generator test system)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)							Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	
1	800	298.18	61.82	140	50	100	50	100	9759.8
2	780	286.81	53.44	139.74	50	100	50	100	9537.92
3	750	271.87	50	128.13	50	100	50	100	9210.34
4	750	271.87	50	128.13	50	100	50	100	9210.34
5	720	255	50	115	50	100	50	100	8889.7
6	700	243.75	50	106.25	50	100	50	100	8679.88
7	700	243.75	50	106.25	50	100	50	100	8679.88
8	700	243.75	50	106.25	50	100	50	100	8679.88
9	800	298.18	61.82	140	50	100	50	100	9759.8
10	900	339.26	92.09	140	50	100	50	128.65	10908.66
11	1000	372.48	100	140	67.49	107.17	50	162.85	12108.21
12	1200	425.42	100	140	100	153.5	63.73	217.35	14626.42
13	1400	481.8	100	140	100	202.82	100	275.38	17292.09
14	1500	516.23	100	140	100	232.95	100	310.82	18690.71
15	1750	575	100	140	100	325.01	100	410	22406.36
16	1800	575	100	140	100	375	100	410	23211.36
17	1500	516.23	100	140	100	232.95	100	310.82	18690.71
18	900	339.26	92.09	140	50	100	50	128.65	10908.66
19	850	321.19	78.77	140	50	100	50	110.04	10327.51
20	800	298.18	61.82	140	50	100	50	100	9759.8
21	780	286.81	53.44	139.74	50	100	50	100	9537.92
22	750	271.87	50	128.13	50	100	50	100	9210.34
23	700	243.75	50	106.25	50	100	50	100	8679.88
24	800	298.18	61.82	140	50	100	50	100	9759.8
Fuel Cost (\$/ day)									288525.9

Table 4.63: Dynamic ELD using hHHO-RES (*Dynamic TS-4: Ten generator test system*)

Time (hr)	Load (MW)	Dispatch of Power Generating Units (MW)										Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	
1	700	410	150	20	20	25	20	25	10	10	10	19075.29
2	750	450.89	150	20	29.11	25	20	25	10	10	10	19905.45
3	850	454.98	150	62.13	82.88	25.00	20.00	25.00	10	10.00	10.00	21579.82
4	950	454.98	150.01	115.02	129.99	25	20.00	25.00	10.00	10	10.00	23275
5	1000	454.99	185.01	130.00	129.99	25.00	20.00	25.00	10.00	10.00	10.00	24139.14
6	1100	455.00	285.01	129.99	130.00	25.00	20.00	25.00	10	10.00	10.00	25879.65
7	1150	455.00	335.01	130.00	130.00	25.00	20.00	25.00	10.00	10.00	10.00	26752.26
8	1200	454.99	385.01	129.99	130.00	25.00	20.00	25.00	10.00	10.00	10.00	27626.44
9	1300	455.00	455.00	130.00	130.00	54.94	20.06	25.00	10.00	10.00	10.00	29453.62
10	1400	455.00	455.00	130.00	129.99	154.98	20.03	25.00	10.00	10.00	10.00	31507.09
11	1450	455.00	454.98	130	130.00	161.98	62.98	25.01	10.02	10.04	10.00	32636.75
12	1500	454.99	454.99	130.00	130.00	161.97	79.94	25.05	42.91	10.15	10.00	33895.36
13	1400	455.00	455.00	130.00	130.00	155.00	20.00	25.00	10.00	10.00	10.00	31506.99
14	1300	454.99	454.99	130.00	130.00	55.02	20.01	25.00	10.00	10.00	10.00	29453.49
15	1200	454.99	385.03	129.99	129.99	25.00	20.00	25.00	10.00	10.00	10.00	27626.44
16	1050	455.00	235.02	130.00	129.98	25	20.00	25.00	10	10	10.00	25008.59
17	1000	455.00	185.00	130.00	130.00	25.00	20.00	25.00	10.00	10.00	10.00	24139.08
18	1100	454.99	285.01	130.00	130.00	25.00	20.00	25.00	10.00	10.00	10.00	25879.67
19	1200	455.00	385.01	130.00	130.00	25.00	20.00	25.00	10	10.00	10.00	27626.42
20	1400	455.00	455.00	130.00	129.99	154.98	20.02	25.00	10.00	10.00	10.01	31507.12
21	1300	454.99	454.98	130.00	130.00	55.03	20.00	25.00	10.00	10.00	10.00	29453.51
22	1100	455.00	285.07	129.96	129.97	25.00	20.00	25.00	10.00	10.00	10.00	25879.67
23	900	454.94	150.00	89.33	105.72	25.01	20.00	25.00	10.00	10.00	10.00	22424.91
24	800	454.97	150.00	36.70	58.33	25.00	20.00	25.00	10.00	10.00	10.00	20739.92
Fuel Cost (\$/ day)												636971.7

The simulation results for hHHO-RES optimizer for various test systems are shown in table 4.60 to table 4.63. The power generated in 5 generating unit test case and the overall operating cost is shown in table 4.60. The optimal fuel cost evaluated by hHHO-RES approach is 41635.2365 \$/day. Table 4.61 gives dispatching of power generating units for hourly demand for 24 hours and overall fuel cost for 6-unit generating system with the optimum cost of 356026.17 \$/day. The power generated in 7 generating unit test case and the overall operating cost is displayed in table- 4.62. The minimum fuel cost evaluated by proposed memetic SMA approach is 288525.93\$/day. Table 4.63 depicts the optimal power generation of 10 generating units for hourly demand for 24 hours and overall fuel cost for this system is 636971.71 \$/day.

4.6.2.4 Memetic Slime Mould Algorithm

The proposed memetic approach hSMA-RES is applied on various test systems discussed in section 4.5.2 for 24 hr load demand. The capability of the said method is verified on different generating systems comprising of 5- generating unit for 1000 iterations; 6, 7 and 10-generating unit test systems for 500 iterations. The 50 search agents and 30 trial runs are considered to validate this algorithm for DELDP. Following are the results and discussions of different test cases.

1. *Dynamics TS-1: Five generator test system (with VPL effect)*

The hSMA-RES optimizer to find minimum fuel cost for a 5-unit generating test system with VPL effect is considered with a 24 hr load demand and its input test data is given in section 4.5.2. The best solutions are stated among the 30 trial solutions for this DELD with 5 generators. Table 4.64 depicts the optimal fuel cost and power dispatch of 5 generating units using hSMA-RES.

2. *Dynamics TS-2: Six generator test system (without VPL effect)*

The hSMA-RES algorithm is used to evaluate the minimum fuel/operating price for a 6-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solutions are tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is tabulated in Table 4.65.

Table 4.64: Dynamic ELD using hSMA-RES(*Dynamic TS-1:5 generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)					Optimal Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	
1	410	10.42	20	30	209.82	139.76	1214.30
2	435	30.57	20	30	124.91	229.52	1348.52
3	475	10	92.57	112.61	209.81	50	1400.72
4	530	54.12	98.54	112.67	124.91	139.76	1577.35
5	558	10.00	85.99	112.46	209.80	139.75	1607.40
6	608	40.12	98.54	30	209.82	229.52	1759.89
7	626	65.21	98.54	112.67	209.82	139.76	1785.62
8	654	10.00	92.03	112.64	209.81	229.51	1800.72
9	690	39.45	98.54	112.67	209.82	229.52	1944.99
10	704	53.45	98.54	112.67	209.82	229.52	1985.71
11	720	69.45	98.54	112.67	209.82	229.52	1996.74
12	740	75.00	112.99	112.68	209.82	229.52	2105.85
13	704	53.45	98.54	112.67	209.82	229.52	1985.71
14	690	39.45	98.54	112.67	209.82	229.52	1944.99
15	654	10.00	92.03	112.65	209.80	229.52	1800.72
16	580	12.12	98.54	30	209.82	229.52	1605.73
17	558	10.00	86.72	111.73	209.81	139.74	1608.21
18	608	42.36	98.54	112.67	124.91	229.52	1757.76
19	654	10.00	92.02	112.65	209.81	229.52	1800.70
20	704	53.45	98.54	112.67	209.82	229.52	1985.71
21	680	29.45	98.54	112.67	209.82	229.52	1897.91
22	605	39.36	98.54	112.67	124.91	229.52	1746.39
23	527	44.03	98.54	30	124.91	229.52	1575.73
24	463	74.64	98.54	30	209.82	50	1408.22
Fuel Cost (\$/ day)							41645.58

3. *Dynamic TS-3: Seven generator test system (without VPL effects)*

The hSMA-RES algorithm is utilized to evaluate the minimum fuel/operating price for a 7-unit generating test system without VPL effect and losses for a 24 hr power demand. The test system details are given in section 4.5.2. The best solutions are tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is recorded in Table 4.66.

Table 4.65: Dynamic ELD using hSMA-RES (*Dynamic TS-2:6 generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)						Optimum Fuel Cost (\$)/hr
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	
1	700	312.70	72.56	159.87	50	54.87	50	8299.38
2	750	327.47	83.39	171.36	50	67.77	50	8873.44
3	850	355.64	104.12	193.32	54.44	92.48	50	10052.33
4	950	379.66	121.83	211.93	73.07	113.51	50	11267.05
5	1000	391.70	130.71	221.28	82.38	123.93	50	11887.02
6	1100	414.78	147.69	239.26	100.33	144.12	53.82	13152.01
7	1150	424.55	154.98	246.90	108.00	152.73	62.84	13795.76
8	1200	434.42	162.11	254.46	115.61	161.36	72.05	14446.38
9	1300	454.00	176.55	269.74	130.89	178.63	90.19	15768.20
10	1400	473.55	190.99	285.00	146.09	195.66	108.71	17117.47
11	1450	485.67	199.99	294.40	150	200	119.94	17802.79
12	1500	500	200	300	150	200	120	18080.5
13	1400	473.54	191.12	285.00	146.10	195.56	108.68	17117.47
14	1300	454.01	176.63	269.79	130.87	178.44	90.27	15768.20
15	1200	434.35	162.18	254.49	115.58	161.30	72.09	14446.38
16	1050	403.67	139.54	230.63	91.71	134.44	50	12515.38
17	1000	391.65	130.67	221.37	82.38	123.92	50	11887.02
18	1100	414.70	147.65	239.27	100.40	144.18	53.80	13152.01
19	1200	434.37	162.18	254.51	115.56	161.31	72.08	14446.38
20	1400	473.58	191.18	284.94	146.10	195.51	108.69	17117.47
21	1300	454.01	176.64	269.78	130.85	178.38	90.34	15768.20
22	1100	414.72	147.75	239.25	100.37	144.09	53.83	13152.01
23	900	367.66	113.03	202.67	63.71	102.93	50	10655.49
24	800	342.22	94.25	182.84	50	80.69	50	9457.83
Fuel Cost (\$)/ day								356026.178

4. *Dynamic TS-4: Ten generator test system (without VPL effect)*

The hSMA-RES algorithm is used in this case to evaluate the minimum fuel/operating price for a 10-unit generating test system without VPL effect and losses for a 24 hr

power demand. The test system details are given in section 4.5.2. The best solution are tabulated among the 30 trial runs. Power generated by different units and the optimum fuel/operating cost is tabulated in Table 4.67.

Table 4.66: Dynamic ELD using hSMA-RES (*TS-3: Seven generator test system*)

Time (hr)	Load Demand (MW)	Dispatch of Power Generating Units (MW)							Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	
1	800	298.18	61.82	140	50	100	50	100	9759.80
2	780	286.81	53.44	139.74	50	100	50	100	9537.92
3	750	271.88	50	128.12	50	100	50	100	9210.34
4	750	271.87	50	128.13	50	100	50	100	9210.34
5	720	255	50	115	50	100	50	100	8889.70
6	700	243.75	50	106.25	50	100	50	100	8679.88
7	700	243.75	50	106.25	50	100	50	100	8679.88
8	700	243.75	50	106.25	50	100	50	100	8679.88
9	800	298.18	61.82	140	50	100	50	100	9759.80
10	900	339.26	92.09	140	50	100	50	128.65	10908.66
11	1000	372.48	100	140	67.49	107.17	50	162.85	12108.21
12	1200	425.42	100	140	100	153.50	63.73	217.35	14626.42
13	1400	465.87	100	140	100	188.89	100	258.99	16661.53
14	1500	516.23	100	140	100	232.95	100	310.82	18690.71
15	1750	575	100	140	100	325	100	410	22406.36
16	1800	575	100	140	100	375	100	410	23211.36
17	1500	516.23	100	140	100	232.95	100	310.82	18690.71
18	900	339.26	92.09	140	50	100	50	128.65	10908.66
19	850	321.19	78.77	140	50	100	50	110.04	10327.51
20	800	298.18	61.82	140	50	100	50	100	9759.80
21	780	286.81	53.44	139.74	50	100	50	100	9537.92
22	750	271.87	50	128.13	50	100	50	100	9210.34
23	700	243.75	50	106.25	50	100	50	100	8679.88
24	800	298.18	61.82	140	50	100	50	100	9759.80
Fuel Cost (\$/ day)									287895.36

Table 4.67: Dynamic ELD using hSMA-RES (*Dynamic TS-4: Ten generator test system*)

Time (hr)	Load (MW)	Dispatch of Power Generating Units (MW)										Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	
1	700	410	150	20	20	25	20	25	10	10	10	19075
2	750	451	150	20	29	25	20	25	10	10	10	19905
3	850	455	150	62	83	25	20	25	10	10	10	21580
4	950	455	150	115	130	25	20	25	10	10	10	23275
5	1000	455	185	130	130	25	20	25	10	10	10	24139
6	1100	455	285	130	130	25	20	25	10	10	10	25880
7	1150	455	335	130	130	25	20	25	10	10	10	26752
8	1200	455	385	130	130	25	20	25	10	10	10	27626
9	1300	455	455	130	130	55	20	25	10	10	10	29453
10	1400	455	455	130	130	155	20	25	10	10	10	31507
11	1450	455	455	130	130	162	63	25	10	10	10	32636
12	1500	455	455	130	130	162	80	25	43	10	10	33895
13	1400	455	455	130	130	155	20	25	10	10	10	31507
14	1300	455	455	130	130	55	20	25	10	10	10	29453
15	1200	455	385	130	130	25	20	25	10	10	10	27626
16	1050	455	235	130	130	25	20	25	10	10	10	25009
17	1000	455	185	130	130	25	20	25	10	10	10	24139
18	1100	455	150	88	107	25	20	25	10	10	10	22425
19	1200	455	385	130	130	25	20	25	10	10	10	27626
20	1400	455	455	130	130	155	20	25	10	10	10	31507
21	1300	455	455	130	130	55	20	25	10	10	10	29453
22	1100	455	285	130	130	25	20	25	10	10	10	25880
23	900	455	150	88	107	25	20	25	10	10	10	22425
24	800	455	150	37	58	25	20	25	10	10	10	20740
		Fuel Cost (\$/day)										633514.58

The simulation results for hSMA-RES optimizer for various test systems are shown in Table 4.64 to Table 4.67. The power generated in 5 generating unit test case and the overall operating cost is tabulated in table 4.64. The optimized fuel cost evaluated by hSMA-RES approach is 41645.58375 \$/day. Table 4.65 gives dispatching of power generating units for hourly demand for 24 hours and overall fuel cost for 6-unit generating system with the optimum cost of 356026.178 \$/day. The power generated in 7 generating unit test case and the overall operating cost is shown in table 4.66. The optimal fuel cost evaluated by the proposed memetic SMA approach is 287895.36 \$/day. Table 4.67 depicts the optimal power generation of 10 generating units for hourly demand for 24 hours and overall fuel cost for this system is 633514.58 \$/day using hSMA-RES.

Table-4.68: Comparison – DELDP with 5 generating unit system

Algorithm	Fuel Cost (\$/day)
SA [310]	47356
APSO [311]	44678
DE [288]	43213
HS [38]	44367.23
HHS [38]	43354.8554
HHO	42838.75994
SMA	43300.64034
hHHO-RES	41635.2365
hSMA-RES	41645.58375

4.6.3 COMPARATIVE ANALYSIS - DYNAMIC ELD PROBLEM

This section includes the comparative analysis of the results obtained using different proposed algorithms – HHO, SMA, hHHO-RES and hSMA-RES for dynamic load dispatch problem (DELDP). The optimized solutions attained for DELDP by the proposed algorithms shows competitive performance when compared with other existing methods for 5-unit test case. Comparison of results in regard to optimal fuel cost for 5 generating unit system with all the proposed algorithms is presented in Table 4.68 and the comparison of results for 6, 7, 10 unit system is presented in Table 4.69. From table 4.68 it has been depicted that the performance of proposed hybrid algorithms, SMA and HHO are better than SA [310], APSO [311], DE [288], HS [38], HHS [38] algorithms.

Table 4.69: Comparison – DELD with 6, 7 and 10 generating units

Test System	6- Generating Unit System			
<i>Proposed Algorithm</i>	HHO	SMA	hHHO-RES	hSMA-RES
<i>Optimal Fuel Cost (\$)/day</i>	356032.59	356072.3	356026.17	356026.178
Test System	7- Generating Unit System			
<i>Proposed Algorithm</i>	HHO	SMA	hHHO-RES	hSMA-RES
<i>Optimal Fuel Cost (\$)/day</i>	288526.02	288805.7	288525.9	287895.36
Test System	10-Generating Unit System			
<i>Proposed Algorithm</i>	HHO	SMA	hHHO-RES	hSMA-RES
<i>Optimal Fuel Cost (\$)/day</i>	636972.8	636969.65	636971.7	633514.58

4.7 CONCLUSION

In this chapter the ELD has been discussed with its mathematical formulation considering all the essential constraints. This is regarded as the most stimulating problems in power system optimization in regard to planning, operation, and control. The proposed algorithms has been tested to find the best possible solution for different IEEE test systems and it has been proved from the results that the proposed optimizer performs superior than other MH optimizer algorithms in most of the cases. The proposed algorithms are tested on static ELD and dynamic ELD problems. Different test cases with and without losses and VPL effect are considered for static ELD problems and four test systems are considered for dynamic ELD problems. The problem has been solved using harris hawks optimizer (HHO), slime mould algorithm (SMA), hHHO-RES and hSMA-RES. The test systems consisting of 5, 6, 7 and 10-unit generators have been successfully tested for dynamic ELD problem with 24- hour load demand using the proposed algorithms. From the simulation results of HHO, SMA, hHHO-RES and hSMA-RES, it is found that the performance of these algorithms is much better and competitive than other well-known existing and currently developed heuristics and MH search algorithms.

INTEGRATED ECONOMIC LOAD DISPATCH

5.1 INTRODUCTION

Traditionally, the economic load dispatch was concerned only with conventional thermal sources based on non-renewable resources of energy. Nowadays, due to inadequate fossil resources and environmental concerns alternate methods of energy generation have gained popularity over conventional thermal generation methods. Alternative energy-generating technologies such as solar and wind have gained popularity as a viable alternative to traditional thermal power generation. The combined operation of thermal with renewable sources has achieved remarkable prominence in the recent research scenario. In today's research scenario, renewable energy sources (RESs) have taken on a significant role and this leads to a reduction of emissions from thermal power plants along with the operational cost of power generated using these resources. The improbable combination of coal and solar or wind under proper situations provides a sophisticated solution for a large-scale generation with reduced emissions, gases, and pollutants. Although the capital investment in renewable sources like solar and wind are more in contrast to the operational cost and are reliant on weather conditions hence have uncertainties in delivering output. These resources always entail some backup technology when supply is less or unavailable due to their intermittent nature that varies the power widely in a short period. Despite all these concerns, the combination of renewable sources with the conventional thermal power plant is advantageous to each other and will lead to a cleaner and most efficient power generating system.

Electrification of the transport system is also effective to eradicate greenhouse gases and air pollutants from fossil-based conventional power plants. The use of electric vehicles is an implicit way to reduce carbon emissions and noise pollution. Electric

vehicles are becoming more popular in the motor vehicle market universally and will ascertain to be a successful solution to diminish pollution in a short time, but this is another new challenge to operate & control the power system. To increase access to EVs, large-scale electricity charging facilities are required to allow the vehicles to be plugged into the power system and charge the batteries directly [312]. An increased number of these vehicles will cause significant uncertainties in the power system operations and control. This is due to the random nature of the charging behavior of electric vehicles and hence increasing the power demand. This rise in energy demand has inspired researchers to cogitate the power generation from RESs. Moreover, researchers agreed that more emphasis is required in this field to decrease the issues related to the escalating power demand and the environment like global warming and deprivation of the ecosystem. The idea of charging and discharging electric vehicles from the grid and to the grid has a significant role in contemporary power system. The continuous load demands have initiated the integration of plug-in electric vehicles and battery electric vehicles into conventional power system making it a smart grid and reducing the fuel cost of the entire power system. This additional power of standalone vehicles can be used as a source for battery energy storage systems.

EVs may serve the same purposes as power generators and grid loads with the use of appropriate vehicle-to-grid (V2G) technology. EVs might engage in the ancillary services markets, pumping energy back onto the grid during periods of high demand and offering services like frequency and voltage management, reactive power for power factor correction, and reserve capacity. According to the vehicle-to-grid (V2G) mode, an electric vehicle's battery may be supposed as a type of mobile distributed energy storage system that not only consumes electricity from the power grid but also feeds electricity back into the grid [313]. Consequently, EVs may be considered a significant distributed energy resource that contributes to the management and operation of the power grid. Meanwhile, in the time-of-use (TOU) electricity price environment, the reasonable arrangement of the charging and discharging of EVs can effectively reduce electricity cost for consumers. A

more discrete and targeted approach to rate design for EVs is time-varying pricing, where electricity prices that vary over the day provide market signals that help shift charging away from the system peak periods and toward low-demand periods. The simplest form of time-varying pricing is a time-of use (TOU) rate, which offers different prices for power consumed during set periods of the day: reduced prices when demand is typically low, and high prices when demand is typically high.

A solution of a combined PV/BES/EVCS power system- (PBES) is projected in [314] to achieve its self-capability and consumption. [315] recommended and simulated a smart EV charging station design with grid connected PV energy generation. [316] incorporated the solar PV modules along with biogas generators at EV charging stations in Bangladesh and [317] in Netherlands. [318] suggested an algorithm based on hybrid optimization and implemented to energy storage management for reducing the real time operating cost. [319] implemented a MILP algorithm for obtaining the charging-discharging pattern of electric vehicles. [320] presents the design features with application of the new solar based EV charging station operated by a motor vehicle (type-1) connector. Further a PSO based approach is suggested in [321] for EVs to obtain the optimal size of PV module and energy storage capacity unit in solar based grid connected system.[322] proposed a combined model with solar and energy storage for the optimized scheduling of the EVs charging position and assessed the ecological and economic benefits. [323] proposed a multi agent PSO optimization algorithm for modelling a PBES system and proved the effectiveness of the approach by considering a realistic power system test case in Shanghai, China. [324] showed a general model for optimizing the difficulties encountered with Electric Energy Storage (EES) systems on applications for economic dispatch. The model is further explored in the Western Electricity Coordinating Committee (WECC) area, which fulfils the 10-minute balance requirement and the hourly charge shift possibilities of a 2030 load scenario and the cost function with changing load is based on piecewise linear equations. The results demonstrated that when EES is dispatched economically, it may save more than offer one single service to create numerous value streams. [325] discussed the

combination of PEVs along with RESs in a load dispatch problem. A ten-unit thermal system with PEVs and RESs comprises of wind and solar power is analyzed for dynamic emission dispatch. A fuzzy decision-making approach with constriction based PSO is used to evaluate the outcomes of this intelligent combination for managing uninterruptable power supply. [130] showed the integration of electric vehicles (EV) into power grids may pose major problems to the system's security and an ED-EV algorithm to optimize the overall dispatch costs while taking into consideration spatial restrictions throughout a short-term execution. The simulation results showed that the proposed ED-EV significantly reduces overall dispatch costs while utilizing technically sound generating sources in the system. [326] provided a thorough strategy to CEED problem and assured the efficacy of employing PEVs and RERs with two test scenarios. The cost function related to wind energy source is incorporated in this dispatch issue computation to obtain a more accurate and realistic estimate. The outcome demonstrated that the use of PEVs does not efficiently reduce overall emissions from industry and both PEVs and RESs must be integrated with the 20-unit thermal system. [327] proposed that the BESSs have the prospective to reduce the expenses both on the utility and the customer finances. An algorithm is developed for economic dispatch of battery energy storage systems with optimized energy and power capacities using multi-pass dynamic programming (MPDP) integrated with a time-shift approach. [328] presented the mathematical formulation combined ELD problem considering BEVs/PEVs/BESS.

The literature discussed above reveals that it is important to have more research on economic load dispatch problem considering the impact of RESs and EVs (PEVs/BEVs/BESSs) for finding an optimum solution so as to curtail the operational fuel cost and maximize the efficacy of the system. BESSs acts as a vital device that utilizes the non-conventional resources and makes it a strong coupling system. The scalar dispatch techniques are not appropriate for microgrids, hence dynamic ELD problem is tested to find the optimized control scheme in given time interval. This is realized with different load conditions to analyze the savings using RESs.

5.2 PROBLEM FORMULATION

The main function of ELD is to maintain the total operational (fuel) costs of generating units as low as possible while meeting the various systems equality and inequality restrictions. The different objective functions are formulated for ELD problem considering the effect of RESs (renewable sources) and EVs (PEVs/BEVs/BESS). These are categorized and formulated in the following sub-sections:

5.2.1 Economic Load Dispatch with Renewable Energy Sources

The general objective function for classical ELD problem, cubical ELD problem, heat and power ELD problem considering renewable energy sources may be described by equation (4.1) to (4.5) discussed in chapter 4 in regard to the constraints stated as follows [248]:

- *Power balance constraint (equality constraint):* As stated earlier, the sum of power produced by entire generators scheduled in plant essentially be equal to the entire load demand and real power loss of a system as stated in equation (4.6) and with RESs the equation is modified as follows:

$$\sum_{n=1}^{NG} P_n^G + P^{\text{Renewable}} = P^{\text{Demand}} + P^{\text{Loss}} \quad (5.1)$$

$$\sum_{n=1}^{NG} P_n^G = P^{\text{Demand}} + P^{\text{Loss}} - P^{\text{Renewable}} \quad (5.2)$$

$$\text{Where, } P^{\text{Loss}} = \sum_{n=1}^{NG} \sum_{m=1}^{NG} P_n^G B_{nm} P_m^G \quad (5.3)$$

and B_{i0} and B_{00} are loss/B- coefficients, then the P^{Loss} can be rewritten as equation (4.8) and (4.9).

- *Generator limit / Inequality constraints:* The power produced by each generating unit in a plant must always exist within the maximum (upper) and minimum (lower) operating range of generator and are stated in equation (4.10). The non-linear constraints remain same as stated in equations (4.12) through equation (4.15).

5.2.2 Economic Load Dispatch with PEVs/ BEVs/BESSs

The general objective function for static and dynamic ELD problem, cubical ELD problem and heat and power ELD problem considering PEVs/BEVs/BESSs may be represented as equation (4.1) to (4.5). The fuel cost function for ELDP considering BEVs/PEVs/BESS must be considered in regard to the following restraints [329]:

- *Power balance /equality constraint:* As stated earlier in equation (4.6), the total power generation by all the generating units must meet the entire load demand and power loss of a system. The equation (4.6) modifies as follows for charging and discharging modes:

$$\text{Case-1: During Charging} \quad \sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} + \sum_{n=1}^{NPEVs} P^{PEVs} + \sum_{n=1}^{NBEVs} P^{BEVs} \quad (5.4)$$

$$\text{Case-2: During Discharging} \quad \sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} - \sum_{n=1}^{NPEVs} P^{PEVs} - \sum_{n=1}^{NBEVs} P^{BEVs} \quad (5.5)$$

$$\text{In general,} \quad \sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} \mp P^{BEVs/PEVs/BESS} \quad (5.6)$$

$$\text{Where,} \quad P^{Loss} = \sum_{n=1}^{NG} \sum_{m=1}^{NG} P_n^G B_{nm} P_m^G \quad (5.7)$$

if B_{i0} , B_{00} are loss/ B-coefficients, then the equation for P^{Loss} can be amended and extended as equation (4.8) and (4.9)

- *Generator limit / Inequality constraints:* The generated power produced by each generating unit in a plant must always exist within the maximum (upper) and minimum (lower) operating range of generator and are stated in equation (4.10). The non-linear constraints remain same as stated in equations (4.12) through equation (4.15).

5.2.3 Economic Load Dispatch with PEVs/BEVs/BESSs and RESs

The overall objective function for dynamic economic load dispatch problem, cubical ELD problem and heat and power ELD problem considering PEVs/BEVs/BESSs and renewable

energy sources (RESs) may be represented as equation (4.1 to (4.5) subjected to the constraints as follow [330]:

- *Power balance (equality) constraint:* As stated earlier in equation (4.6), the total power produced by all the generating units must meet the entire load demand including power loss of a system. Equation (5.1) revised during charging and discharging phase as follows:

Case-1: During Charging

During the charging phase for PEVs and BEVs the power balance constraints can be mathematically modelled as

$$\sum_{n=1}^{NG} P_n^G + P^{Renewable} = P^{Demand} + P^{Loss} + \sum_{n=1}^{NPEVs} P^{PEVs} + \sum_{n=1}^{NBEVs} P^{BEVs} \quad (5.8)$$

Case-2: During Discharging

During the discharging phase for PEVs and BEVs the power balance constraints can be mathematically modelled as:

$$\sum_{n=1}^{NG} P_n^G + P^{Renewable} = P^{Demand} + P^{Loss} - \sum_{n=1}^{NPEVs} P^{PEVs} - \sum_{n=1}^{NBEVs} P^{BEVs} \quad (5.9)$$

$$\sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} \mp P^{BEVs/PEVs/BESS} - P^{Renewable} \quad (5.10)$$

$$\text{where, } P^{Loss} = \sum_{n=1}^{NG} \sum_{m=1}^{NG} P_n^G B_{nm} P_m^G \quad (5.11)$$

While considering the combined case of EVs/BESSs and RESs. The aforementioned equations for the charging of EVs can be reframed as equation (5.12) and discharging equation can be represented as equation (5.13) and equation for the overall power generation can be modelled as per equation (5.14).

$$\sum_{n=1}^{NG} P_n^G + P^{Renewable} = P^{Demand} + P^{Loss} + \sum_{n=1}^{NEVs} P^{EVs} + \sum_{n=1}^{NBESS} P^{BESS} \quad (5.12)$$

$$\sum_{n=1}^{NG} P_n^G + P^{Renewable} = P^{Demand} + P^{Loss} - \sum_{n=1}^{NEVs} P^{EVs} - \sum_{n=1}^{NBESS} P^{BESS} \quad (5.13)$$

$$\sum_{n=1}^{NG} P_n^G = P^{Demand} + P^{Loss} \mp P^{EVs} \mp P^{BESS} - P^{Renewable} \quad (5.14)$$

- *Generator limit / Inequality constraints:* The power produced by each generating unit in a plant must always exist within the maximum (upper) and minimum (lower) operating range of generator and are stated in equation (4.10). The non-linear constraints remain same as stated in equations (4.12) through equation (4.15).

5.3 BATTERY DEGRADATION

For an EV to operate efficiently, the BESSs must fulfill precise standards for safety, charging, and discharging speeds, energy, and power density. Batteries now have a number of drawbacks, including a low energy density, a large amount of weight, and a high price. The present barrier to the broad adoption of EVs, despite continued research into battery improvement, is the problem of battery deterioration. The electric vehicle's battery degradation results in high investment costs and a limited operating range. The operation of BES significantly affects its lifecycle and degradation. How deep it is discharged and the number of its charging/discharging cycles greatly influence BESSs degradation. With the increase in depth of discharge of BESSs, its life cycle decreases. The impact of battery degradation has been ignored in the proposed research. The battery State of Charge (SOC), ambient cell temperature, depth of cycle C-rate, and ampere-hour count are only a few of the variables considered while estimating battery degradation. To determine a battery's health and predicted lifespan, the minimum and maximum SOC limits, calendar aging, and cyclical aging must be considered. The latter two are crucial indicators of a decline in battery performance [331]. Additionally, it is expected that any battery utilized throughout the driving cycle, whether it included supercapacitors or fuel cells or not, will have been depleted and need to be recharged. Furthermore, it is logical to presume that the battery has the ability to complete a necessary driving cycle before it approaches the End-of-life. This substantially influences the battery's ability to charge and discharge. SOC, which is normally set between a minimum and maximum value of 0.2 to 0.9, and the operating

temperature of the battery is also managed by systems that are installed. Another fundamental premise is that the energy at a given time is a function of the energy at the previous time t and the simultaneous loss in capacity during the same period. Mathematically this is modeled as below:

$$E_{Bat}^t = E_{Bat}^{t-1} + Q_{Bat}^{t-1} \quad (5.15)$$

Here E_{Bat}^t denotes the present energy, E_{Bat}^{t-1} represents the energy at time $t-1$ and Q_{Bat}^{t-1} represents the loss at $t-1$. The CB^{Rated} (battery rated capacity), is presumed to be the ratio between the battery current, I_{Bat} and the battery charge, Q_{Bat} . After that, it is possible to estimate the state of health (SOH) of the battery using the equation (5.16) as below:

$$SOH = \frac{CB^{Max}}{CB^{Rated}} \times 100\% \quad (5.16)$$

where CB^{Max} is the maximum releasable battery capacity, while CB^{Rated} is the battery rated capacity which reduces over time and gives rise to maximum battery capacity CB^{Max} . A large value of the rated capacity of the battery and a larger DOD- Depth of Discharge accelerates the battery degradation. DOD is regarded as an important parameter in battery degradation and it is the numerical complement of SOC. It could be taken as the power of the battery that has been utilized before recharging (beginning of the new charging phase). This can be expressed as $(100 - SOC) \%$ or $(1 - SOC)$. The Depth of discharge and rated capacity of the battery are mathematically related as equation (5.17) while the relationship between the SOC and CB^{Rated} is described by the expression in equation (5.18).

$$t \approx \frac{2N \times DOD}{CB^{Rated}} \quad (5.17)$$

$$SOC^t = \left| -\frac{1}{CB^{Rated}} \right| \quad (5.18)$$

The SOC can be seen as designating the upper limit and is expressed as the difference between the upper and lower cutoff SOC. To avoid over charge and discharge of the battery the minimum and maximum limits are assumed as expressed in equation (5.19).

$$SOC_{\min}^L \leq SOC^t \geq SOC_{\max}^U \quad (5.19)$$

The DOD at an instantaneous time, t , can be calculated by equation (5.20) involving the rated battery energy capacity, E_{rbec}^t , and the charging and discharging energy capacity of the battery E_{cdec}^t .

$$DOD^t = \frac{E_{rbec}^t - E_{cdec}^t}{E_{rbec}^t} \quad (5.20)$$

5.4 POWER FROM RENEWABLE ENERGY SOURCES (RESs)

Renewable energy is defined as energy that is found in nature and may be used over and over again. In general, solar and wind energy are the most preferable sources in utilization under RESs as they are constantly accessible and have no shortage. Solar power is extracted from sun's energy and wind power depends on the velocity of wind. The uncertainties prevail as both are weather dependent and should be used in combination with some conventional power plant. It is critical to understand the computation of solar and wind power when integrating renewable energy sources into traditional power producing systems to satisfy load demand.

5.4.1 Calculation of Solar Power

Photovoltaics made up of lenses or mirrors and solar tracking systems are used in solar power systems to focus a large number of sunrays into a narrow beam and electrical current is produced. It is vital to understand solar irradiance and solar insolation in order to compute the quantity of electricity generated. Solar insolation is a measure of cumulative solar energy over a specific period of time, whereas solar irradiance is a measure of solar power over a defined region. The greatest quantity of solar insolation on a surface at a certain tilt angle may be computed as a function of latitude depending on the sun's location in the sky. The following formulas are used to calculate solar irradiance and solar insolation.

The number of sun hours is the duration between sunrise and sunset:

$$Sunrise = 12 - \frac{1}{15^0} \cos^{-1} \left(\frac{-\sin \varphi \sin \delta}{\cos \varphi \cos \delta} \right) \quad (5.21a)$$

$$Sunset = 12 + \frac{1}{15^0} \cos^{-1} \left(\frac{-\sin \varphi \sin \delta}{\cos \varphi \cos \delta} \right) \quad (5.21b)$$

Where, δ is the declination angle, which is based on the day and is given by

$$\delta = 23.45^0 \sin \left(\frac{360}{365} (d - 81) \right) \quad (5.22)$$

Where d denotes the number of days since the beginning of the year and φ is the latitude of the location concentrated.

The direct component of the solar radiation is determined from the air mass:

$$I_D = 1.353 \times 0.7^{(AM^{0.678})} \quad (5.23)$$

The air mass (AM) can be determined using the following formula:

$$AM = \frac{1}{\cos \theta} \quad (5.24)$$

Where, θ is the latitude in degrees.

The solar power produced by PV generator is based on the climatic data (temperature and radiation) in addition to the manufacturer data. The solar power of PV generator can be calculated as follows [2],[332]:

$$P_{solar} = r_s A \eta_s \quad (5.25)$$

$$\text{Where, } \eta_s = \eta_{reference} [1 - \gamma (T_{cell} - T_{reference})] \quad (5.26)$$

Here, r_s , A and η_s signifies solar radiation, area of the PV module and efficiency of solar generator respectively. The solar generator efficiency varies with the cell temperature T_{cell} and $\eta_{reference}$ is the reference efficiency, $T_{reference}$ is the reference temperature of the cell and γ is the temperature coefficient of short current. The solar radiation r_s is described by the

below given beta distribution function with $r_s^{\max}$ considered as maximum value of solar radiation:

$$f(r_s) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \times \left(\frac{r_s}{r_s^{\max}}\right)^{(\alpha-1)} \left(1 - \frac{r_s}{r_s^{\max}}\right)^{(\beta-1)} \quad (5.27)$$

$$\text{Where } \alpha = \mu \left[\frac{\mu(1-\mu)}{\sigma^2 - 1} \right] \quad (5.28)$$

$$\beta = (1-\mu) \left[\frac{\mu(1-\mu)}{\sigma^2 - 1} \right] \quad (5.29)$$

5.4.2 Calculation of Wind Power

Wind energy is stochastic in nature, means its velocity and direction go on changing with time. This uncertain stochastic nature of wind could be resolved by using various statistical techniques. Such as the gamma function, Weibull probability distribution function, etc. Wind energy is produced by converting the kinetic energy of wind into rotational kinetic energy in the turbine and then converting it into electrical energy. The amount of power generated depends upon wind space and the swept area of the turbine. While planning a wind farm it is important to know the expected power and the energy output of each turbine to calculate its economic values. It is of economic importance to know the produced energy by different turbines under different speeds and its rated wind speed is the minimum speed. Wind power is calculated by knowing the wind speed. The mean wind speed and direction are calculated at each level of the meteorological masts with wind speed sensors by first converting the 20Hz wind speed WS measured by the cup anemometers and direction WD measured by the vanes into 20Hz orthogonal wind components in the meteorological zonal direction (west-east) represented by u_m and meteorological zonal direction (south-north) represented by v_m and calculated as follows [332]:

$$u_m = -WS \sin\left(\frac{\Pi \times WD}{180}\right) \quad (5.30)$$

$$v_m = -WS \cos\left(\frac{\Pi \times WD}{180}\right) \quad (5.31)$$

Positive u_m and v_m values correspond to traditional cartesian directions, signifying east and north wind, respectively. The vector mean of the orthogonal wind components is used to compute the mean wind speed for each interval as follows:

$$\bar{V} = (\bar{u}_m^2 + \bar{v}_m^2)^{1/2} \quad (5.32)$$

The compass convention is used to record wind direction, with north equating to north and increasing clockwise. The Cartesian convention for vector direction, on the other hand, starts at the positive x-axis and works its way clockwise, showing the vector's direction. The direction of the wind is computed using the compass convention and components of average wind speed as follows:

$$\overline{WD} = a \tan 2\left(\frac{\bar{u}_m}{\bar{v}_m}\right) \times \frac{180}{\Pi} \quad (5.33)$$

Where the function $a \tan 2(x)$ is the inverse tangent that takes into account the quadrant of each signal $\bar{u}_m$ and $\bar{v}_m$ and has the default range of $\pm\Pi$.

Thus, the wind power is calculated using equation (5.21)

$$W_{power} = 1/2 \times \rho \times A \times \bar{V}^3 \times C_p \quad (5.34)$$

Where, ρ is density, A is swept area, $\bar{V}^3$ is wind speed and C_p is the coefficient of power.

The Weibull distribution function is a versatile distribution function based on the value of shape parameter and is used for the estimation of wind power (Reddy et.al.2013). The probability distribution function for the calculation of wind power can be represented mathematically as:

$$pdf(v; k, \lambda) = \frac{k}{\lambda} \left(\frac{v}{\lambda}\right)^{k-1} \exp\left[-\left(\frac{v}{\lambda}\right)^k\right] \quad (5.35)$$

Where v , k and λ signifies wind speed, shape factor and scale factor at a given location.

Because of the intermittent nature of wind power (P_w), it is a random variable. The mathematical function for wind power output and wind speed can be mathematically described as:

$$P_w = \begin{cases} 0 & (v^w \leq v_{in} \text{ or } v^w \geq v_{out}) \\ P_{wr} & (v_r \leq v^w \leq v_{out}) \\ P_{wr} \frac{(v^w - v_{in})}{(v_r - v_{in})} & (v_{in} \leq v^w \leq v_r) \end{cases} \quad (5.36)$$

For wind speed (v^w), less than cut in speed (v_{in}) or for wind speed (v^w) greater than cut-out speed v_{out} wind power is equal to zero. Wind power is equal to the rated wind power if wind speed is between the rated speed and the cut-out speed. So, for the first and second eventuality in equation (5.36), the wind power is a discrete variable (Hetzler et al.2008). The probability of wind power being 0 and P_{wr} be calculated as per equation (5.24) & (5.25) respectively as described below:

$$\Pr(P_w=0) = \left[1 - \exp\left[-\left(\frac{v_{in}}{\lambda}\right)^k\right] + \exp\left[-\left(\frac{v_{out}}{\lambda}\right)^k\right] \right] \quad (5.24)$$

$$\Pr(P_w=P_{wr}) = \left[\exp\left[-\left(\frac{v_r}{\lambda}\right)^k\right] - \exp\left[-\left(\frac{v_{out}}{\lambda}\right)^k\right] \right] \quad (5.25)$$

Between v_{in} and v_r , wind power is continuous variable and its probability density function can be written as,

$$pdf(PW) = \frac{KLv_{in}}{(P_{wr})^\lambda} \left[\frac{1 + \left(\frac{LP_w}{P_{wr}}\right)v_{in}}{\lambda} \right] \times \exp\left[-\left(\frac{1 + \left(\frac{LP_w}{P_{wr}}\right)v_{in}}{\lambda} \right)^k \right] \quad (5.26)$$

Here $L = \frac{v_r - v_{in}}{v_{in}}$, ratio of linear range of wind speed to cut in wind speed. Ever since correctness of wind power prediction is not meticulous and exact. So, based on above empirical formulas, maximum generation scheduling can be computed.

5.5 TEST SYSTEMS

The economic load dispatch problem has been described with integration of renewable resources, plug-in electric vehicles, battery electric vehicles/ BESS along with the system and physical limits of thermal generating units. The economic load dispatch problem has been solved and tested for 6-unit, 7-unit, and 10-unit systems. The data for generating units, fuel cost coefficients, and load demand has been taken from standard IEEE test systems and discussed in section 4.5. To validate the proposed algorithms, standard power systems consisting 6, 7, and 10 generating units have been considered with RESs, EVs, both EVs and RESs. The data for EVs and RESs has been considered from behara et al. [325], debnath et al. [6] and tariq et al. [145]. In the case of RESs, the generating cost parameter is not taken into account. According to the renewable energy law, the wind and solar power generation must be always adopted when it is generating, since there is no generation cost for them compared to the fossil fuel cost and thus it is ignored in the optimization process.

The renewable energy source data for 6- unit system is referred from [333], [6] (saber et al. 2011, Debnath et al. 2015) with wind farm capacity as 25.5 MW and solar farm capacity as 40 MW. The capacity is determined by considering the solar insolation and wind speed data from national renewable energy laboratory. The standard value of PV panel efficiency is taken as 16% and area A of the solar farm is determined as 250731.33 sq. m. Considering 1000-W/m² maximum solar insolation and 16% efficiency, the maximum capacity of the solar farm is $\approx$ 40 MW. The wind farm size is considered as 25.5 MW with 17 wind turbines of 1.5 MW each. The wind power generation and solar power generation forecasting for seven thermal generating unit system is taken from (Augustine et al.,2012) [334] and (Tariq et al. 2020) [145] as shown in Fig. 5.1 and 5.2. The renewable

energy source data for 10- unit system is referred from (Gholami et al. 2014, Behara et al. 2021) [335], [325] with wind farm capacity as 30 MW and is taken from national renewable energy laboratory.

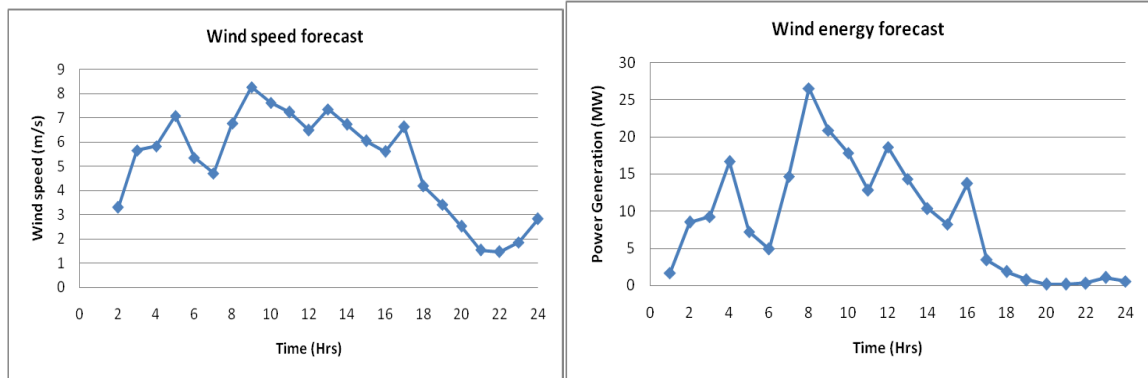


Fig. 5.1: Scaled data of wind speed and power generation for 24 hours [145]

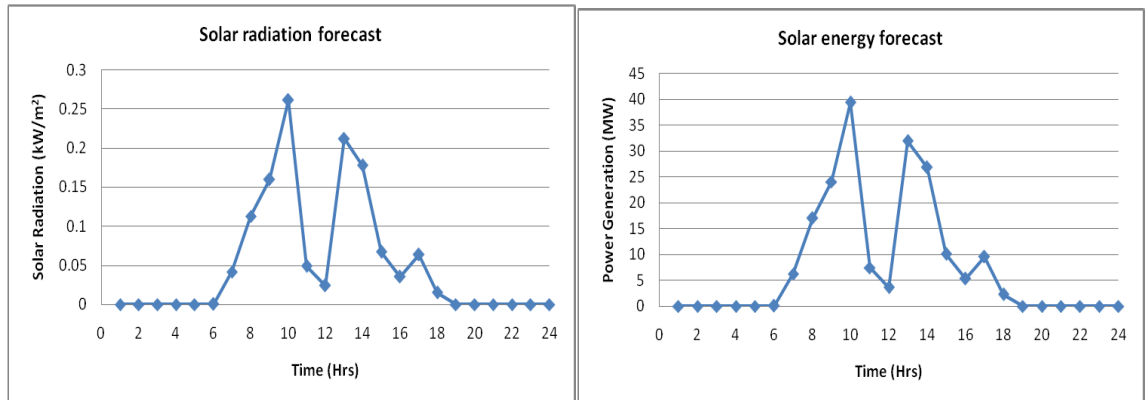


Fig.5.2: Scaled data of radiation and power generation of PV panels for 24 hours [145]

The expected total number of vehicles (EVs) is considered to be 50,000 in which 20,000 EVs are charged from grid during off peak hours and 30,000 EVs are discharged into grid during peak hours. It is also assumed that EVs charge and discharge once in a day with total time period of 24 hrs. The average distance covered by each EV in 365 days (1 year) is 12000 miles, average length of travel in a day is 32.88 miles/day and mileage of each EV is 4 miles/KWh. Therefore, EV requires $(32.88/4) = 8.22\text{KWh/day}$ and

(50,000x8.22KWh) =411MWh excess energy is given by 50,000 EVs each day. Departure state of EVs battery charge is taken as 50% and the system efficiency is 85%.

5.6 RESULTS AND DISCUSSIONS

This section confers the outcomes of the suggested algorithms such as HHO, SMA, hHHO-RES and hSMA-RES used to solve economic load dispatch problem considering the impact of RESs, PEVs/BEVs/BESS and combined RESs with PEVs/BEVs/BESS. The suggested methods are tested using the MATLAB 2018a Windows 10, CPU@2.10Ghz-4GB RAM Core i5 processor. The cost comparison has been done using various suggested methods with different load and source situations.

5.6.1 Harris Hawks Optimizer for Integrated Economic Load Dispatch

In this section the outcomes of ELD problem considering the impact of PEVs/BEV/BESS, RESs and both RESs and PEVs using the Harris Hawks Optimizer (HHO) is discussed. The data considered for this method is 50 search agents, 500 iterations and 30 maximum trial runs. The effectiveness of the proposed algorithm is tested on 6-unit, 7-unit and 10-unit test system with the said conditions.

5.6.1.1 Six Generator Test System (ELD with Electric Vehicles)

Harris Hawks Optimizer Algorithm is suggested to get optimized outcomes for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A six generator test system without valve point loading effect and without losses [6] is considered. **Table 5.1** displays that the fuel price is **397193.21** \$/day using the Harris Hawks Optimizer Algorithm.

5.6.1.2 Six Generator Test System (ELD with RESs)

Harris Hawks Optimizer-HHO Algorithm is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect, with loss coefficient matrix as zero is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40

MW respectively. **Table 5.2** displays the fuel price for 24 hours and the total fuel price for a day is **316495.72** \$/day using the proposed Harris Hawks Optimizer Algorithm.

5.6.1.3 Six generator test system (ELD with Electric Vehicles and RESs)

The proposed Harris Hawks Optimizer-HHO Algorithm is applied to attain optimized outcomes for an integrated economic load dispatch with the collective impact of EVs and RESs. A six generator test system [6] without valve point loading effect, with loss coefficient matrix as zero is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.3** displays that the fuel price is **326621.3** \$/day using the proposed HHO algorithm.

5.6.1.4 Seven Generator Test System (ELD with Electric Vehicles)

Harris Hawks Optimizer Algorithm is suggested to achieve optimized outcomes for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A seven generator test system without valve point loading effect and loss coefficient is considered [145]. **Table 5.4** displays that the fuel price is **296172.3197** \$/day using the Harris Hawks Optimizer algorithm.

5.6.1.5 Seven generator test system (ELD with RES)

Harris Hawks Optimizer-HHO Algorithm is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A seven-generator test system without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with data taken from [145]. **Table 5.5** displays that the fuel price is **283632.1** \$/day using the Harris Hawks Optimizer Algorithm.

5.6.1.6 Seven generator test system (ELD with EVs and RES)

Harris Hawks Optimizer Algorithm is suggested to get optimized outcomes for economic load dispatch with the combined effect of EVs and RESs. A seven generator test system without valve point loading effect, with loss coefficient matrix as zero is considered. The Electric vehicles and renewable energy sources wind and solar are incorporated with wind

and solar power considered from [145]. **Table 5.6** displays that the fuel price is **291213.44** \$/day using the Harris Hawks Optimizer Algorithm.

Table 5.1: Six unit generating system with EVs using HHO Method

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆		
1	700	352.72	99.50	190.13	50.00	89.41	50.00	-131.76	9834.43
2	750	352.94	103.28	190.89	50.00	87.89	50.00	-85.00	9873.09
3	850	367.15	112.59	202.17	61.72	98.87	50.00	-42.50	10564.56
4	950	379.67	125.64	210.36	72.99	111.34	50.00	0.00	11267.25
5	1000	392.20	129.99	220.79	82.53	124.48	50.00	0.00	11887.03
6	1100	410.35	146.03	241.79	102.77	147.31	51.75	0.00	13152.39
7	1150	429.15	156.35	243.49	109.17	150.81	61.02	0.00	13796.10
8	1200	442.53	162.73	252.15	112.86	156.85	72.87	0.00	14447.13
9	1300	458.22	175.35	266.64	127.04	178.34	94.51	0.10	15770.06
10	1400	471.82	189.10	282.36	148.41	200.00	110.45	2.14	17147.01
11	1450	493.87	200.00	300.00	150.00	200.00	120.00	13.87	17994.97
12	1500	500.00	200.00	300.00	150.00	200.00	120.00	34.78	82862.50
13	1400	481.45	194.92	290.51	150.00	200.00	117.90	34.78	17593.33
14	1300	459.73	179.90	273.89	137.39	176.69	86.28	13.87	15954.50
15	1200	435.49	165.65	254.57	116.05	157.44	72.94	2.14	14474.65
16	1050	404.57	141.65	229.31	97.25	127.46	50.00	0.24	12519.09
17	1000	394.07	133.14	221.89	81.52	127.20	50.00	-7.82	11984.77
18	1100	420.10	146.04	236.48	104.81	149.68	61.10	18.21	13386.30
19	1200	439.09	169.25	264.32	120.43	174.31	78.24	45.65	15046.90
20	1400	485.09	198.46	293.46	150.00	200.00	118.64	45.65	17742.83
21	1300	453.77	179.75	274.54	135.34	181.10	93.70	18.21	16011.99
22	1100	412.30	147.43	239.59	103.30	147.36	52.83	2.81	13188.22
23	900	366.69	114.45	205.11	65.21	104.77	50.00	-6.24	10731.43
24	800	354.79	103.67	193.05	50.00	90.99	50.00	-42.50	9962.68
		Fuel Cost (\$/day)							397193.21

Table 5.2: Six unit generating system with RESs using HHO Method

Time (hr)	Power Demand (MW)	Generated Power (MW)								Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	P _{Wind}	P _{Solar}	
1	700	309.004408	69.4151965	157.915213	50	53.125182	50	10.54	0	8179.70129
2	750	320.374469	78.8922442	166.317212	50	62.1460743	50	22.27	0	8616.4801
3	850	350.82862	99.314555	187.580442	50	86.7763829	50	25.5	0	9747.96776
4	950	377.015638	117.097429	205.769173	67.9388688	106.678892	50	25.5	0	10954.2282
5	1000	385.101365	127.317703	217.710792	74.9982819	119.371858	50	25.5	0	11569.8801
6	1100	409.181119	144.400947	230.648584	99.0238157	140.638805	50.6067303	25.5	0	12826.6176
7	1150	421.254585	150.65136	241.411628	107.799056	151.421007	51.8723632	25.5	0.09	13465.9805
8	1200	423.38552	157.55011	246.606541	107.188575	156.872469	65.4367857	25.5	17.46	13887.1526
9	1300	449.185247	162.95015	259.821305	122.802949	166.971358	81.3189905	25.5	31.45	15012.6821
10	1400	466.730806	184.461545	268.367434	133.979678	182.567607	102.38293	25.5	36.01	16285.306
11	1450	467.03427	189.680943	280.910223	150	194.411645	104.402919	25.5	38.06	16933.4016
12	1500	481.877396	199.544948	290.329161	150	200	116.818495	25.5	35.93	17645.393
13	1400	458.76064	184.277365	282.493412	133.350174	179.827251	99.0111583	25.5	36.78	16274.7857
14	1300	443.734384	167.613291	263.774433	116.13363	175.198263	77.135999	24.82	31.59	15019.9923
15	1200	421.895854	158.398032	253.732936	113.221049	155.600318	66.7118111	20.74	9.7	14049.9499
16	1050	398.465867	135.257825	228.677262	84.6651543	125.393892	50	14.62	12.92	12168.4657
17	1000	382.014056	127.840702	212.246432	78.9885844	123.410225	50	25.5	0	11570.2663
18	1100	411.240456	144.793899	236.414832	97.0179793	136.499769	54.9930657	19.04	0	12908.9909
19	1200	432.806912	157.695726	254.208082	107.489976	156.844436	65.4548678	25.5	0	14114.1038
20	1400	464.165527	187.796094	282.860354	143.340192	200	103.817834	18.02	0	16873.0198
21	1300	446.59233	173.485266	259.034361	128.946441	178.313519	88.1280822	25.5	0	15429.2154
22	1100	406.305186	147.272143	233.227127	96.6137482	141.692279	53.4695169	21.42	0	12878.6943
23	900	368.743209	114.969845	199.237056	64.3123066	102.737583	50	0	0	10655.6418
24	800	342.416675	94.5878371	181.435143	50	79.0103448	50	2.55	0	9427.80132
Fuel Cost (\$) per day										316495.72

Table 5.3: Six unit generating system with EVs and RESs using HHO Method

Time (hr)	Load (MW)	Generated Power (MW)									Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	EVs	P _{Wind}	P _{Solar}	
1	700	350.2359	97.80242	186.2723	50	86.9094	50	-131.76	10.54	0	9709.0176
2	750	344.9641	97.62013	184.7779	50.15796	85.20989	50	-85	22.27	0	9608.3015
3	850	359.5117	106.2589	194.7594	56.72579	99.74414	50	-42.5	25.5	0	10256.611
4	950	372.78	120.2294	205.7119	67.57628	108.2024	50	0	25.5	0	10954.215
5	1000	383.0121	127.2416	218.1123	79.67714	116.4568	50	0	25.5	0	11569.938
6	1100	409.0216	143.8601	236.2669	93.18509	142.1662	50	0	25.5	0	12826.493
7	1150	417.0582	148.1462	244.8321	101.5765	151.962	60.83498	0	25.5	0.09	13465.808
8	1200	428.1336	152.7484	249.0604	109.6958	157.1833	60.21852	0	25.5	17.46	13887.304
9	1300	440.6112	164.9614	257.225	123.894	173.7455	82.71484	0.102	25.5	31.45	15013.973
10	1400	457.48	182.8825	278.014	131.2252	188.0081	103.0222	2.142	25.5	36.01	16313.87
11	1450	473.018	191.4748	286.1752	150	194.3121	105.332	13.872	25.5	38.06	17121.975
12	1500	500	200	300	150	200	120	34.782	25.5	35.93	21432.5
13	1400	468.45	186.0875	280.1062	150	185.2897	102.5686	34.782	25.5	36.78	16744.578
14	1300	448.7611	165.9244	266.4025	122.5708	173.0855	80.7177	13.872	24.82	31.59	15203.01
15	1200	427.9851	160.5619	252.1898	107.9022	157.7969	65.26609	2.142	20.74	9.7	14077.552
16	1050	398.94164	136.7076	224.01563	87.383356	125.64767	50	0.2359	14.62	12.92	12171.362
17	1000	388.6092	128.7128	215.4397	76.95403	122.6	50	-7.8157	25.5	0	11666.952
18	1100	415.7768	146.4731	242.1999	95.85108	148.8661	50	18.207	19.04	0	13141.906
19	1200	440.4415	161.3897	258.0479	124.728	161.6738	73.87047	45.651	25.5	0	14711.133
20	1400	477.5411	194.4343	291.2054	150	200	114.4505	45.651	18.02	0	17495.194
21	1300	446.1455	173.8251	271.0762	128.5807	181.1289	91.95069	18.207	25.5	0	15671.441
22	1100	413.9315	144.9185	239.564	95.97835	136.999	50	2.8114	21.42	0	12914.464
23	900	367.7589	113.8469	204.9523	67.52866	102.1543	50	-6.2411	0	0	10731.493
24	800	355.82055	102.09678	191.70956	50	90.323109	50	-42.5	2.55	0	9932.2082
Fuel Cost (\$) per day											326621.3

5.6.1.7 Ten generator test system (ELD with Electric Vehicles)

Harris Hawks Optimizer-HHO algorithm is implemented to attain optimized cost for economic load dispatch with the effect of EVs as V2G and G2V. A ten generator test system without valve point loading effect without losses is considered [325]. **Table 5.7** displays that the fuel price is **656671.4** \$/day using the Harris Hawks Optimizer algorithm.

Table 5.4: Seven unit generating system with EVs using HHO Method

Time (hr)	Power Demand (MW)	Generated Power (MW)							EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇		
1	800	311.402	71.55802	140	50	100	50	100	-22.96	10018.4876
2	780	297.6574	61.43257	140	50	100	50	100	-19.09	9749.62996
3	750	280.681	50	134.979	50	100	50	100	-15.66	9380.53524
4	750	283.6871	51.09204	137.3808	50	100	50	100	-22.16	9451.72628
5	720	269.1467	50	126.0033	50	100	50	100	-25.15	9158.02606
6	700	253.605	50	113.915	50	100	50	100	-17.52	8863.51062
7	700	251.6708	50	112.4092	50	100	50	100	-14.08	8827.2636
8	700	259.6795	50	118.6405	50	100	50	100	28.32	8977.91496
9	800	314.0537	74.14947	140	50	100	50	102.8669	31.07	10110.7841
10	900	347.2889	98.74282	140	50	100	50	137.7382	23.77	11189.3852
11	1000	378.5233	100	140	73.23597	111.2434	50	167.5573	20.56	12360.1824
12	1200	443.9887	100	140	100	169.76	82.76547	236.5858	73.1	15583.2656
13	1400	487.2474	100	140	100	207.4115	100	280.3711	15.03	17499.2241
14	1500	522.4878	100	140	100	237.9821	100	316.2901	16.76	18929.8341
15	1750	574.9976	100	140	100	340.0824	100	410	15.08	22644.9324
16	1800	574.9925	100	140	100	396.4375	100	410	-21.43	23568.6375
17	1500	529.5585	100	140	100	243.454	100	324.3175	-37.33	19225.1723
18	900	345.0606	96.20009	140	50	100	50	135.0093	-16.27	11100.5004
19	850	327.9159	84.17252	140	50	100	50	117.2516	19.34	10550.7977
20	800	321.4356	79.37338	140	50	100	50	109.921	50.73	10335.9023
21	780	301.0494	63.93057	140	50	100	50	100	24.98	9815.54464
22	750	280.6444	50	134.9456	50	100	50	100	-15.59	9379.77019
23	700	263.5625	50	121.6575	50	100	50	100	-35.22	9051.48752
24	800	323.4955	80.62968	140	50	100	50	112.1549	-56.28	10399.8049
Fuel Cost (\$/ day)										296172.32

Table 5.5: Seven unit generating system with RESs using HHO Method

Time (hr)	Power Demand (MW)	Generated Power (MW)									Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	P _{Wind}	P _{Solar}	
1	800	297.1995	61.10053	140	50	100	50	100	1.7	0	9740.81038
2	780	283.3051	51.06412	137.1307	50	100	50	100	8.5	0	9444.48632
3	750	266.6627	50	124.0673	50	100	50	100	9.27	0	9110.50817
4	750	262.5028	50	120.8372	50	100	50	100	16.66	0	9031.4045
5	720	250.9396	50	111.8404	50	100	50	100	7.22	0	8813.58986
6	700	240.9711	50	104.0889	50	100	50	100	4.91	0.03	8628.53334
7	700	231.9764	50	97.09359	50	100	50	100	14.66	6.27	8463.66626
8	700	219.2473	50	87.19272	50	100	50	100	26.56	17	8233.7778
9	800	274.6987	50	130.3213	50	100	50	100	20.88	24.1	9264.69035
10	900	318.5474	76.99819	140	50	100	50	107.2044	17.85	39.4	10244.2887
11	1000	366.5788	100	140	62.85175	103.536	50	156.8234	12.8	7.41	11862.1406
12	1200	420.5186	100	140	100	147.8904	59.3361	209.9549	18.65	3.65	14338.4424
13	1400	465.6892	100	140	100	188.5517	100	259.5092	14.35	31.9	16661.533
14	1500	503.5485	100	140	100	221.7914	100	297.51	10.35	26.8	18165.4926
15	1750	574.865	100	140	100	314.96	100	401.815	8.26	10.1	22120.4678
16	1800	574.9972	100	140	100	355.9928	100	410	13.71	5.3	22900.5842
17	1500	511.4124	100	140	100	229.8238	100	305.7539	3.44	9.57	18506.0257
18	900	337.9768	91.06016	140	50	100	50	126.7831	1.87	2.31	10859.5942
19	850	320.9666	78.20297	140	50	100	50	110.0804	0.75	0	10318.8867
20	800	298.0845	61.74554	140	50	100	50	100	0.17	0	9757.8959
21	780	286.8812	53.28533	139.6834	50	100	50	100	0.15	0	9536.2638
22	750	271.7012	50	127.9888	50	100	50	100	0.31	0	9206.99419
23	700	243.1493	50	105.7807	50	100	50	100	1.07	0	8668.73813
24	800	297.8466	61.57343	140	50	100	50	100	0.58	0	9753.31557
Fuel Cost (\$) per day											283632.1

Table 5.6: Seven unit generating system with EVs and RESs using HHO Method

Time (hrs)	Power Demand (MW)	Generated Power (MW)							EVs (MW)	P _{Wind} (MW)	P _{Solar} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇				
1	800	310.4227	70.83731	140	50	100	50	100	-22.96	1.7	0	9999.1879
2	780	292.7628	57.827199	140	50	100	50	100	-19.09	8.5	0	9654.9999
3	750	275.4683	50	130.9217	50	100	50	100	-15.66	9.27	0	9279.5565
4	750	274.97054	50	130.52946	50	100	50	100	-22.16	16.66	0	9269.8972
5	720	265.08569	50	122.84431	50	100	50	100	-25.15	7.22	0	9080.486
6	700	250.82626	50	111.75374	50	100	50	100	-17.52	4.91	0.03	8811.4874
7	700	239.89644	50	103.25356	50	100	50	100	-14.08	14.66	6.27	8608.7341
8	700	235.17947	50	99.580529	50	100	50	100	28.32	26.56	17	8522.103
9	800	290.17359	55.916406	140	50	100	50	100	31.07	20.88	24.1	9605.1373
10	900	327.44188	83.193972	140	50	100	50	115.88414	23.77	17.85	39.4	10518.122
11	1000	373.69879	100	140	67.426159	107.49158	50	161.73347	20.56	12.8	7.41	12112.506
12	1200	437.51971	100	140	100	164.83195	76.707048	231.7413	73.1	18.65	3.65	15289.309
13	1400	471.19855	100	140	100	193.30232	100	264.27913	15.03	14.35	31.9	16865.314
14	1500	508.86092	100	140	100	227.19533	100	303.55375	16.76	10.35	26.8	18401.618
15	1750	574.9951	100	140	100	321.72491	100	410	15.08	8.26	10.1	22354.948
16	1800	574.99723	100	140	100	377.42277	100	410	-21.43	13.71	5.3	23251.336
17	1500	524.55006	100	140	100	239.95921	100	319.81072	-37.33	3.44	9.57	19038.139
18	900	344.29957	94.967731	140	50	100	50	132.8227	-16.27	1.87	2.31	11051.091
19	850	328.00673	83.51171	140	50	100	50	117.07156	19.34	0.75	0	10542.103
20	800	321.33235	78.875323	140	50	100	50	110.35233	50.73	0.17	0	10333.945
21	780	300.96705	63.862956	140	50	100	50	100	24.98	0.15	0	9813.8625
22	750	280.46944	50	134.81056	50	100	50	100	-15.59	0.31	0	9376.3826
23	700	262.95984	50	121.19016	50	100	50	100	-35.22	1.07	0	9040.0539
24	800	323.59745	79.831946	140	50	100	50	112.27061	-56.28	0.58	0	10393.122
Fuel Cost (\$) per day												291213.44

Table 5.7: Ten unit generating system with EVs using HHO Method

Time (hr)	Load (MW)	Generated Power (MW)										EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀		
1	700	428.858	150.000	20.000	24.102	25.000	20.000	25.000	10.000	10.000	10.000	-22.96	19456.257
2	750	454.984	150.000	20.681	43.425	25.000	20.000	25.000	10.000	10.000	10.000	-19.09	20223.263
3	850	454.856	150.000	72.143	88.660	25.000	20.000	25.000	10.000	10.000	10.000	-15.66	21843.96
4	950	454.983	157.177	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-22.16	23655.613
5	1000	454.916	210.234	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-25.15	24576.306
6	1100	454.216	303.304	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-17.52	26185.872
7	1150	454.928	349.152	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-14.08	26998.32
8	1200	454.847	413.473	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	28.32	28122.36
9	1300	454.926	455.000	130.000	130.000	86.144	20.000	25.000	10.000	10.000	10.000	31.07	30083.194
10	1400	454.990	455.000	130.000	130.000	162.000	36.780	25.000	10.000	10.000	10.000	23.77	32033.844
11	1450	454.990	455.000	130.000	130.000	162.000	80.000	25.000	13.570	10.000	10.000	20.56	33124.74
12	1500	454.992	455.000	130.000	130.000	162.000	80.000	25.000	55.000	55.000	26.1078	73.1	35892.66
13	1400	454.998	455.000	130.000	130.000	162.000	28.032	25.000	10.000	10.000	10.000	15.03	31835.208
14	1300	454.937	455.000	130.000	130.000	71.823	20.000	25.000	10.000	10.000	10.000	16.76	29792.248
15	1200	454.887	400.193	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	15.08	27890.462
16	1050	454.744	256.686	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-21.43	25381.931
17	1000	454.627	222.703	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-37.33	24788.389
18	1100	454.139	302.131	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-16.27	26164.126
19	1200	454.428	404.912	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	19.34	27965.458
20	1400	454.973	455.000	130.000	130.000	162.000	63.757	25.000	10.000	10.000	10.000	50.73	32653.382
21	1300	454.962	455.000	130.000	130.000	80.018	20.000	25.000	10.000	10.000	10.000	24.98	29959.058
22	1100	454.520	301.070	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	-15.59	26151.949
23	900	454.620	150.000	105.506	125.095	25.000	20.000	25.000	10.000	10.000	10.000	-35.22	23023.292
24	800	454.856	150.000	65.254	86.170	25.000	20.000	25.000	10.000	10.000	10.000	-56.28	21685.689
Fuel Cost (\$) per day													649487.58

Table 5.8: Ten unit generating system with RESs using HHO Method

Time (hr)	Load (MW)	Generated Power (MW)											Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	P _{Wind}	
1	700	393.36	150	20	20	25	20	25	10	10	10	16.64	18799.4698
2	750	430.7003	150	20	24.51968	25	20	25	10	10	10	24.78	19493.7788
3	850	454.9957	150	48.73521	72.62905	25	20	25	10	10	10	23.64	21182.0714
4	950	454.8939	150	101.3474	125.0288	25	20	25	10	10	10	18.73	22955.9808
5	1000	454.9012	183.0088	130	130	25	20	25	10	10	10	2.09	24102.8337
6	1100	454.9504	277.3996	130	130	25	20	25	10	10	10	7.65	25746.3091
7	1150	454.9599	322.2601	130	130	25	20	25	10	10	10	12.78	26529.0986
8	1200	454.9472	364.2328	130	130	25	20	25	10	10	10	20.82	27262.2686
9	1300	454.9972	455	130	130	48.64283	20	25	10	10	10	6.36	29325.4861
10	1400	454.9986	455	130	130	144.2114	20	25	10	10	10	10.79	31281.5654
11	1450	454.9961	455	130	130	162	45.14624	25	10	10.00762	10	17.85	32225.2665
12	1500	454.9243	455	130	130	162	80	25	20.53574	10	10	22.54	33305.1792
13	1400	454.9016	455	130	130	125.0984	20	25	10	10	10	30	30882.94
14	1300	454.9888	455	130	130	28.98117	20	25	10	10	10	26.03	28931.9384
15	1200	454.963	359.397	130	130	25	20	25	10	10	10	25.64	27177.9806
16	1050	454.9671	212.0429	130	130	25	20	25	10	10	10	22.99	24608.6137
17	1000	454.9134	165.9566	130	130	25	20	25	10	10	10	19.13	23806.8709
18	1100	454.3777	268.9623	130	130	25	20	25	10	10	10	16.66	25589.7302
19	1200	454.9909	367.3091	130	130	25	20	25	10	10	10	17.7	27316.7898
20	1400	454.7696	455	130	130	139.0704	20	25	10	10	10	16.16	31170.6839
21	1300	454.9452	455	130	130	55.04478	20	25	10	10	10	0.01	29453.3827
22	1100	454.9344	281.4856	130	130	55.04478	20	25	10	10	10	3.58	25817.2754
23	900	454.7824	150	87.33409	104.9535	25	20	25	10	10	10	2.93	22375.2355
24	800	454.9648	150	36.50831	58.52693	25	20	25	10	10	10	0	20739.9177
Fuel Cost (\$ per day)													630080.67

Table 5.9: Ten unit generating system with EVs and RESs using HHO Method

Time (hr)	Load (MW)	Generated Power (MW)										EVs (MW)	P _{wind} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀			
1	700	415.3033	150	20	21.0167	25	20	25	10	10	10	-22.96	16.64	19180.1129
2	750	446.2526	150	20	28.05738	25	20	25	10	10	10	-19.09	24.78	19810.8816
3	850	454.9976	150	60.84692	76.17549	25	20	25	10	10	10	-15.66	23.64	21445.4408
4	950	454.9727	150	118.4573	130	25	20	25	10	10	10	-22.16	18.73	23333.5386
5	1000	454.9317	208.1283	130	130	25	20	25	10	10	10	-25.15	2.09	24539.9492
6	1100	454.9651	294.9049	130	130	25	20	25	10	10	10	-17.52	7.65	26051.8007
7	1150	455	336.2999	130	130	25	20	25	10	10	10	-14.08	12.78	26775.0663
8	1200	454.8505	392.6495	130	130	25	20	25	10	10	10	28.32	20.82	27757.8005
9	1300	454.9168	455	130	130	79.79319	20	25	10	10	10	31.07	6.36	29953.7354
10	1400	454.9861	455	130	130	162	25.99391	25	10	10	10	23.77	10.79	31788.8594
11	1450	454.977	455	130	130	162	65.73305	25	10	10	10	20.56	17.85	32699.2541
12	1500	454.8188	455	130	130	162	80	25	55	47.90569	10.83549	73.1	22.54	35269.3005
13	1400	454.8275	455	130	130	140.2025	20	25	10	10	10	15.03	30	31195.2073
14	1300	454.9756	455	130	130	45.75436	20	25	10	10	10	16.76	26.03	29267.1401
15	1200	454.7635	374.6765	130	130	25	20	25	10	10	10	15.08	25.64	27441.8647
16	1050	454.95	233.49	130	130	25	20	25	10	10	10	-21.43	22.99	24981.4685
17	1000	454.7884	203.4116	130	130	25	20	25	10	10	10	-37.33	19.13	24455.5547
18	1100	454.8979	284.7121	130	130	25	20	25	10	10	10	-16.27	16.66	25872.9242
19	1200	454.9229	386.7171	130	130	25	20	25	10	10	10	19.34	17.7	27655.1777
20	1400	454.9634	455	130	130	162	47.54013	25	10	10.06649	10	50.73	16.16	32281.1976
21	1300	454.9815	455	130	130	79.98853	20	25	10	10	10	24.98	0.01	29958.7829
22	1100	454.9771	297.0329	130	130	25	20	25	10	10	10	-15.59	3.58	26089.12
23	900	454.577	150	106.9163	120.7967	25	20	25	10	10	10	-35.22	2.93	22973.4521
24	800	454.9946	150	64.40887	86.87653	25	20	25	10	10	10	-56.28	0	21685.6605
Fuel Cost (\$) per day														642463.29

5.6.1.8 Ten generator test system (ELD with RES)

Harris Hawks Optimizer Algorithm is suggested to get optimized outcomes for economic load dispatch with the effect of RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.8** displays that the fuel price is **630080.6666** \$/day using the Harris Hawks Optimizer Algorithm.

5.6.1.9 Ten generator test system (ELD with EVs and RES)

Harris Hawks Optimizer Algorithm is applied to get optimized outcomes for economic load dispatch with the impact of EVs and RESs. A ten- generator test system without valve point loading effect and losses is considered by taking into account the effect of EVs and RESs with maximum capacity of 30W. **Table 5.9** displays that the fuel price is **642463.2901** \$/day using the HHO algorithm.

The simulation results for HHO algorithm for various test systems are shown in Table 5.1 through Table 5.9. Table 5.1 gives dispatching of power generating units by considering only electric vehicles for hourly demand for 24 hours and overall fuel cost for 6-unit generating system. The negative sign depicts the discharging state and positive sign shows the charging state of the EVs with fuel cost of 397193.21 \$/hr. Table 5.2 gives dispatching of power generating units by considering only renewable energy sources (RESs) for hourly demand for 24 hours and overall fuel cost attained for 6-unit test system is 316495.72 \$/hr. Table 5.3 shows the dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost achieved for 6-unit test system is 326621.3 \$/hr.

Similarly, Table 5.4 gives dispatching of power generating units by considering only electric vehicles (EVs) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is evaluated as 296172.3197 \$/hr. Table 5.5 gives dispatching of power generating units by considering only RESs for hourly demand for 24 hours and overall fuel

cost for 7-unit test system is reduced to 283632.1 \$/hr. Table 5.6 gives dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is assessed as 291213.44 \$/hr.

In a similar manner, the overall fuel cost achieved for ten-unit test system considering only EVs is 649487.58 \$/hr and is depicted in Table 5.7 with dispatching of power for hourly demand for 24 hours. Table 5.8 gives dispatching of power generating units by considering only RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 10-unit test system depicted as 630080.6666 \$/hr. Table 5.9 gives dispatching of power generating units by considering both EVs and RESs for hourly demand for 24 hours and overall fuel cost for 10-unit test system attained is 642463.2901 \$/hr. It has been observed that the fuel cost is considerably reduced with RESs as compared to cost achieved by adding the load for EVs.

5.6.2. Slime Mould Algorithm for Integrated Economic Load Dispatch

To substantiate the Slime Mould algorithm-SMA for an integrated ELD problem with the impact of PEVs/BEVs/BESS and RESs 50 search agents are considered with 500 iterations and 30 maximum trial runs. The efficacy of the proposed algorithm is tested on three different test systems with six, seven and ten generating units with different load situations. The problem has been considered with the impact of only EVs, only RESs and combined EVs and RESs.

5.6.2.1 Six Generator Test System (ELD with Electric Vehicles)

Slime Mould Algorithm-SMA is proposed to attain optimized results for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A six generator test system without valve point loading effect and without losses [6] is considered. **Table 5.10** displays that the fuel price of **397231.67** \$/day using the proposed SMA.

5.6.2.2 Six Generator Test System (ELD with RESs)

Slime Mould Algorithm is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect and losses is considered in this case. The renewable energy sources considered are wind and solar farm with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.11** displays that the fuel price with the impact of renewable sources is **316539.6001** \$/day using the proposed SMA method.

5.6.2.3 Six Generator Test System (ELD with EVs and RESs)

SMA is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system[6] without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.12** displays that the fuel price is **326662.0772** \$/day using the Slime Mould algorithm.

5.6.2.4 Seven generator test system (ELD with EVs)

Slime Mould algorithm is implemented to achieve boosted result for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A seven generator test system without valve point loading effect and loss coefficient is considered [145]. **Table-5.13** displays that the fuel price by taking the impact of EVs is **295522.05** \$/day using the proposed SMA.

5.6.2.5 Seven generator test system (ELD with RES)

Slime Mould Algorithm is proposed to get optimized outcomes for the economic load dispatch problem with the effect of renewable energy sources. A seven-generator test system without considering the valve point loading effect and losses is taken into consideration. The renewable energy sources considered are wind farm and solar farm with data taken from [145]. **Table-5.14** displays that the fuel price of the given test system is **283784.62** \$/day using the proposed SMA.

Table 5.10: Six unit generating system with EVs using SMA

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆		
1	700	349.452	100.300	194.528	60.033	75.599	51.849	-131.76	9838.26
2	750	356.594	99.938	186.849	58.360	83.259	50.000	-85.00	9874.00
3	850	370.977	109.037	191.035	68.810	100.738	51.904	-42.50	10567.27
4	950	388.776	113.141	211.755	62.187	124.140	50.000	0.00	11270.34
5	1000	390.979	117.655	223.814	80.618	134.002	52.932	0.00	11890.38
6	1100	407.173	153.477	244.741	91.720	151.750	51.139	0.00	13154.18
7	1150	411.653	153.902	254.182	104.533	154.976	70.756	0.00	13798.03
8	1200	439.992	164.263	255.955	105.522	157.231	77.037	0.00	14447.90
9	1300	448.071	177.168	268.933	128.185	192.803	84.941	0.10	15771.75
10	1400	473.414	191.028	286.841	144.019	191.028	115.813	2.14	17147.29
11	1450	493.872	200.000	300.000	150.000	200.000	120.000	13.87	17994.97
12	1500	500.000	200.000	300.000	150.000	200.000	120.000	34.78	82862.50
13	1400	480.731	196.533	294.915	147.688	196.533	118.382	34.78	17593.82
14	1300	461.444	181.107	264.838	134.937	181.198	90.348	13.87	15954.48
15	1200	445.208	153.357	250.107	122.972	159.605	70.894	2.14	14476.66
16	1050	396.632	135.125	222.572	98.727	145.375	51.805	0.24	12521.07
17	1000	382.975	125.441	222.668	83.906	137.165	55.661	-7.82	11988.56
18	1100	420.439	158.569	243.995	102.719	132.910	59.576	18.21	13388.04
19	1200	436.129	170.130	264.306	125.028	172.598	77.459	45.65	15047.07
20	1400	484.493	198.078	297.181	148.719	198.078	119.103	45.65	17743.27
21	1300	447.961	180.364	281.945	130.312	184.865	92.760	18.21	16013.47
22	1100	424.430	142.380	235.486	97.778	141.731	61.007	2.81	13189.56
23	900	360.602	111.792	199.897	77.764	106.165	50.020	-6.24	10733.60
24	800	355.144	104.230	186.727	52.544	90.946	52.908	-42.50	9965.22
		Fuel Cost (\$/day)							397231.67

Table 5.11: Six unit generating system with RESs using SMA

Time (hr)	Load (MW)	Generated Power (MW)								Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	P _{wind}	P _{solar}	
1	700	310.667	63.023	165.770	50.000	50.000	50.000	10.54	0	8180.8422
2	750	312.098	88.006	166.788	51.750	59.088	50.000	22.27	0	8618.6799
3	850	339.599	90.267	185.660	50.992	107.303	50.678	25.5	0	9753.416
4	950	361.353	118.812	190.319	84.851	119.165	50.001	25.5	0	10961.175
5	1000	395.460	122.980	221.320	72.829	111.364	50.546	25.5	0	11571.601
6	1100	404.870	140.446	246.906	100.709	126.041	55.528	25.5	0	12829.803
7	1150	427.829	146.684	238.676	107.397	153.135	50.690	25.5	0.09	13466.985
8	1200	417.688	160.215	255.071	116.377	151.660	56.028	25.5	17.46	13889.085
9	1300	450.735	168.626	255.449	129.041	156.822	82.376	25.5	31.45	15014.383
10	1400	460.492	179.875	272.768	132.412	185.187	107.757	25.5	36.01	16285.389
11	1450	470.325	188.286	282.819	142.191	188.286	114.533	25.5	38.06	16933.666
12	1500	480.940	200.000	291.664	150.000	200.000	115.965	25.5	35.93	17645.411
13	1400	458.246	180.320	271.137	136.880	180.320	110.816	25.5	36.78	16275.74
14	1300	438.971	159.915	260.442	134.709	171.837	77.716	24.82	31.59	15021.505
15	1200	426.823	156.960	240.416	111.159	169.301	64.900	20.74	9.7	14051.709
16	1050	390.589	141.882	217.833	87.880	130.780	53.496	14.62	12.92	12170.362
17	1000	393.098	122.003	210.343	82.366	116.274	50.415	25.5	0	11571.089
18	1100	420.827	148.186	231.959	98.241	131.478	50.269	19.04	0	12910.328
19	1200	427.408	168.983	243.922	111.490	149.353	73.344	25.5	0	14115.913
20	1400	468.529	187.707	281.970	141.805	187.707	114.263	18.02	0	16873.13
21	1300	452.290	165.802	261.764	137.270	174.715	82.658	25.5	0	15430.269
22	1100	413.801	133.620	242.634	87.252	144.198	57.076	21.42	0	12881.316
23	900	369.385	119.982	196.921	57.454	105.288	50.970	0	0	10657.256
24	800	338.100	102.909	172.286	55.716	78.438	50.000	2.55	0	9430.5473
		Fuel Cost (\$/day)								316539.6

Table 5.12: Six unit generating system with EVs and RESs using SMA

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	P _{wind} (MW)	P _{solar} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆				
1	700	350.642003	105.957111	188.587971	50	76.0329139	50	-131.76	10.54	0	9710.2997
2	750	342.677153	106.001625	174.26518	53.8525922	85.9332149	50.000235	-85	22.27	0	9610.6715
3	850	363.66434	102.596825	183.948073	67.7819245	95.8721537	53.1366835	-42.5	25.5	0	10261.426
4	950	373.877159	119.687457	217.225588	54.3351472	109.086402	50.2882469	0	25.5	0	10956.981
5	1000	381.165546	118.201428	224.010035	75.0668126	124.840359	51.2158197	0	25.5	0	11571.841
6	1100	415.652532	151.449272	227.317835	89.5950868	140.485274	50	0	25.5	0	12828.118
7	1150	424.24107	147.704707	244.457104	107.515509	143.439381	57.0522287	0	25.5	0.09	13466.033
8	1200	423.44859	149.707462	251.471493	116.740746	149.63519	66.0365196	0	25.5	17.46	13888.185
9	1300	440.974467	169.437658	270.10196	119.521439	165.079521	78.0369556	0.102	25.5	31.45	15014.372
10	1400	467.510773	178.671065	271.930969	138.131682	185.127046	99.2604653	2.142	25.5	36.01	16313.656
11	1450	479.033235	186.564325	281.457937	149.809392	195.296309	108.150802	13.872	25.5	38.06	17122.364
12	1500	500	200	300	150	200	120	34.782	25.5	35.93	21432.5
13	1400	469.45536	194.827121	279.561671	139.770682	187.126542	101.760625	34.782	25.5	36.78	16744.492
14	1300	445.153201	167.345063	276.491001	123.717606	169.572489	75.1826407	13.872	24.82	31.59	15204.676
15	1200	422.556734	158.269762	246.045776	112.242022	169.032544	63.555161	2.142	20.74	9.7	14079.099
16	1050	390.377736	144.045456	213.241971	88.8180092	131.593476	54.619252	0.2359	14.62	12.92	12174.852
17	1000	402.994594	117.153894	216.042111	78.5036402	117.621203	50.0002575	-7.8157	25.5	0	11669.606
18	1100	407.943786	145.523761	239.928479	111.473991	143.85463	50.4423527	18.207	19.04	0	13142.908
19	1200	432.816886	158.66367	265.869572	109.499543	175.053166	78.2485636	45.651	25.5	0	14713.411
20	1400	479.180519	195.315409	293.129266	146.876939	195.315409	117.813858	45.651	18.02	0	17495.71
21	1300	446.646441	172.349262	257.738772	133.57231	181.245809	101.154407	18.207	25.5	0	15673.648
22	1100	414.885912	147.576808	231.145133	84.525434	146.97175	56.2863638	2.8114	21.42	0	12916.655
23	900	377.18534	113.438045	199.368555	64.7453803	98.3685117	53.1352681	-6.2411	0	0	10734.176
24	800	340.14746	104.196349	193.530827	52.249387	96.5548436	53.2711331	-42.5	2.55	0	9936.3968
		Fuel Cost (\$/day)									326662.08

5.6.2.6 Seven generator test system (ELD with EVs and RES)

Slime Mould Algorithm is suggested to get optimized outcomes for economic load dispatch with the combined effect of EVs and RESs. A seven-generator test system without valve point loading effect, with loss coefficient matrix as zero is considered. The Electric vehicles and renewable energy sources wind and solar are incorporated with wind and solar power considered from [145]. **Table 5.15** displays that the fuel price is **291464.95** \$/day using the proposed SMA.

5.6.2.7 Ten generator test system (ELD with Electric Vehicles)

SMA algorithm is implemented to attain optimized cost for economic load dispatch with the effect of EVs as V2G and G2V. A ten generator test system without valve point loading effect without losses [325]. **Table 5.16** displays that the fuel price is **652693.5** \$/day using the proposed SMA method.

5.6.2.8 Ten generator test system (ELD with RES)

SMA algorithm is suggested to get optimized outcomes for economic load dispatch with the effect of RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.17** displays that the fuel price is **633021.0529** \$/day using the proposed SMA method.

5.6.2.9 Ten generator test system (ELD with EVs and RES)

SMA algorithm is applied to get optimized outcomes for economic load dispatch with the impact of EVs and RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.18** displays that the fuel price is **645886.7769** \$/day using the Slime Mould algorithm (SMA).

Table 5.13: Seven unit generating system with EVs using SMA

Time (hr)	Load (MW)	Generated Power (MW)							EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇		
1	800	310.653	66.065	139.447	50.109	100.000	50.000	106.686	-22.96	10019.334
2	780	297.661	68.396	133.033	50.000	100.000	50.000	100.000	-19.09	9751.553
3	750	275.660	50.000	140.000	50.000	100.000	50.000	100.000	-15.66	9380.9391
4	750	282.160	50.000	140.000	50.000	100.000	50.000	100.000	-22.16	9451.8199
5	720	266.473	50.444	126.137	51.414	100.000	50.681	100.001	-25.15	9161.1319
6	700	249.300	50.000	118.220	50.000	100.000	50.000	100.000	-17.52	8863.8071
7	700	253.949	52.671	107.460	50.000	100.000	50.000	100.000	-14.08	8828.7277
8	700	248.445	51.582	128.293	50.000	100.000	50.000	100.000	28.32	8980.1585
9	800	312.014	74.714	140.000	50.000	100.000	50.000	104.342	31.07	10110.841
10	900	342.559	96.922	139.000	56.811	100.000	52.649	135.829	23.77	11193.483
11	1000	390.743	91.548	140.000	74.330	100.808	50.000	173.131	20.56	12366.484
12	1200	483.655	96.632	140.000	96.274	166.964	62.251	227.323	73.1	15603.753
13	1400	465.874	100.000	140.000	100.000	188.888	100.000	258.988	15.03	16661.53
14	1500	514.024	97.703	140.000	99.780	271.760	93.544	299.949	16.76	18952.759
15	1750	573.930	96.848	138.174	99.318	349.186	99.850	407.775	15.08	22671.763
16	1800	549.759	99.825	139.048	99.137	423.666	99.995	409.999	-21.43	23634.199
17	1500	508.674	99.998	136.536	100.000	261.811	99.999	330.313	-37.33	19242.679
18	900	348.325	78.568	140.000	50.000	100.000	50.000	149.377	-16.27	11105.062
19	850	326.344	93.169	140.000	52.231	100.000	50.562	107.033	19.34	10553.72
20	800	320.331	86.241	140.000	50.583	100.000	50.107	103.468	50.73	10337.101
21	780	301.754	66.759	136.397	50.070	100.000	50.000	100.001	24.98	9816.4905
22	750	275.590	50.000	140.000	50.000	100.000	50.000	100.000	-15.59	9380.1789
23	700	253.676	50.000	131.544	50.000	100.000	50.000	100.000	-35.22	9053.0511
24	800	313.641	90.756	140.000	50.000	100.000	50.000	111.883	-56.28	10401.491
	Fuel Cost(\$/day)									295522.05

Table 5.14: Seven unit generating system with RESs using SMA

Time (hr)	Power Demand (MW)	Generated Power (MW)									Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	P _{Wind}	P _{Solar}	
1	800	293.143445	65.1565546	140	50	100	50	100	1.7	0	9741.0823
2	780	281.5	50	140	50	100	50	100	8.5	0	9444.59575
3	750	254.434982	59.4308039	125.531326	50.1937396	100.000098	50.000188	101.138864	9.27	0	9115.41224
4	750	256.299373	51.1732639	125.867363	50	100	50	100	16.66	0	9032.23743
5	720	239.83559	54.3612183	118.174795	50.0036923	100.347264	50.051453	100.005988	7.22	0	8817.57709
6	700	252.903475	50	92.0985565	50	100	50	100.057969	4.91	0.03	8630.88107
7	700	244.151278	50	84.918722	50	100	50	100	14.66	6.27	8466.03771
8	700	222.067949	50	84.3720512	50	100	50	100	26.56	17	8233.90508
9	800	265.02	50	140	50	100	50	100	20.88	24.1	9266.1892
10	900	317.288557	79.5037795	139.999869	50.0764308	100.000047	50.0000071	105.881309	17.85	39.4	10244.4157
11	1000	369.208146	100	140	68.8009156	100	50	151.780938	12.8	7.41	11862.6858
12	1200	435.964574	96.1426396	139.540631	92.3173219	150.332114	57.0947373	206.307982	18.65	3.65	14346.3578
13	1400	494.378684	98.7569328	139.936512	98.4489423	190.912157	66.7685289	264.548244	14.35	31.9	16679.814
14	1500	484.403873	99.9994741	139.968221	99.5146804	211.567381	80.197253	347.199118	10.35	26.8	18200.0504
15	1750	556.172743	99.9997507	139.999555	99.9993187	329.373118	99.998942	406.096573	8.26	10.1	22133.5699
16	1800	563.86121	99.1907121	139.43449	98.9657313	379.052549	90.4900343	409.995274	13.71	5.3	22954.7209
17	1500	507.193841	100	140	100	235.154651	100	304.641508	3.44	9.57	18506.4805
18	900	342.006327	95.7593159	139.544877	52.2780413	100.000102	50.094325	116.137011	1.87	2.31	10861.6122
19	850	326.961599	82.1486892	140	50.1397117	100	50	100	0.75	0	10319.9679
20	800	299.106119	61.9885477	138.050438	50.6848947	100	50	100	0.17	0	9758.73862
21	780	289.85	50	140	50	100	50	100	0.15	0	9536.44116
22	750	277.776001	50	121.913999	50	100	50	100	0.31	0	9207.58475
23	700	251.346529	50	97.5834712	50	100	50	100	1.07	0	8669.81355
24	800	299.170267	60.6563665	137.495644	50.2831525	100.148908	50.000001	101.665661	0.58	0	9754.44926
Fuel Cost(\$) per day											283784.62

Table 5.15: Seven unit generating system with EVs and RESs using SMA

Time (hr)	Power Demand (MW)	Generated Power (MW)									EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	P _{Wind}	P _{Solar}		
1	800	308.782287	60.0793344	135.758963	50.7470858	100.000054	50.1622131	115.730063	1.7	0	-22.96	10004.4015
2	780	290.302959	60.2870413	140	50	100	50	100	8.5	0	-19.09	9655.09979
3	750	279.587332	50	126.802669	50	100	50	100	9.27	0	-15.66	9279.82778
4	750	265.5	50	140	50	100	50	100	16.66	0	-22.16	9271.33175
5	720	256.467607	55.3154172	126.146976	50	100	50	100	7.22	0	-25.15	9082.64174
6	700	256.904988	50	105.080564	50	100	50.594448	100	4.91	0.03	-17.52	8813.48011
7	700	246.654485	50	96.4955149	50	100	50	100	14.66	6.27	-14.08	8609.46478
8	700	235.961379	50	98.7986215	50	100	50	100	26.56	17	28.32	8522.11285
9	800	290.820208	55.269792	140	50	100	50	100	20.88	24.1	31.07	9605.14425
10	900	341.21585	76.2902888	139.734481	50.0000018	100.863475	50.0000115	108.415892	17.85	39.4	23.77	10520.9686
11	1000	366.05131	99.5123523	139.999996	66.3644783	112.0139	50.6341274	165.773836	12.8	7.41	20.56	12113.5307
12	1200	421.929905	99.9812678	139.432396	99.3260579	157.58359	94.3900638	238.156721	18.65	3.65	73.1	15296.03
13	1400	471.408587	93.361444	138.715673	91.5913512	177.822197	99.876214	296.004534	14.35	31.9	15.03	16896.4099
14	1500	498.48879	96.3507302	139.999972	99.0493923	223.272027	96.1703185	326.27877	10.35	26.8	16.76	18418.069
15	1750	574.501141	99.997458	139.957218	99.8838377	352.715977	76.2153931	403.448975	8.26	10.1	15.08	22419.5504
16	1800	551.176769	98.5232742	139.999134	90.5720688	412.149235	99.9997941	409.999725	13.71	5.3	-21.43	23343.3446
17	1500	518.379411	100	140	98.9052284	255.393291	90.0263136	321.615756	3.44	9.57	-37.33	19051.1379
18	900	344.305237	95.3599098	139.606297	54.8901743	102.394178	50.000003	125.534202	1.87	2.31	-16.27	11053.1854
19	850	328.861107	77.4451613	139.999997	50.4912497	100.450467	50.0000018	121.342017	0.75	0	19.34	10542.9983
20	800	310.155007	91.5961649	137.577305	52.2515607	100.000003	50.2832866	108.696673	0.17	0	50.73	10338.8882
21	780	293.474532	71.3554676	140	50	100	50	100	0.15	0	24.98	9814.78774
22	750	282.498352	50.0001843	132.555601	50.1512154	100.000268	50.07435	100.000028	0.31	0	-15.59	9376.74046
23	700	270.667849	50	113.482151	50	100	50	100	1.07	0	-35.22	9041.00461
24	800	332.409799	83.2902012	140	50	100	50	100	0.58	0	-56.28	10394.7985
Fuel Cost (\$/day)												291464.95

Table 5.16: Ten unit generating system with EVs using SMA

Time (hr)	Load (MW)	Generated Power (MW)										EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀		
1	700	432.96	150	20	20	25	20	25	10	10	10	-22.96	19456.3005
2	750	443.03521	150	20	56.05479	25	20	25	10	10	10	-19.09	20224.3445
3	850	431.10507	209.4927	20	105.0622	25	20	25	10	10	10	-15.66	21884.947
4	950	452.23142	150	130	130	25	20	34.92858	10	10	10	-22.16	23765.4274
5	1000	361.31171	373.511	91.21914	96.85958	25	20	25	12.24857	10	10	-25.15	24706.7756
6	1100	405.66279	357.8547	123.8767	117.0386	29.37149	22.0328	26.27401	10.41229	10	14.9967	-17.52	26325.6802
7	1150	446.05536	368.3918	116.7034	118.1968	25.00019	31.4854	25.02007	10.24631	11.9419	11.0388	-14.08	27107.779
8	1200	452.47864	455	84.1879	127.4955	25	29.158	25	10	10	10	28.32	28195.1916
9	1300	420.09668	454.9994	129.6179	124.3437	108.7453	20.8222	28.31027	16.19173	13.7546	14.1882	31.07	30356.6113
10	1400	451.18042	452.1821	129.9704	122.1976	144.1606	21.3212	25.00173	34.17888	13.9384	29.6387	23.77	32349.8921
11	1450	454.6681	454.9988	121.9116	129.2592	140.6499	57.3841	31.12057	42.59552	14.0562	23.916	20.56	33426.4727
12	1500	454.38095	449.0582	130	129.9157	161.9635	79.9869	25.00466	44.83646	54.9827	42.9709	73.1	35978.4335
13	1400	447.05889	455	130	130	112.4584	20	27.91679	43.48106	34.3581	14.7568	15.03	32248.0057
14	1300	454.80326	455	92.64548	130	89.66299	35.2764	25	10	10	14.3719	16.76	29983.9641
15	1200	444.33561	455	75.05239	130	28.65697	20	25	17.03504	10	10	15.08	27996.8719
16	1050	440.23813	332.7565	103.5488	89.66992	25	20	27.98215	10	12.2345	10	-21.43	25477.1596
17	1000	393.26105	323.1265	116.1741	101.9497	26.17522	20.3677	26.26454	10	10	10.0111	-37.33	24874.9086
18	1100	408.54765	357.3185	120.0368	111.4029	32.21864	20.4473	25.02438	20.13545	10.6244	10.514	-16.27	26334.1972
19	1200	435.72599	455	97.16135	130	25	20	25	10	10	11.4527	19.34	28012.9354
20	1400	451.90854	454.9256	128.2176	130	161.8037	50.0931	25.00004	11.06311	27.6956	10.0227	50.73	32763.5854
21	1300	447.1344	455	130	123.2734	69.50784	20	25	35.06439	10	10	24.98	30155.3851
22	1100	421.5498	365.3201	91.16089	127.7955	27.96438	20.8385	25.85353	11.32725	11.279	12.501	-15.59	26268.056
23	900	453.51125	150.0009	99.63842	121.0998	27.77946	20.3142	25.54851	16.42197	10.8745	10.031	-35.22	23106.8523
24	800	454.41512	150	21.86488	130	25	20	25	10	10	10	-56.28	21693.7256
Fuel Cost (\$) per day													652693.5

Table 5.17: Ten unit generating system with RESs using SMA

Time (hr)	Power Demand (MW)	Generated Power (MW)											Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	P _{wind}	
1	700	393.360	150.000	20.000	20.000	25.000	20.000	25.000	10.000	10.000	10.000	16.64	18799.4698
2	750	435.320	150.000	20.000	20.000	25.000	20.000	25.000	10.000	10.000	10.000	24.78	19493.8317
3	850	383.504	150.000	62.856	130.000	25.000	20.000	25.000	10.000	10.000	10.000	23.64	21204.55214
4	950	448.822	311.890	33.999	23.641	36.232	20.350	25.000	10.000	11.163	10.173	18.73	23100.01121
5	1000	380.362	308.928	78.621	130.000	25.000	20.000	25.000	10.000	10.000	10.000	2.09	24184.38154
6	1100	403.884	346.433	116.790	115.293	25.584	21.220	26.300	10.000	16.651	10.196	7.65	25890.20248
7	1150	427.965	427.957	129.952	49.458	25.000	20.181	25.023	11.263	10.396	10.025	12.78	26618.34193
8	1200	420.621	385.839	130.000	130.000	37.720	20.000	25.000	10.000	10.000	10.000	20.82	27323.80644
9	1300	453.070	455.000	130.000	130.000	25.000	24.957	27.976	10.000	27.638	10.000	6.36	29498.92146
10	1400	441.483	453.855	129.307	130.000	25.939	23.372	41.209	10.010	23.887	10.147	10.79	31563.71115
11	1450	455.000	452.306	125.583	123.051	146.063	23.108	25.002	39.646	26.744	15.633	17.85	32552.14662
12	1500	452.365	452.030	129.502	128.790	160.666	73.434	25.764	19.224	25.684	10.000	22.54	33416.30983
13	1400	447.394	451.131	123.990	129.957	111.210	35.002	26.272	11.298	11.888	21.859	30	31091.20402
14	1300	454.987	451.301	118.901	129.997	28.987	20.770	25.271	13.832	17.855	12.070	26.03	29074.28164
15	1200	443.496	454.766	123.872	33.925	38.506	24.738	25.000	10.001	10.055	10.000	25.64	27312.22761
16	1050	454.250	215.653	120.846	130.000	25.000	20.000	25.000	15.383	10.000	10.879	22.99	24667.4594
17	1000	405.517	215.353	130.000	130.000	25.000	20.000	25.000	10.000	10.000	10.000	19.13	23845.16283
18	1100	432.744	316.089	113.955	108.440	25.000	29.495	26.459	10.588	10.000	10.571	16.66	25698.38522
19	1200	451.000	435.304	63.394	130.000	25.000	20.000	25.000	10.000	10.000	12.602	17.7	27381.93886
20	1400	432.135	444.996	125.161	122.380	161.659	21.594	40.133	15.223	10.558	10.000	16.16	31493.29601
21	1300	432.729	455.000	105.470	130.000	93.529	28.262	25.000	10.000	10.000	10.000	0.01	29633.13411
22	1100	430.950	297.247	130.000	130.000	25.000	20.000	25.000	10.000	17.720	10.504	3.58	25918.63595
23	900	356.618	178.338	120.244	130.000	25.000	31.870	25.000	10.000	10.000	10.000	2.93	22493.97852
24	800	405.326	150.000	124.674	20.000	25.000	20.000	25.000	10.000	10.000	10.000	0	20765.66238
Fuel Cost (\$) per day													633021.0529

Table 5.18: Ten unit generating system with EVs and RESs using SMA

Time (hr)	Power Demand (MW)	Generated Power (MW)											EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	P _{wind}		
1	700	416.32	150	20	20	25	20	25	10	10	10	16.64	-22.96	19180.1155
2	750	454.31	150	20	20	25	20	25	10	10	10	24.78	-19.09	19811.0497
3	850	421.816	150.255	126.135	38.9136	25.3874	20	29.3595	10.0577	10.0917	10.0036	23.64	-15.66	21517.647
4	950	442.626	150	121.725	130	25	20	25	10	10	19.079	18.73	-22.16	23436.9022
5	1000	433.222	257.025	118.477	91.8604	31.1579	31.393	26.8789	11.1676	11.4804	10.3968	2.09	-25.15	24701.2779
6	1100	448.701	417.205	80.4359	55.1464	31.4514	20	25.0026	10.3868	10.7798	10.7613	7.65	-17.52	26158.7708
7	1150	375.334	415.966	130	130	25	20	25	10	10	10	12.78	-14.08	26847.0291
8	1200	398.327	455	119.404	119.265	25	30.833	25	10	14.6714	10	20.82	28.32	27920.8418
9	1300	433.012	455	128.667	129.276	68.521	28.527	25.4156	14.4785	10.3139	31.4993	6.36	31.07	30254.4485
10	1400	448.6	455	117.959	130	162	20	27.999	14.3732	27.0485	10	10.79	23.77	32006.0209
11	1450	452.721	455	129.981	129.703	154.85	56.541	25.0102	10.2947	14.0103	24.598	17.85	20.56	32817.9611
12	1500	455	455	130	130	162	80	25	55	48.56	10	22.54	73.1	35267.0478
13	1400	451.848	455	99.7018	130	162	20	25	10	10	21.4801	30	15.03	31404.0905
14	1300	449.954	442.842	120.245	109.852	66.1325	20.871	34.4637	10.1022	26.2629	10.0042	26.03	16.76	29605.6892
15	1200	434.186	454.999	72.7271	111.605	30.524	20.151	28.9523	15.168	10.0003	11.1271	25.64	15.08	27610.7476
16	1050	453.508	236.733	130	117.667	25	20	25	20.5326	10	10	22.99	-21.43	25078.3238
17	1000	452.788	259.835	42.877	129.443	48.3396	20.902	27.9653	13.8868	10.0012	12.1631	19.13	-37.33	24650.1892
18	1100	432.83	367.247	98.1016	95.6655	29.4491	20	25	10.002	10.8841	10.431	16.66	-16.27	25945.3445
19	1200	450.434	454.479	126.705	45.982	25.3291	36.027	25.3344	10.035	16.866	10.4488	17.7	19.34	27874.0598
20	1400	450.376	429.523	120.523	130	159.204	63.11	30.2815	13.4751	22.0559	16.0229	16.16	50.73	32630.9978
21	1300	448.536	447.299	127.149	117.687	50.9898	73.636	25.7101	10.4038	13.1675	10.3917	0.01	24.98	30229.3994
22	1100	443.072	352.147	121.604	84.3774	26.3569	24.087	28.8472	11.0102	10.0052	10.5033	3.58	-15.59	26204.6384
23	900	422.29	150	130	130	25	20	25	10	10	10	2.93	-35.22	22987.988
24	800	403.054	168.934	50.6809	130	25	20	25	13.6105	10	10	0	-56.28	21746.1962
Fuel Cost (\$) per day														645886.777

The simulation results for SMA algorithm for various test systems are shown in Table 5.10 through Table 5.18. Table 5.10 gives dispatching of power generating units by considering only electric vehicles for hourly demand for 24 hours and overall fuel cost for 6-unit generating system. The negative sign depicts the discharging state and positive sign shows the charging state of the EVs with fuel cost of 397231.67 \$/hr. Table 5.11 gives dispatching of power generating units by considering only renewable energy sources (RESs) for hourly demand for 24 hours and overall fuel cost attained for 6-unit test system is 316539.6 \$/hr. Table 5.12 shows the dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost achieved for 6-unit test system is 326662.0772 \$/hr.

Similarly, Table 5.13 gives dispatching of power generating units by considering only electric vehicles (EVs) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is evaluated as 295522.05 \$/hr. Table 5.14 gives dispatching of power generating units by considering only RESs for hourly demand for 24 hours and overall fuel cost for 7-unit test system is reduced to 283784.62 \$/hr. Table 5.15 gives dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is assessed as 291464.95 \$/hr.

The overall fuel cost achieved for ten unit test system considering only EVs is 652693.5\$/hr and is depicted in Table 5.16 with dispatching of power for hourly demand for 24 hours. Table 5.17 gives dispatching of power generating units by considering only RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 10-unit test system depicted as 633021.0529\$/hr. Table 5.18 gives dispatching of power generating units by considering both EVs and RESs for hourly demand for 24 hours and overall fuel cost for 10-unit test system attained is 645886.777\$/hr.

5.6.3. Memetic Harris Hawk Optimization for Integrated Economic Load Dispatch

To substantiate an integrated ELD problem with the impact of PEVs/BEVs/BESS and RESs using proposed memetic harris hawk optimizer developed by combining HHO with random exploratory search method (hHHO-RES) 50 search agents are considered with 500 iterations and 30 maximum trial runs. The efficacy of the proposed algorithm is tested on three different test systems with six, seven and ten generating units with different load situations. The problem has been considered with the impact of only EVs, only RESs and combined EVs and RESs discussed in following subsections.

5.6.3.1 Six Generator Test System (ELD with Electric Vehicles)

The proposed memetic HHO (hHHO-RES) is implemented to attain optimized results for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A six generator test system without valve point loading effect and without losses [6] is considered. **Table 5.19** displays that the fuel price is **397186.91** \$/day using the proposed hHHO-RES algorithm.

5.6.3.2 Six Generator Test System (ELD with RESs)

Memetic HHO (hHHO-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.20** displays that the fuel price is **316486.72** \$/day using the proposed hHHO-RES algorithm.

5.6.3.3 Six Generator Test System (ELD with EVs and RESs)

Memetic HHO (hHHO-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.21** displays that the fuel price is **326614.1822** \$/day using the proposed hHHO-RES algorithm.

5.6.3.4 Seven generator test system (ELD with Electric Vehicles)

Memetic HHO (hHHO-RES) is implemented to achieve boosted for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A seven generator test system without valve point loading effect and loss coefficient is considered [145]. **Table 5.22** displays that the fuel price is **296172.24** \$/day using the proposed hHHO-RES algorithm.

5.6.3.5 Seven generator test system (ELD with RES)

Memetic HHO (hHHO-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A seven generator test system without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with data taken from [145]. **Table 5.23** displays that the fuel price with renewable sources is **283631.92** \$/day using the proposed hHHO-RES.

5.6.3.6 Seven generator test system (ELD with EVs and RES)

Memetic HHO (hHHO-RES) is suggested to get optimized outcomes for economic load dispatch with the combined effect of EVs and RESs. A seven -generator test system without valve point loading effect and losses is considered in this case. The Electric vehicles and renewable energy sources wind and solar are incorporated with wind and solar power considered from [145]. **Table 5.24** displays that the fuel price with the impact of EVs and Renewable sources is **291213.39** \$/day using the proposed hHHO-RES.

5.6.3.7 Ten generator test system (ELD with Electric Vehicles)

Memetic HHO (hHHO-RES) algorithm is implemented to attain optimized cost for economic load dispatch with the effect of EVs as vehicle to grid (V2G) and grid to vehicle (G2V). A ten generator test system without valve point loading effect without losses is considered [325]. **Table 5.25** displays that the fuel price with the impact of EVs is **649486.69** \$/day using the proposed hHHO-RES method.

Table 5.19: Six unit generating system with EVs using hHHO-RES

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆		
1	700	351.289	100.9497	189.8913	51.00252	88.6278	50	-131.76	9834.3814
2	750	352.066	101.5225	190.496	51.60718	89.308	50	-85	9873.01344
3	850	365.864	111.6892	201.2275	62.33861	101.381	50	-42.5	10564.4803
4	950	379.661	121.8559	211.9589	73.06992	113.454	50	0	11267.0543
5	1000	391.659	130.6963	221.2906	82.40168	123.952	50	0	11887.0166
6	1100	414.751	147.7113	239.2509	100.3618	144.157	53.7677	0	13152.0064
7	1150	424.554	154.9342	246.875	107.9861	152.734	62.9166	0	13795.7631
8	1200	434.356	162.1571	254.4992	115.6103	161.312	72.0657	0	14446.3814
9	1300	453.981	176.6177	269.7631	130.8742	178.483	90.3824	0.102	15769.5658
10	1400	473.986	191.3582	285.3226	146.4337	195.988	109.054	2.142	17146.6742
11	1450	493.872	200	300	150	200	120	13.872	17994.9709
12	1500	500	200	300	150	200	120	34.782	82862.5
13	1400	481.255	196.714	290.9758	150	200	115.838	34.782	17593.2653
14	1300	456.681	178.6068	271.8629	132.9739	180.846	92.902	13.872	15953.7345
15	1200	434.776	162.4666	254.8258	115.9369	161.679	72.4576	2.142	14474.4072
16	1050	403.714	139.5786	230.6664	91.77748	134.5	50	0.2359	12518.3619
17	1000	393.535	132.0783	222.7493	83.86034	125.593	50	-7.8157	11984.6844
18	1100	418.321	150.3415	242.0272	103.1382	147.28	57.0992	18.207	13385.6296
19	1200	443.306	168.7519	261.4602	122.5714	169.143	80.419	45.6514	15046.4068
20	1400	484.407	199.0368	293.4276	150	200	118.78	45.6514	17742.8242
21	1300	457.53	179.2332	272.5238	133.6349	181.59	93.6952	18.207	16011.8212
22	1100	415.302	148.1175	239.6795	100.7906	144.639	54.282	2.8114	13188.0215
23	900	369.161	114.1187	203.792	64.90323	104.266	50	-6.2411	10731.3684
24	800	353.866	102.8486	191.8959	53.00684	90.8826	50	-42.5	9962.57489
Fuel Cost (\$/day)									397186.91

Table 5.20: Six unit generating system with RESs using hHHO-RES

Time (hr)	Load (MW)	Generated Power (MW)								Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	P _{wind}	P _{solar}	
1	700	309.603	70.234	157.469	50.000	52.153	50.000	10.54	0	8179.6831
2	750	320.894	78.553	166.251	50.000	62.032	50.000	22.27	0	8616.477
3	850	349.443	99.589	188.456	50.000	87.012	50.000	25.5	0	9747.9463
4	950	373.543	117.347	207.200	68.311	108.100	50.000	25.5	0	10954.107
5	1000	385.540	126.188	216.531	77.643	118.598	50.000	25.5	0	11569.786
6	1100	409.536	143.869	235.195	96.306	139.594	50.000	25.5	0	12826.34
7	1150	419.537	151.238	242.973	104.084	148.345	58.234	25.5	0.09	13465.431
8	1200	425.934	155.951	247.948	109.060	153.942	64.205	25.5	17.46	13886.955
9	1300	442.796	168.376	261.064	122.175	168.697	79.943	25.5	31.45	15012.061
10	1400	461.507	182.163	275.617	136.728	185.069	97.407	25.5	36.01	16284.288
11	1450	470.908	189.090	282.928	144.039	193.294	106.181	25.5	38.06	16932.903
12	1500	482.353	197.523	291.830	150.000	200.000	116.863	25.5	35.93	17645.332
13	1400	461.356	182.052	275.499	136.610	184.937	97.266	25.5	36.78	16273.924
14	1300	442.902	168.454	261.146	122.257	168.789	80.042	24.82	31.59	15019.189
15	1200	428.388	157.760	249.858	110.969	156.090	66.496	20.74	9.7	14049.468
16	1050	397.049	134.668	225.483	86.594	128.668	50.000	14.62	12.92	12168.237
17	1000	385.540	126.188	216.531	77.643	118.598	50.000	25.5	0	11569.786
18	1100	411.018	144.961	236.348	97.459	140.891	50.284	19.04	0	12908.668
19	1200	429.357	158.473	250.611	111.722	156.937	67.400	25.5	0	14113.709
20	1400	470.033	188.446	282.248	143.359	192.529	105.364	18.02	0	16872.307
21	1300	448.962	172.919	265.859	126.970	174.092	85.698	25.5	0	15428.532
22	1100	410.515	144.590	235.956	97.067	140.451	50.000	21.42	0	12878.321
23	900	367.663	113.015	202.627	63.738	102.956	50.000	0	0	10655.491
24	800	341.462	93.709	182.249	50.000	80.030	50.000	2.55	0	9427.7734
	Fuel Cost (\$/day)									316486.72

Table 5.21: Six unit generating system with EVs and RESs using hHHO-RES

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	P _{wind} (MW)	P _{solar} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆				
1	700	348.475	98.876	187.703	50.000	86.166	50.000	-131.76	10.54	0	9708.9621
2	750	345.970	97.031	185.755	50.000	83.974	50.000	-85	22.27	0	9608.2612
3	850	359.745	107.180	196.468	57.580	96.027	50.000	-42.5	25.5	0	10256.459
4	950	373.542	117.347	207.200	68.311	108.100	50.000	0	25.5	0	10954.107
5	1000	385.540	126.188	216.531	77.643	118.598	50.000	0	25.5	0	11569.786
6	1100	409.536	143.869	235.195	96.306	139.594	50.000	0	25.5	0	12826.34
7	1150	419.537	151.238	242.973	104.084	148.345	58.234	0	25.5	0.09	13465.431
8	1200	425.934	155.951	247.949	109.060	153.942	64.205	0	25.5	17.46	13886.955
9	1300	442.816	168.391	261.079	122.190	168.714	79.962	0.102	25.5	31.45	15013.408
10	1400	461.927	182.473	275.943	137.054	185.436	97.799	2.142	25.5	36.01	16313.128
11	1450	473.627	191.094	285.043	146.155	195.674	108.719	13.872	25.5	38.06	17121.725
12	1500	500.000	200.000	300.000	150.000	200.000	120.000	34.782	25.5	35.93	21432.5
13	1400	468.175	187.076	280.803	141.914	190.903	103.630	34.782	25.5	36.78	16743.715
14	1300	445.622	170.458	263.261	124.372	171.169	82.580	13.872	24.82	31.59	15202.572
15	1200	428.808	158.069	250.184	111.295	156.457	66.888	2.142	20.74	9.7	14077.315
16	1050	397.105	134.709	225.527	86.638	128.717	50.000	0.2359	14.62	12.92	12171.2
17	1000	387.416	127.569	217.990	79.101	120.239	50.000	-7.8157	25.5	0	11666.785
18	1100	414.588	147.591	239.124	100.235	144.014	53.615	18.207	19.04	0	13141.34
19	1200	438.307	165.068	257.572	118.683	164.768	75.753	45.6514	25.5	0	14710.539
20	1400	479.181	195.186	289.363	150.000	200.000	113.902	45.6514	18.02	0	17495.137
21	1300	452.531	175.549	268.635	129.747	177.215	89.029	18.207	25.5	0	15670.875
22	1100	411.103	145.023	236.413	97.524	140.965	50.363	2.8114	21.42	0	12914.17
23	900	369.161	114.119	203.792	64.903	104.266	50.000	-6.2411	0	0	10731.368
24	800	353.254	102.398	191.420	52.531	90.347	50.000	-42.5	2.55	0	9932.1028
Fuel Cost (\$/day)											326614.1822

Table 5.22: Seven unit generating system with EVs using hHHO-RES

Time (hr)	Load (MW)	Generated Power (MW)							EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇		
1	800	311.401	71.559	140.000	50.000	100.000	50.000	100.000	-22.96	10018.488
2	780	297.658	61.432	140.000	50.000	100.000	50.000	100.000	-19.09	9749.63
3	750	280.684	50.000	134.976	50.000	100.000	50.000	100.000	-15.66	9380.5352
4	750	283.696	51.145	137.319	50.000	100.000	50.000	100.000	-22.16	9451.7262
5	720	269.147	50.000	126.003	50.000	100.000	50.000	100.000	-25.15	9158.0261
6	700	253.605	50.000	113.915	50.000	100.000	50.000	100.000	-17.52	8863.5106
7	700	251.670	50.000	112.410	50.000	100.000	50.000	100.000	-14.08	8827.2636
8	700	259.680	50.000	118.640	50.000	100.000	50.000	100.000	28.32	8977.915
9	800	314.343	73.727	140.000	50.000	100.000	50.000	103.000	31.07	10110.782
10	900	347.854	98.419	140.000	50.000	100.000	50.000	137.497	23.77	11189.382
11	1000	378.069	100.000	140.000	71.831	112.060	50.000	168.600	20.56	12360.15
12	1200	444.472	100.000	140.000	100.000	170.162	81.509	236.957	73.1	15583.25
13	1400	486.973	100.000	140.000	100.000	207.350	100.000	280.707	15.03	17499.223
14	1500	522.000	100.000	140.000	100.000	237.998	100.000	316.762	16.76	18929.831
15	1750	574.998	100.000	140.000	100.000	340.082	100.000	410.000	15.08	22644.932
16	1800	575.000	100.000	140.000	100.000	396.431	100.000	410.000	-21.43	23568.625
17	1500	529.080	100.000	140.000	100.000	244.195	100.000	324.055	-37.33	19225.166
18	900	345.143	96.421	140.000	50.000	100.000	50.000	134.706	-16.27	11100.499
19	850	328.178	83.920	140.000	50.000	100.000	50.000	117.242	19.34	10550.797
20	800	321.450	78.963	140.000	50.000	100.000	50.000	110.316	50.73	10335.9
21	780	301.049	63.931	140.000	50.000	100.000	50.000	100.000	24.98	9815.5446
22	750	280.644	50.000	134.946	50.000	100.000	50.000	100.000	-15.59	9379.7702
23	700	263.561	50.000	121.659	50.000	100.000	50.000	100.000	-35.22	9051.4875
24	800	323.457	80.442	140.000	50.000	100.000	50.000	112.382	-56.28	10399.804
Fuel Cost (\$/ day)										296172.24

Table 5.23: Seven unit generating system with RESs using hHHO-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)									Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	P _{Wind}	P _{Solar}	
1	800	297.20303	61.096971	140	50	100	50	100	1.7	0	9740.8104
2	780	283.43373	50.951184	137.11509	50	100	50	100	8.5	0	9444.4861
3	750	266.66063	50	124.06937	50	100	50	100	9.27	0	9110.5082
4	750	262.50375	50	120.83625	50	100	50	100	16.66	0	9031.4045
5	720	250.93876	50	111.84124	50	100	50	100	7.22	0	8813.5899
6	700	240.97124	50	104.08876	50	100	50	100	4.91	0.03	8628.5333
7	700	231.97689	50	97.093115	50	100	50	100	14.66	6.27	8463.6663
8	700	219.24749	50	87.192515	50	100	50	100	26.56	17	8233.7778
9	800	274.69875	50	130.32125	50	100	50	100	20.88	24.1	9264.6904
10	900	318.56553	76.837768	140	50	100	50	107.34671	17.85	39.4	10244.288
11	1000	366.99602	100	140	63.21947	102.3727	50	157.20181	12.8	7.41	11862.126
12	1200	419.61461	100	140	100	148.41299	58.306047	211.36635	18.65	3.65	14338.413
13	1400	465.87333	100	140	100	188.89004	100	258.98663	14.35	31.9	16661.53
14	1500	503.43702	100	140	100	221.75706	100	297.65592	10.35	26.8	18165.492
15	1750	574.99947	99.999349	139.99938	99.999726	312.16253	99.998821	404.48073	8.26	10.1	22120.322
16	1800	574.99978	99.999983	139.99998	99.999954	355.99032	99.999982	410	13.71	5.3	22900.582
17	1500	511.74809	100	140	100	229.03029	100	306.21162	3.44	9.57	18506.018
18	900	337.75022	90.973783	140	50	100	50	127.096	1.87	2.31	10859.593
19	850	320.9153	78.569126	140	50	100	50	109.76558	0.75	0	10318.885
20	800	298.08393	61.746067	140	50	100	50	100	0.17	0	9757.8959
21	780	286.75428	53.397932	139.69779	50	100	50	100	0.15	0	9536.2636
22	750	271.70063	50	127.98937	50	100	50	100	0.31	0	9206.9942
23	700	243.14813	50	105.78188	50	100	50	100	1.07	0	8668.7381
24	800	297.84788	61.572123	140	50	100	50	100	0.58	0	9753.3156
	Fuel Cost (\$/day)										283631.92

Table 5.24: Seven unit generating system with EVs and RESs using hHHO-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)									EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	P _{Wind}	P _{Solar}		
1	800	310.4224	70.83757	140	50	100	50	100	1.7	0	-22.96	9999.1879
2	780	292.7639	57.82607	140	50	100	50	100	8.5	0	-19.09	9654.9999
3	750	275.4694	50	130.921	50	100	50	100	9.27	0	-15.66	9279.5565
4	750	274.9688	50	130.531	50	100	50	100	16.66	0	-22.16	9269.8972
5	720	265.0856	50	122.844	50	100	50	100	7.22	0	-25.15	9080.486
6	700	250.8262	50	111.754	50	100	50	100	4.91	0.03	-17.52	8811.4874
7	700	239.8969	50	103.253	50	100	50	100	14.66	6.27	-14.08	8608.7341
8	700	235.1775	50	99.5825	50	100	50	100	26.56	17	28.32	8522.103
9	800	290.173	55.91697	140	50	100	50	100	20.88	24.1	31.07	9605.1373
10	900	327.1582	83.16935	140	50	100	50	116.192	17.85	39.4	23.77	10518.12
11	1000	372.5807	100	140	67.5622	107.257	50	162.95	12.8	7.41	20.56	12112.486
12	1200	438.6603	100	140	100	165.08	76.0843	230.975	18.65	3.65	73.1	15289.293
13	1400	471.0476	100	140	100	193.417	100	264.315	14.35	31.9	15.03	16865.314
14	1500	509.2074	100	140	100	226.806	100	303.597	10.35	26.8	16.76	18401.616
15	1750	574.9996	99.99995	140	99.9999	321.725	99.9998	409.995	8.26	10.1	15.08	22354.947
16	1800	575	99.99982	140	100	377.421	99.9999	409.999	13.71	5.3	-21.43	23251.335
17	1500	524.6008	100	140	100	240.277	100	319.442	3.44	9.57	-37.33	19038.137
18	900	343.6317	95.30788	140	50	100	50	133.15	1.87	2.31	-16.27	11051.086
19	850	327.9066	83.72062	140	50	100	50	116.963	0.75	0	19.34	10542.102
20	800	321.3887	78.91801	140	50	100	50	110.253	0.17	0	50.73	10333.945
21	780	300.9627	63.86727	140	50	100	50	100	0.15	0	24.98	9813.8625
22	750	280.47	50	134.81	50	100	50	100	0.31	0	-15.59	9376.3826
23	700	262.9594	50	121.191	50	100	50	100	1.07	0	-35.22	9040.0539
24	800	323.2469	80.28707	140	50	100	50	112.166	0.58	0	-56.28	10393.119
Fuel Cost (\$) per day												291213.39

Table 5.25: Ten unit generating system with EVs using hHHO-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)										EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀		
1	700	428.8593	150	20	24.1007	25	20	25	10	10	10	-22.96	19456.2569
2	750	454.9989	150	20.51429	43.5768	25	20	25	10	10	10	-19.09	20223.2628
3	850	454.942	150.0014	71.67146	89.0439	25.0003	20.0005	25	10.00025	10.0001	10.0001	-15.66	21843.9403
4	950	454.9941	157.1798	129.9881	129.998	25.0002	20.0001	25	10	10	10	-22.16	23655.6097
5	1000	454.9771	210.1831	130	129.988	25.0005	20.0007	25.0001	10.0004	10	10	-25.15	24576.2723
6	1100	454.9987	302.5286	129.9913	130	25.0002	20.0004	25.0001	10.00054	10.0006	10	-17.52	26185.2459
7	1150	455	349.0822	129.9944	130	25.003	20.0003	25.0001	10.00002	10	10	-14.08	26998.2803
8	1200	454.9946	413.3451	129.994	129.985	25	20.0001	25	10.00024	10.0005	10.0007	28.32	28122.254
9	1300	454.9994	454.9998	129.998	129.994	86.0767	20.0013	25.0001	10.00002	10	10.0002	31.07	30082.9486
10	1400	454.9996	454.9923	129.9924	129.996	161.997	36.7593	25.0102	10.01982	10	10.0034	23.77	32034.0322
11	1450	454.9994	454.9939	129.9954	129.982	161.989	79.9689	25.0196	13.54278	10.0213	10.0474	20.56	33125.1948
12	1500	454.9679	454.9996	129.9991	129.948	161.996	79.9086	25.0015	54.94574	54.97	26.3629	73.1	35894.0343
13	1400	454.9938	454.9958	129.9945	129.996	161.991	28.0511	25.0009	10.0053	10.0009	10.0008	15.03	31835.3556
14	1300	454.9934	454.9988	129.9974	129.996	71.7676	20.0017	25.0017	10.00029	10.0034	10.0001	16.76	29792.1136
15	1200	454.9894	400.099	129.999	129.99	25.0017	20.0001	25.0001	10.00066	10.0003	10.0001	15.08	27890.3922
16	1050	454.9959	256.4464	129.9857	130	25.0001	20	25	10.00007	10.0011	10.0006	-21.43	25381.7547
17	1000	454.9991	222.357	129.9958	129.978	25	20	25	10	10.0003	10	-37.33	24788.114
18	1100	454.9878	301.2989	129.9858	129.996	25	20.0004	25	10.00047	10.001	10	-16.27	26163.4517
19	1200	454.9906	404.3674	129.9837	129.997	25.0001	20.0001	25.0003	10.00041	10.0001	10	19.34	27964.9772
20	1400	454.9892	454.973	129.9912	130	162	63.7494	25.0039	10.00093	10.004	10.0188	50.73	32653.6071
21	1300	454.9999	454.9904	129.9932	129.993	79.9833	20.0042	25.0019	10.00102	10.0119	10.0013	24.98	29959.1115
22	1100	454.9958	300.6025	129.9925	129.998	25	20.0001	25.0002	10.00013	10	10.0003	-15.59	26151.5695
23	900	454.9021	150.0021	107.2591	123.051	25.0001	20.0001	25.0019	10.00225	10.0007	10.0001	-35.22	23023.2353
24	800	454.9481	150.0055	64.9825	86.3429	25.0005	20	25	10.00017	10.0002	10.0001	-56.28	21685.6771
	Fuel Cost (\$) per day												649486.69

Table 5.26: Ten unit generating system with RESs using hHHO-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)											Optimum Fuel Cost
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	P _{Wind}	
1	700	393.36	150	20	20	25	20	25	10	10	10	16.64	18799.4698
2	750	430.7005	150	20	24.5195	25	20	25	10	10	10	24.78	19493.7788
3	850	454.9924	150.0004	50.4393	70.92779	25.0001	20	25	10	10.0001	10	23.64	21182.0659
4	950	454.9891	150.0122	105.621	120.6428	25.0005	20.0031	25.0001	10.0012	10	10.00036	18.73	22955.9626
5	1000	454.9967	182.9211	129.995	129.9961	25.0005	20	25.0003	10.0003	10.00002	10.00008	2.09	24102.773
6	1100	454.9709	277.3983	130	129.9792	25.001	20.0001	25.0002	10	10.00007	10.00024	7.65	25746.3084
7	1150	454.9989	322.2213	129.999	130	25.0002	20	25	10.0001	10.0003	10	12.78	26529.0706
8	1200	454.9942	364.1881	129.995	129.9996	25.0008	20.0009	25.0002	10	10	10.0008	20.82	27262.2466
9	1300	454.9943	454.9919	130	129.998	48.6515	20.0037	25.0001	10.0001	10.00025	10.00031	6.36	29325.5381
10	1400	454.9947	454.996	129.998	129.9998	144.217	20.0004	25.0016	10.0001	10.00045	10.00218	10.79	31281.6345
11	1450	454.9737	454.9995	129.984	129.9963	161.994	45.1604	25.0294	10.0094	10.00318	10.00016	17.85	32225.702
12	1500	454.9977	454.9997	129.982	130	161.999	79.9844	25.0585	20.3991	10.03972	10.00004	22.54	33304.8643
13	1400	454.9824	454.9975	129.999	129.9946	125.017	20.002	25.0001	10.0008	10.00161	10.00556	30	30882.7016
14	1300	454.9966	454.9969	129.999	129.9999	28.9726	20.0022	25	10	10.003	10.00004	26.03	28931.9522
15	1200	454.9886	359.4306	129.992	129.9475	25.0001	20.0003	25	10.0001	10.00053	10.00025	25.64	27177.9954
16	1050	454.9968	212.013	130	129.9988	25.0011	20.0002	25	10.0002	10.00003	10.00005	22.99	24608.5979
17	1000	454.995	165.8782	130	129.9966	25	20.0002	25	10	10.00008	10.00029	19.13	23806.8172
18	1100	454.9972	268.3533	129.998	129.9916	25	20	25	10	10.00001	10	16.66	25589.2389
19	1200	454.999	367.3055	129.994	129.999	25.0017	20.0004	25	10	10.00005	10	17.7	27316.7918
20	1400	454.9989	454.9993	129.993	129.9972	138.846	20.0016	25.0002	10.0034	10.00002	10.0008	16.16	31169.7914
21	1300	454.9999	454.998	130	129.9978	54.9937	20	25.0006	10.0001	10	10.00013	0.01	29453.2094
22	1100	454.9958	281.4279	129.997	129.9969	25.0008	20	25.0002	10.0012	10.00017	10.00008	3.58	25817.245
23	900	454.9898	150.0029	87.3584	104.7014	25.0145	20.0004	25.0002	10.0009	10.00135	10.00021	2.93	22375.2427
24	800	454.9917	150.0001	36.4019	58.60632	25	20	25	10	10	10	0	20739.9152
Fuel Cost (\$) per day													630078.9132

Table 5.27: Ten unit generating system with EVs and RESs using hHHO-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)											EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀	P _{Wind}		
1	700	410.000	150.000	20.000	20.000	25.000	20.000	25.000	10.000	10.000	10.000	16.64	-22.96	19075.288
2	750	446.253	150.000	20.000	28.057	25.000	20.000	25.000	10.000	10.000	10.000	24.78	-19.09	19810.8816
3	850	454.977	150.001	57.989	79.052	25.001	20.000	25.000	10.000	10.000	10.000	23.64	-15.66	21445.4205
4	950	454.999	150.000	118.435	129.995	25.000	20.000	25.000	10.000	10.000	10.000	18.73	-22.16	23333.5319
5	1000	454.999	208.067	129.993	130.000	25.001	20.000	25.000	10.000	10.000	10.000	2.09	-25.15	24539.9074
6	1100	454.998	294.885	130.000	129.987	25.000	20.000	25.000	10.000	10.000	10.000	7.65	-17.52	26051.7839
7	1150	454.989	336.313	130.000	129.996	25.000	20.000	25.000	10.000	10.000	10.000	12.78	-14.08	26774.978
8	1200	454.997	392.507	129.996	130.000	25.000	20.000	25.000	10.001	10.000	10.000	20.82	28.32	27757.6815
9	1300	454.998	454.999	129.997	129.999	79.709	20.004	25.000	10.001	10.000	10.003	6.36	31.07	29953.4845
10	1400	454.997	454.983	129.998	130.000	161.994	26.001	25.001	10.000	10.000	10.004	10.79	23.77	31788.9278
11	1450	454.990	455.000	129.980	129.982	161.990	65.750	25.000	10.015	10.001	10.002	17.85	20.56	32699.4737
12	1500	454.962	454.998	129.986	130.000	161.978	79.972	25.112	54.971	48.576	10.007	22.54	73.1	35268.0026
13	1400	454.995	454.991	129.999	129.999	140.032	20.002	25.010	10.001	10.002	10.000	30	15.03	31194.6318
14	1300	454.995	455.000	129.997	129.999	45.735	20.001	25.000	10.001	10.002	10.000	26.03	16.76	29267.1124
15	1200	454.997	374.449	129.995	129.998	25.000	20.001	25.000	10.000	10.000	10.000	25.64	15.08	27441.6736
16	1050	454.979	233.462	130.000	129.998	25.001	20.000	25.000	10.000	10.000	10.000	22.99	-21.43	24981.4507
17	1000	454.999	203.239	129.985	129.975	25.001	20.000	25.000	10.000	10.000	10.000	19.13	-37.33	24455.4169
18	1100	454.989	284.621	130.000	129.999	25.000	20.000	25.000	10.000	10.000	10.000	16.66	-16.27	25872.854
19	1200	454.997	386.685	129.957	130.000	25.000	20.000	25.000	10.001	10.000	10.000	17.7	19.34	27655.1478
20	1400	454.961	454.993	129.983	129.996	161.984	47.638	25.001	10.005	10.004	10.005	16.16	50.73	32281.1797
21	1300	454.992	454.996	129.984	130.000	79.992	20.002	25.001	10.001	10.001	10.001	0.01	24.98	29958.836
22	1100	454.996	297.018	129.999	129.997	25.001	20.000	25.000	10.000	10.000	10.000	3.58	-15.59	26089.1108
23	900	454.987	150.002	107.135	120.160	25.000	20.001	25.002	10.001	10.000	10.001	2.93	-35.22	22973.3498
24	800	454.975	150.003	66.261	85.039	25.001	20.001	25.000	10.000	10.000	10.000	0	-56.28	21685.6767
	Fuel Cost (\$) per day													642355.8017

5.6.3.8 Ten generator test system (ELD with RES)

Memetic HHO (hHHO-RES) algorithm is suggested to get optimized outcomes for economic load dispatch with the effect of RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.26** displays that the fuel price is **630078.9132** \$/day using the proposed hHHO-RES method.

5.6.3.9 Ten generator test system (ELD with EVs and RES)

Memetic HHO (hHHO-RES) algorithm is applied to get optimized outcomes for economic load dispatch with the impact of EVs and RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.27** displays that the fuel price is **642355.802** \$/day using the proposed hHHO-RES method.

The simulation results for memetic HHO algorithm for various test systems are shown in Table-5.19 through Table 5.27. Table 5.19 gives dispatching of power generating units by considering only electric vehicles for hourly demand for 24 hours and overall fuel cost for 6-unit generating system. The negative sign depicts the discharging state and positive sign shows the charging state of the EVs with fuel cost of 397186.91\$/hr. Table 5.20 gives dispatching of power generating units by considering only renewable energy sources (RESs) for hourly demand for 24 hours and overall fuel cost attained for 6-unit test system is 316486.72 \$/hr. Table 5.21 shows the dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost achieved for 6-unit test system is 326614.1822 \$/hr.

Similarly, Table 5.22 gives dispatching of power generating units by considering only electric vehicles (EVs) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is evaluated as 296172.24 \$/hr. Table 5.23 gives dispatching of power generating units by considering only RESs for hourly demand for 24 hours and overall fuel

cost for 7-unit test system is reduced to 283631.92 \$/hr. Table 5.24 gives dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is assessed as 291213.39 \$/hr.

In a similar manner, the overall fuel cost achieved for ten unit test system considering only EVs is 649486.69 \$/hr and is depicted in Table 5.25 with dispatching of power for hourly demand for 24 hours. Table 5.26 gives dispatching of power generating units by considering only RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 10-unit test system depicted as 630078.9132 \$/hr. Table 5.27 gives dispatching of power generating units by considering both EVs and RESs for hourly demand for 24 hours and overall fuel cost for 10-unit test system attained is 642355.8017 \$/hr.

5.6.4. Memetic Slime Mould Algorithm for Integrated Economic Load Dispatch

To validate an integrated ELD problem with the impact of PEVs/BEVs/BESS and RESs using proposed memetic Slime Mould Algorithm developed by combining SMA with random exploratory search method (hSMA-RES) 50 search agents are considered with 500 iterations and 30 maximum trial runs. The efficacy of the proposed algorithm is tested on three different test systems with six, seven and ten generating units with different load situations. The problem has been considered with the impact of only EVs, only RESs and combined EVs and RESs discussed in following subsections.

5.6.4.1 Six Generator Test System (ELD with Electric Vehicles)

The proposed memetic SMA (hSMA-RES) is implemented to attain optimized results for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A six generator test system without valve point loading effect and without losses [6] is considered. **Table 5.28** displays that the fuel price is **397186.91** \$/day using the proposed hSMA-RES algorithm.

5.6.4.2 Six Generator Test System (ELD with RESs)

Memetic SMA (hSMA-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.29** displays that the fuel price is **316486.716** \$/day using the proposed hSMA-RES algorithm.

5.6.4.3 Six Generator Test System (ELD with EVs and RESs)

Memetic SMA (hSMA-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A six generator test system [6] without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with maximum capacity of 25.5 MW and 40 MW respectively. **Table 5.30** displays that the fuel price is **326614.1824** \$/day using the proposed hSMA-RES algorithm.

5.6.4.4 Seven generator test system (ELD with Electric Vehicles)

Memetic SMA (hSMA-RES) is implemented to achieve boosted values for economic load dispatch with the effect of EVs as Vehicle to Grid (V2G) or Grid to Vehicle (G2V). A seven generator test system without valve point loading effect and loss coefficient is considered [145]. **Table 5.31** displays that the fuel price is **295334.54** \$/day using the proposed hSMA-RES algorithm with the impact of load of plugin electric vehicles or battery electric vehicles.

5.6.4.5 Seven generator test system (ELD with RES)

Memetic SMA (hSMA-RES) is proposed to get optimized outcomes for economic load dispatch with the effect of RESs. A seven generator test system without valve point loading effect and losses is considered. The renewable energy sources considered are wind and solar with data taken from [145]. **Table 5.32** displays that the fuel price is **283631.9144** \$/day using the proposed hSMA-RES in case of integrated fossil fired plants and renewable energy sources load dispatch problem.

Table 5.28: Six unit generating system with EVs using hSMA-RES

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆		
1	700	351.2895	100.9456	189.885	51.00529	88.63468	50	-131.76	9834.38135
2	750	352.0744	101.5135	190.499	51.6083	89.30523	50	-85	9873.01344
3	850	365.8605	111.6977	201.236	62.33306	101.373	50	-42.5	10564.4803
4	950	379.6603	121.8772	211.937	73.0761	113.449	50	0	11267.0543
5	1000	391.6576	130.6987	221.291	82.41557	123.9376	50	0	11887.0166
6	1100	414.7453	147.6959	239.271	100.3609	144.1501	53.7764	0	13152.0064
7	1150	424.574	154.9452	246.883	107.9716	152.7265	62.9002	0	13795.7631
8	1200	434.3567	162.1441	254.495	115.602	161.3404	72.0613	0	14446.3815
9	1300	453.9866	176.6385	269.747	130.8782	178.4704	90.3809	0.102	15769.5658
10	1400	474.0173	191.3751	285.299	146.4153	195.9913	109.044	2.142	17146.6742
11	1450	493.872	200	300	150	200	120	13.872	17994.9709
12	1500	500	200	300	150	200	120	34.782	82862.5
13	1400	481.2405	196.7137	290.981	150	200	115.846	34.782	17593.2653
14	1300	456.6781	178.6368	271.826	132.9771	180.8375	92.9161	13.872	15953.7345
15	1200	434.792	162.4369	254.833	115.9441	161.691	72.4446	2.142	14474.4072
16	1050	403.7337	139.5773	230.674	91.74378	134.5074	50	0.2359	12518.3619
17	1000	393.5536	132.0871	222.735	83.85747	125.583	50	-7.8157	11984.6844
18	1100	418.3027	150.3296	242.024	103.1271	147.3098	57.1136	18.207	13385.6296
19	1200	443.3292	168.748	261.426	122.5726	169.1333	80.4421	45.6514	15046.4068
20	1400	484.4015	199.03	293.44	150	200	118.78	45.6514	17742.8242
21	1300	457.5096	179.2316	272.494	133.6361	181.6187	93.7166	18.207	16011.8212
22	1100	415.2715	148.123	239.701	100.7955	144.6298	54.291	2.8114	13188.0215
23	900	369.1412	114.1229	203.798	64.90598	104.2726	50	-6.2411	10731.3684
24	800	353.8703	102.838	191.896	53.01266	90.88291	50	-42.5	9962.57489
		Fuel Cost (\$/day)							397186.91

Table 5.29: Six unit generating system with RESs using hSMA-RES

Time (hr)	Load (MW)	Generated Power (MW)								Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	P _{wind}	P _{solar}	
1	700	309.603	70.2357	157.47	50	52.1509	50	10.54	0	8179.68306
2	750	320.892	78.5548	166.255	50	62.0287	50	22.27	0	8616.47697
3	850	349.446	99.5932	188.458	50.0001	87.0019	50	25.5	0	9747.94626
4	950	373.546	117.34	207.191	68.3131	108.109	50	25.5	0	10954.1074
5	1000	385.538	126.191	216.539	77.6438	118.589	50	25.5	0	11569.7864
6	1100	409.53	143.867	235.195	96.3209	139.587	50	25.5	0	12826.3401
7	1150	419.549	151.225	242.951	104.074	148.343	58.268	25.5	0.09	13465.4312
8	1200	425.93	155.967	247.968	109.043	153.942	64.19	25.5	17.46	13886.9551
9	1300	442.78	168.362	261.075	122.161	168.717	79.955	25.5	31.45	15012.0613
10	1400	461.531	182.161	275.597	136.739	185.044	97.419	25.5	36.01	16284.2881
11	1450	470.905	189.122	282.947	144.027	193.261	106.18	25.5	38.06	16932.9032
12	1500	482.339	197.525	291.843	150	200	116.86	25.5	35.93	17645.3323
13	1400	461.346	182.058	275.5	136.64	184.914	97.262	25.5	36.78	16273.9239
14	1300	442.892	168.453	261.176	122.251	168.793	80.025	24.82	31.59	15019.1892
15	1200	428.407	157.744	249.863	110.948	156.083	66.514	20.74	9.7	14049.4679
16	1050	397.065	134.682	225.474	86.5758	128.663	50	14.62	12.92	12168.2373
17	1000	385.544	126.19	216.525	77.6535	118.587	50	25.5	0	11569.7864
18	1100	411.015	144.976	236.35	97.4442	140.891	50.283	19.04	0	12908.6679
19	1200	429.374	158.455	250.597	111.715	156.939	67.42	25.5	0	14113.7087
20	1400	470.021	188.408	282.252	143.393	192.544	105.36	18.02	0	16872.307
21	1300	448.981	172.902	265.862	126.99	174.069	85.695	25.5	0	15428.5318
22	1100	410.523	144.58	235.95	97.068	140.459	50	21.42	0	12878.3208
23	900	367.658	113.012	202.627	63.7341	102.969	50	0	0	10655.4905
24	800	341.46	93.7091	182.25	50	80.031	50	2.55	0	9427.77335
		Fuel Cost (\$/day)								316486.716

Table 5.30: Six unit generating system with EVs and RESs using hSMA-RES

Time (hr)	Load (MW)	Generated Power (MW)						EVs (MW)	P _{wind} (MW)	P _{solar} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆				
1	700	348.4713	98.87732	187.7062	50	86.16512	50	-131.76	10.54	0	9708.962064
2	750	345.97028	97.03108	185.7527	50	83.97593	50	-85	22.27	0	9608.26117
3	850	359.7552	107.1799	196.4571	57.5899	96.01789	50	-42.5	25.5	0	10256.45917
4	950	373.54789	117.3553	207.2089	68.2998	108.0881	50	0	25.5	0	10954.10738
5	1000	385.54069	126.1758	216.527	77.6476	118.6089	50	0	25.5	0	11569.78642
6	1100	409.53212	143.8728	235.2124	96.3109	139.5718	50	0	25.5	0	12826.34008
7	1150	419.52937	151.229	242.9683	104.084	148.3409	58.25807	0	25.5	0.09	13465.43118
8	1200	425.95553	155.952	247.9479	109.028	153.9541	64.20255	0	25.5	17.46	13886.95509
9	1300	442.81654	168.391	261.0494	122.227	168.7242	79.94403	0.102	25.5	31.45	15013.4076
10	1400	461.9135	182.473	275.9347	137.065	185.4671	97.77826	2.142	25.5	36.01	16313.1281
11	1450	473.66486	191.1165	285.0587	146.13	195.6524	108.6898	13.872	25.5	38.06	17121.72532
12	1500	500	200	300	150	200	120	34.782	25.5	35.93	21432.5
13	1400	468.17738	187.0524	280.7916	141.933	190.9039	103.6436	34.782	25.5	36.78	16743.71461
14	1300	445.64249	170.4441	263.2328	124.37	171.1713	82.60154	13.872	24.82	31.59	15202.57239
15	1200	428.83381	158.0469	250.1686	111.31	156.4445	66.89782	2.142	20.74	9.7	14077.31468
16	1050	397.11604	134.7217	225.5234	86.6316	128.7032	50	0.2359	14.62	12.92	12171.19997
17	1000	387.42286	127.555	217.9953	79.0946	120.248	50	-7.8157	25.5	0	11666.78468
18	1100	414.58901	147.5993	239.1331	100.211	143.9864	53.64834	18.207	19.04	0	13141.33957
19	1200	438.31756	165.0628	257.6006	118.676	164.7499	75.74435	45.6514	25.5	0	14710.53891
20	1400	479.17334	195.1986	289.3604	150	200	113.8991	45.6514	18.02	0	17495.13725
21	1300	452.52673	175.5324	268.6305	129.773	177.1973	89.04748	18.207	25.5	0	15670.87518
22	1100	411.09683	144.9986	236.4298	97.5388	140.9704	50.35692	2.8114	21.42	0	12914.17034
23	900	369.16195	114.1227	203.7917	64.9053	104.2594	50	-6.2411	0	0	10731.36841
24	800	353.24291	102.3942	191.4252	52.5253	90.36232	50	-42.5	2.55	0	9932.102796
		Fuel Cost (\$/ day)									326614.1824

Table 5.31: Seven unit generating system with EVs using hSMA-RES

Time (hr)	Load (MW)	Generated Power (MW)							EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇		
1	800	311.401	71.5589	140	50	100	50	100	-22.96	10018.488
2	780	297.658	61.4321	140	50	100	50	100	-19.09	9749.63
3	750	280.684	50	134.976	50	100	50	100	-15.66	9380.5352
4	750	283.696	51.1447	137.319	50	100	50	100	-22.16	9451.7262
5	720	269.147	50	126.003	50	100	50	100	-25.15	9158.0261
6	700	253.605	50	113.915	50	100	50	100	-17.52	8863.5106
7	700	251.67	50	112.41	50	100	50	100	-14.08	8827.2636
8	700	259.68	50	118.64	50	100	50	100	28.32	8977.915
9	800	314.344	73.727	140	50	100	50	102.999	31.07	10110.782
10	900	347.854	98.4188	140	50	100	50	137.497	23.77	11189.382
11	1000	378.068	100	140	71.829	112.057	50	168.606	20.56	12360.151
12	1200	444.469	100	140	100	170.161	81.506	236.963	73.1	15583.25
13	1400	465.874	100	140	100	188.888	100	258.988	15.03	16661.53
14	1500	521.999	100	140	100	237.999	100	316.762	16.76	18929.831
15	1750	575	100	140	100	340.08	100	410	15.08	22644.93
16	1800	575	100	140	100	396.43	100	410	-21.43	23568.624
17	1500	529.079	100	140	100	244.195	100	324.055	-37.33	19225.166
18	900	345.141	96.4233	140	50	100	50	134.706	-16.27	11100.499
19	850	328.178	83.9202	140	50	100	50	117.242	19.34	10550.797
20	800	321.45	78.963	140	50	100	50	110.32	50.73	10335.9
21	780	301.049	63.9309	140	50	100	50	100	24.98	9815.5446
22	750	280.644	50	134.946	50	100	50	100	-15.59	9379.7702
23	700	263.561	50	121.659	50	100	50	100	-35.22	9051.4875
24	800	323.456	80.4418	140	50	100	50	112.382	-56.28	10399.804
Fuel Cost (\$/day)										295334.54

5.6.4.6 Seven generator test system (ELD with EVs and RES)

Memetic SMA (hSMA-RES) is suggested to get optimized outcomes for economic load dispatch with the combined effect of EVs and RESs. A seven generator test system without valve point loading effect and losses is considered. The Electric vehicles and renewable energy sources wind and solar are incorporated with wind and solar power considered from [145]. **Table 5.33** displays that the fuel price is **291213.3819** \$/day using the proposed hSMA-RES.

5.6.4.7 Ten generator test system (ELD with Electric Vehicles)

Memetic SMA (hSMA-RES) algorithm is implemented to attain optimized cost for economic load dispatch with the effect of EVs as V2G and G2V. A ten generator test system without valve point loading effect without losses [325]. **Table 5.34** displays that the fuel price is **649483.15** \$/day using the proposed hSMA-RES method.

5.6.4.8 Ten generator test system (ELD with RES)

Memetic SMA (hSMA-RES) algorithm is suggested to get optimized outcomes for economic load dispatch with the effect of RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.35** displays that the fuel price is **630077.257** \$/day using the proposed hSMA-RES method.

5.6.4.9 Ten generator test system (ELD with EVs and RES)

Memetic SMA (hSMA-RES) algorithm is applied to get optimized outcomes for economic load dispatch with the impact of EVs and RESs. A ten generator test system without valve point loading effect without losses with wind as renewable energy source of maximum capacity 30 MW [325]. **Table 5.36** displays that the fuel price is **642463.2901** \$/day using the proposed hSMA-RES method.

Table 5.32: Seven unit generating system with RESs using hSMA-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)							P _{Wind} (MW)	P _{Solar} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇			
1	800	297.203	61.097	140	50	100	50	100	1.7	0	9740.8104
2	780	283.433	50.9521	137.115	50	100	50	100	8.5	0	9444.4861
3	750	266.661	50	124.069	50	100	50	100	9.27	0	9110.5082
4	750	262.504	50	120.836	50	100	50	100	16.66	0	9031.4045
5	720	250.939	50	111.841	50	100	50	100	7.22	0	8813.5899
6	700	240.971	50	104.089	50	100	50	100	4.91	0.03	8628.5333
7	700	231.977	50	97.0931	50	100	50	100	14.66	6.27	8463.6663
8	700	219.248	50	87.1925	50	100	50	100	26.56	17	8233.7778
9	800	274.699	50	130.321	50	100	50	100	20.88	24.1	9264.6904
10	900	318.565	76.8377	140	50	100	50	107.347	17.85	39.4	10244.288
11	1000	366.996	100	140	63.2194	102.376	50	157.199	12.8	7.41	11862.126
12	1200	419.614	100	140	100	148.414	58.3019	211.371	18.65	3.65	14338.413
13	1400	465.874	100	140	100	188.888	100	258.988	14.35	31.9	16661.53
14	1500	503.438	100	140	100	221.755	100	297.657	10.35	26.8	18165.492
15	1750	575	100	140	100	312.417	100	404.223	8.26	10.1	22120.313
16	1800	575	100	140	100	355.99	100	410	13.71	5.3	22900.581
17	1500	511.749	100	140	100	229.031	100	306.21	3.44	9.57	18506.018
18	900	337.75	90.9747	140	50	100	50	127.096	1.87	2.31	10859.593
19	850	320.915	78.5691	140	50	100	50	109.766	0.75	0	10318.885
20	800	298.084	61.7461	140	50	100	50	100	0.17	0	9757.8959
21	780	286.754	53.3975	139.698	50	100	50	100	0.15	0	9536.2636
22	750	271.701	50	127.989	50	100	50	100	0.31	0	9206.9942
23	700	243.148	50	105.782	50	100	50	100	1.07	0	8668.7381
24	800	297.848	61.5721	140	50	100	50	100	0.58	0	9753.3156
	Fuel Cost (\$/day)										283631.91

Table 5.33: Seven unit generating system with EVs and RESs using hSMA-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)							P _{Wind} (MW)	P _{Solar} (MW)	EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇				
1	800	310.422	70.8376	140	50	100	50	100	1.7	0	-22.96	9999.187938
2	780	292.764	57.8261	140	50	100	50	100	8.5	0	-19.09	9654.999857
3	750	275.469	50	130.921	50	100	50	100	9.27	0	-15.66	9279.556464
4	750	274.969	50	130.531	50	100	50	100	16.66	0	-22.16	9269.897234
5	720	265.086	50	122.844	50	100	50	100	7.22	0	-25.15	9080.485947
6	700	250.826	50	111.754	50	100	50	100	4.91	0.03	-17.52	8811.487385
7	700	239.897	50	103.253	50	100	50	100	14.66	6.27	-14.08	8608.734132
8	700	235.178	50	99.5825	50	100	50	100	26.56	17	28.32	8522.103014
9	800	290.173	55.917	140	50	100	50	100	20.88	24.1	31.07	9605.137343
10	900	327.158	83.1693	140	50	100	50	116.192	17.85	39.4	23.77	10518.12031
11	1000	372.575	100	140	67.5657	107.26	50	162.949	12.8	7.41	20.56	12112.48622
12	1200	438.661	100	140	100	165.076	76.0826	230.98	18.65	3.65	73.1	15289.29264
13	1400	471.048	100	140	100	193.416	100	264.316	14.35	31.9	15.03	16865.31357
14	1500	509.208	100	140	100	226.809	100	303.594	10.35	26.8	16.76	18401.61582
15	1750	575	100	140	100	321.72	100	410	8.26	10.1	15.08	22354.94507
16	1800	575	100	140	100	377.42	100	410	13.71	5.3	-21.43	23251.33185
17	1500	524.6	100	140	100	240.279	100	319.441	3.44	9.57	-37.33	19038.13696
18	900	343.631	95.3073	140	50	100	50	133.151	1.87	2.31	-16.27	11051.08567
19	850	327.907	83.7205	140	50	100	50	116.962	0.75	0	19.34	10542.1022
20	800	321.389	78.9184	140	50	100	50	110.253	0.17	0	50.73	10333.94463
21	780	300.963	63.8673	140	50	100	50	100	0.15	0	24.98	9813.862532
22	750	280.47	50	134.81	50	100	50	100	0.31	0	-15.59	9376.382571
23	700	262.959	50	121.191	50	100	50	100	1.07	0	-35.22	9040.053876
24	800	323.248	80.2871	140	50	100	50	112.165	0.58	0	-56.28	10393.11862
Fuel Cost (\$/day)												291213.3819

Table 5.34: Ten unit generating system with EVs using hSMA-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)										EVs (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀		
1	700	428.85941	150	20	24.1006	25	20	25	10	10	10	-22.96	19456.257
2	750	454.99996	150	20.79901	43.291	25	20	25	10	10	10	-19.09	20223.263
3	850	454.99978	150	70.23498	90.4252	25	20	25	10	10	10	-15.66	21843.91
4	950	454.99999	157.16	130	130	25	20	25	10	10	10	-22.16	23655.6
5	1000	455	210.15	130	130	25	20	25	10	10	10	-25.15	24576.242
6	1100	454.99999	302.52	130	130	25	20	25	10	10	10	-17.52	26185.228
7	1150	454.99998	349.08	130	130	25	20	25	10	10	10	-14.08	26998.258
8	1200	454.99998	413.32	130	130	25	20	25	10	10	10	28.32	28122.224
9	1300	455	455	130	130	86.07	20	25	10	10	10	31.07	30082.915
10	1400	455	455	130	130	162	36.769999	25	10	10	10	23.77	32033.782
11	1450	455	455	130	130	162	80	25	13.56	10	10	20.56	33124.645
12	1500	454.99999	455	130	130	162	79.999973	25.001	54.9997	55	26.0993	73.1	35892.573
13	1400	455	455	130	130	162	28.030003	25	10	10	10	15.03	31835.197
14	1300	455	455	130	130	71.76	20	25	10	10	10	16.76	29792.019
15	1200	455	400.08	130	130	25	20	25	10	10	10	15.08	27890.363
16	1050	454.99999	256.43	130	130	25	20	25	10	10	10	-21.43	25381.728
17	1000	454.99999	222.33	130	130	25	20	25	10	10	10	-37.33	24788.101
18	1100	454.99999	301.27	130	130	25	20	25	10	10	10	-16.27	26163.419
19	1200	455	404.34	130	130	25	20	25	10	10	10	19.34	27964.953
20	1400	455	455	130	130	162	63.729997	25	10	10	10	50.73	32653.203
21	1300	455	455	130	130	79.98	20	25	10	10	10	24.98	29958.918
22	1100	454.99999	300.59	130	130	25	20	25	10	10	10	-15.59	26151.555
23	900	454.99999	150	105.7587	124.461	25	20	25	10	10	10	-35.22	23023.139
24	800	454.99978	150	65.39464	85.8856	25	20	25	10	10	10	-56.28	21685.654
Fuel Cost (\$) per day													649483.15

Table 5.35: Ten unit generating system with RESs using hSMA-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)										P _{Wind} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀		
1	700	393.36	150	20	20	25	20	25	10	10	10	16.64	18799.47
2	750	430.7005	150	20	24.5195	25	20	25	10	10	10	24.78	19493.779
3	850	454.9991	150	50.18493	71.176	25	20	25	10	10	10	23.64	21182.063
4	950	455	150	104.4163	121.854	25	20	25	10	10	10	18.73	22955.91
5	1000	455	182.91	130	130	25	20	25	10	10	10	2.09	24102.76
6	1100	455	277.35	130	130	25	20	25	10	10	10	7.65	25746.269
7	1150	455	322.22	130	130	25	20	25	10	10	10	12.78	26529.065
8	1200	455	364.18	130	130	25	20	25	10	10	10	20.82	27262.223
9	1300	455	455	130	130	48.64	20	25	10	10	10	6.36	29325.476
10	1400	455	455	130	130	144.21	20	25	10	10	10	10.79	31281.559
11	1450	455	455	130	130	162	45.15	25	10	10	10	17.85	32225.209
12	1500	455	455	130	130	162	80	25	20.46	10	10	22.54	33304.463
13	1400	455	455	130	130	125	20	25	10	10	10	30	30882.54
14	1300	455	455	130	130	28.97	20	25	10	10	10	26.03	28931.902
15	1200	455	359.36	130	130	25	20	25	10	10	10	25.64	27177.949
16	1050	455	212.01	130	130	25	20	25	10	10	10	22.99	24608.589
17	1000	455	165.87	130	130	25	20	25	10	10	10	19.13	23806.807
18	1100	455	268.34	130	130	25	20	25	10	10	10	16.66	25589.232
19	1200	455	367.3	130	130	25	20	25	10	10	10	17.7	27316.782
20	1400	455	455	130	130	138.84	20	25	10	10	10	16.16	31169.721
21	1300	455	455	130	130	54.99	20	25	10	10	10	0.01	29453.19
22	1100	455	281.42	130	130	25	20	25	10	10	10	3.58	25817.222
23	900	454.9998	150	86.37856	105.692	25	20	25	10	10	10	2.93	22375.164
24	800	454.9996	150	36.52392	58.4765	25	20	25	10	10	10	0	20739.914
	Fuel Cost (\$ per day)												630077.26

Table 5.36: Ten unit generating system with EVs and RESs using hSMA-RES

Time (hr)	Power Demand (MW)	Generated Power (MW)										EVs (MW)	P _{Wind} (MW)	Optimum Fuel Cost (\$/hr)
		PG ₁	PG ₂	PG ₃	PG ₄	PG ₅	PG ₆	PG ₇	PG ₈	PG ₉	PG ₁₀			
1	700	415.303	150	20	21.0167	25	20	25	10	10	10	-22.96	16.64	19180.113
2	750	446.253	150	20	28.0574	25	20	25	10	10	10	-19.09	24.78	19810.882
3	850	454.998	150	60.847	76.1755	25	20	25	10	10	10	-15.66	23.64	21445.441
4	950	454.973	150	118.46	130	25	20	25	10	10	10	-22.16	18.73	23333.539
5	1000	454.932	208.128	130	130	25	20	25	10	10	10	-25.15	2.09	24539.949
6	1100	454.965	294.905	130	130	25	20	25	10	10	10	-17.52	7.65	26051.801
7	1150	455	336.3	130	130	25	20	25	10	10	10	-14.08	12.78	26775.066
8	1200	454.851	392.65	130	130	25	20	25	10	10	10	28.32	20.82	27757.801
9	1300	454.917	455	130	130	79.793	20	25	10	10	10	31.07	6.36	29953.735
10	1400	454.986	455	130	130	162	25.994	25	10	10	10	23.77	10.79	31788.859
11	1450	454.977	455	130	130	162	65.733	25	10	10	10	20.56	17.85	32699.254
12	1500	454.819	455	130	130	162	80	25	55	47.9057	10.835	73.1	22.54	35269.301
13	1400	454.828	455	130	130	140.2	20	25	10	10	10	15.03	30	31195.207
14	1300	454.976	455	130	130	45.754	20	25	10	10	10	16.76	26.03	29267.14
15	1200	454.764	374.677	130	130	25	20	25	10	10	10	15.08	25.64	27441.865
16	1050	454.95	233.49	130	130	25	20	25	10	10	10	-21.43	22.99	24981.469
17	1000	454.788	203.412	130	130	25	20	25	10	10	10	-37.33	19.13	24455.555
18	1100	454.898	284.712	130	130	25	20	25	10	10	10	-16.27	16.66	25872.924
19	1200	454.923	386.717	130	130	25	20	25	10	10	10	19.34	17.7	27655.178
20	1400	454.963	455	130	130	162	47.54	25	10	10.0665	10	50.73	16.16	32281.198
21	1300	454.982	455	130	130	79.989	20	25	10	10	10	24.98	0.01	29958.783
22	1100	454.977	297.033	130	130	25	20	25	10	10	10	-15.59	3.58	26089.12
23	900	454.577	150	106.92	120.797	25	20	25	10	10	10	-35.22	2.93	22973.452
24	800	454.995	150	64.409	86.8765	25	20	25	10	10	10	-56.28	0	21685.661
													Fuel Cost (\$/day)	642463.29

The simulation results for memetic SMA algorithm for various test systems are shown in Table 5.28 through Table 5.36. Table 5.28 gives dispatching of power generating units by considering only electric vehicles for hourly demand for 24 hours and overall fuel cost for 6-unit generating system. The negative sign depicts the discharging state and positive sign shows the charging state of the EVs with fuel cost of 397186.91\$/hr. Table 5.29 gives dispatching of power generating units by considering only renewable energy sources (RESs) for hourly demand for 24 hours and overall fuel cost attained for 6-unit test system is 316486.716 \$/hr. Table 5.30 shows the dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost achieved for 6-unit test system is 326614.1824 \$/hr. Similarly, Table 5.31 gives dispatching of power generating units by considering only electric vehicles (EVs) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is evaluated as 295334.54 \$/hr.

Table 5.32 gives dispatching of power generating units by considering only RESs for hourly demand for 24 hours and overall fuel cost for 7-unit test system is reduced to 283631.9144 \$/hr. Table 5.33 gives dispatching of power generating units by considering both EVs (electric vehicles) and RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 7-unit test system is assessed as 291213.3819 \$/hr. In a similar manner, the overall fuel cost achieved for ten unit test system considering only EVs is 649483.15\$/hr and is depicted in Table 5.34 with dispatching of power for hourly demand for 24 hours. Table 5.35 gives dispatching of power generating units by considering only RESs (renewable energy sources) for hourly demand for 24 hours and overall fuel cost for 10-unit test system depicted as 630077.257 \$/hr. Table 5.36 gives dispatching of power generating units by considering both EVs and RESs for hourly demand for 24 hours and overall fuel cost for 10-unit test system attained is 642463.2901 \$/hr.

5.7 COMPARISON OF RESULTS

The integrated ELD problem considering the impact of PEVs/BEVs/BESS and RESs has been solved using the proposed HHO, SMA and proposed memetic hHHO-RES, hSMA-RES approaches. Comparison of results of the proposed methods is presented in table 5.37 considering different impacts for six, seven and ten generating units taking into account only EVs, only RESs and both EVs and RESs. The results of without EVs and RESs obtained in chapter-4 are compared with the results obtained with EVs and RESs for all the proposed algorithms and are presented in Table 5.38. From the comparison table it is observed that the generation cost by considering the load of EVs and considering only conventional sources are more than the cost of generation without considering the load of EVs. When renewable energy sources are also considered with the conventional thermal plants and EVs are behaving as source and load during charging and discharging process than the cost is reduced. Table 5.39 gives the comparison of different test systems with other algorithms. From the comparison table, it has been noticed that performance of proposed memetic methods is better than the other algorithms.

Table 5.37: Comparison of Results for 6-unit, 7-unit, 10-unit system

Test Systems	Algorithm	Fuel Cost under different conditions (\$/hr)		
		<i>With EVs</i>	<i>With RESs</i>	<i>With EVs and RESs</i>
6 Units	HHO	397193.21	316495.72	326621.3
	SMA	397231.67	316539.6	326662.08
	hHHO-RES	397186.91	316486.72	326614.1822
	hSMA-RES	397186.91	316486.716	326614.1824
7 Units	HHO	296172.32	283632.1	291213.44
	SMA	295522.05	283784.62	291464.95
	hHHO-RES	296172.24	283631.92	291213.39
	hSMA-RES	295334.54	283631.91	291213.3819
10 Units	HHO	649487.58	630080.667	642463.29
	SMA	652693.5	633021.0529	645886.777
	hHHO-RES	649486.69	630078.9132	642355.8017
	hSMA-RES	649483.15	630077.26	642463.29

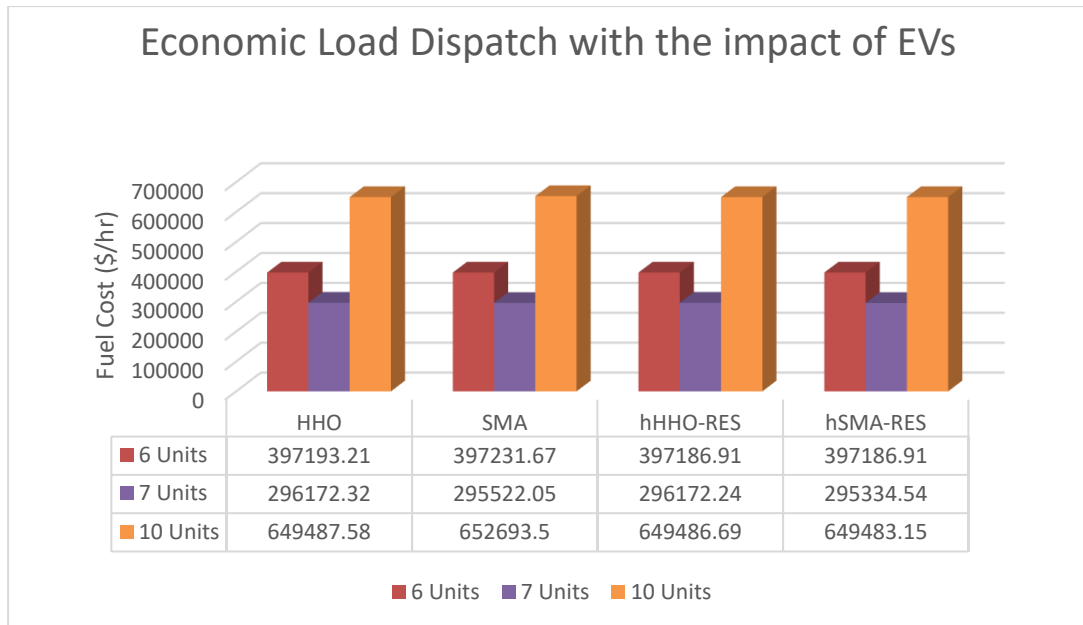


Fig.5.3: Comparison of results with the impact of EVs

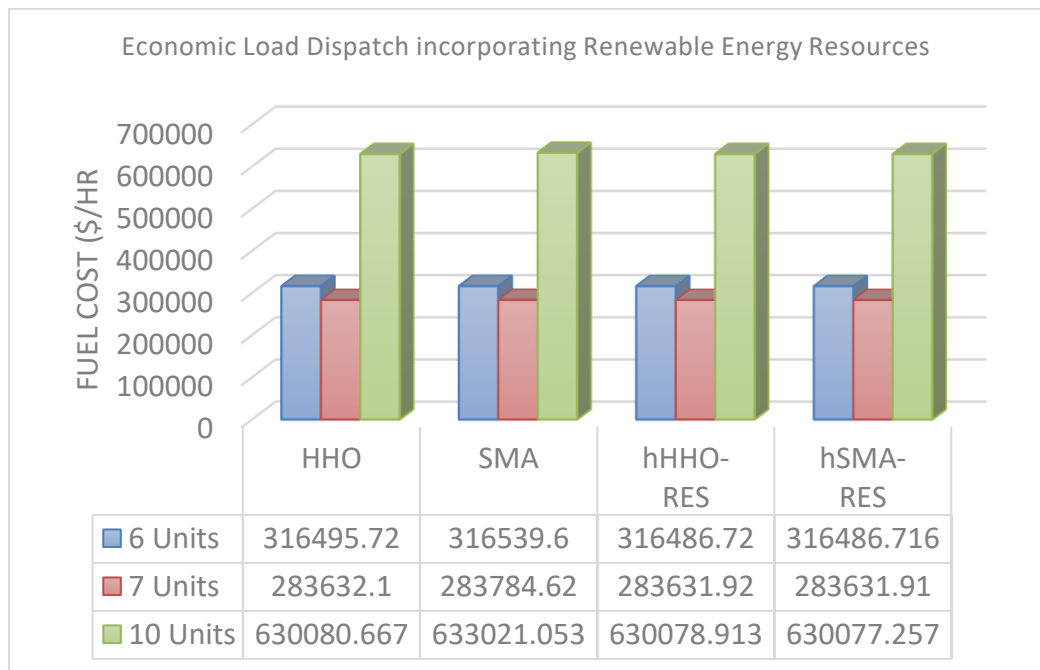


Fig. 5.4: Comparison of results with the impact of RESs

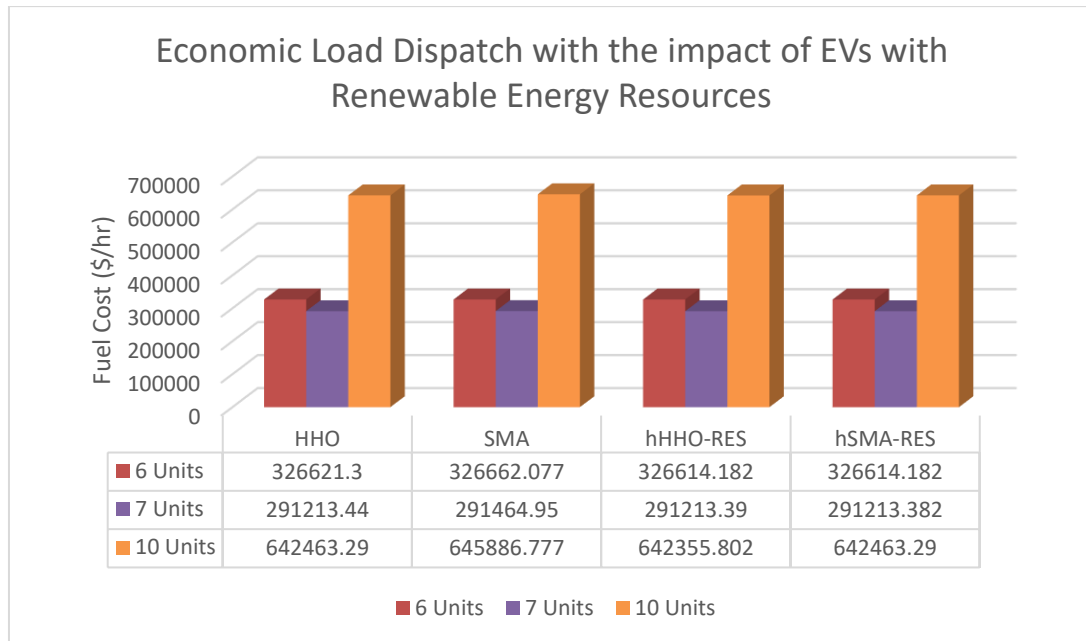


Fig.5.5: Comparison of results with the impact of EVs and RESs

Table 5.38: Comparison of result without and with EVs and RESs

Test Systems	Algorithm	Fuel Cost under different conditions (\$/day)			
		<i>Without EVs & RES</i>	<i>With EVs</i>	<i>With RES</i>	<i>With EVs & RES</i>
6 Units	HHO	356032.59	397193.21	316495.72	326621.3
	SMA	356072.32	397231.67	316539.6	326662.077
	hHHO-RES	356026.17	397186.91	316486.72	326614.182
	hSMA-RES	356026.178	397186.91	316486.72	326614.182
7 Units	HHO	288526.02	296172.32	283632.1	291213.44
	SMA	288805.7	295522.05	283784.62	291464.95
	hHHO-RES	288525.93	296172.24	283631.92	291213.39
	hSMA-RES	287895.36	295334.54	283631.91	291213.382
10 Units	HHO	636972.78	649487.58	630080.667	642463.29
	SMA	640038.29	652693.5	633021.053	645886.777
	hHHO-RES	636971.71	649486.69	630078.913	642355.802
	hSMA-RES	633514.578	649483.15	630077.257	642463.29

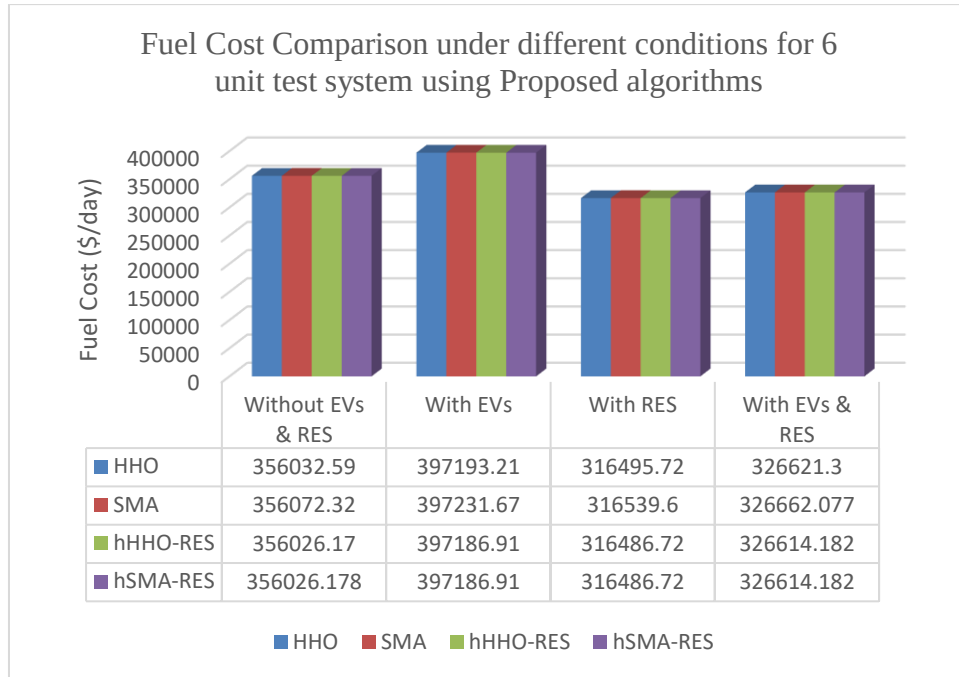


Fig.5.6: Fuel Cost comparison for six unit generating system

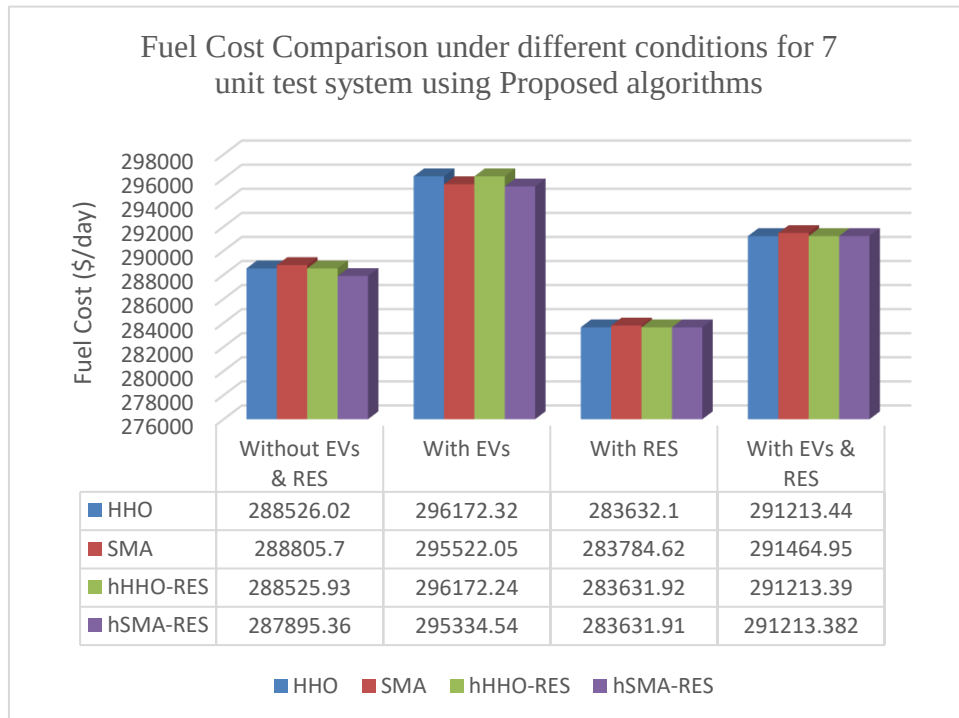


Fig.5.7: Fuel Cost comparison for seven unit generating system

Table 5.39: Comparison of result for 7-unit system and 10-unit system

7-unit system (With RESs)						
Algorithm	HHO	SMA	hHHO-RES	hSMA-RES	BA [251]	dBA [251]
Fuel Cost (\$/day)	283632.1	283784.6	283631.9	283631.9	283846	283642
10-unit system (With EVs)						
Algorithm	HHO	SMA	hHHO-RES	hSMA-RES	PSO [252]	-
Fuel Cost (\$/day)	649487.6	652693.5	649486.7	649483.2	653147.8	-

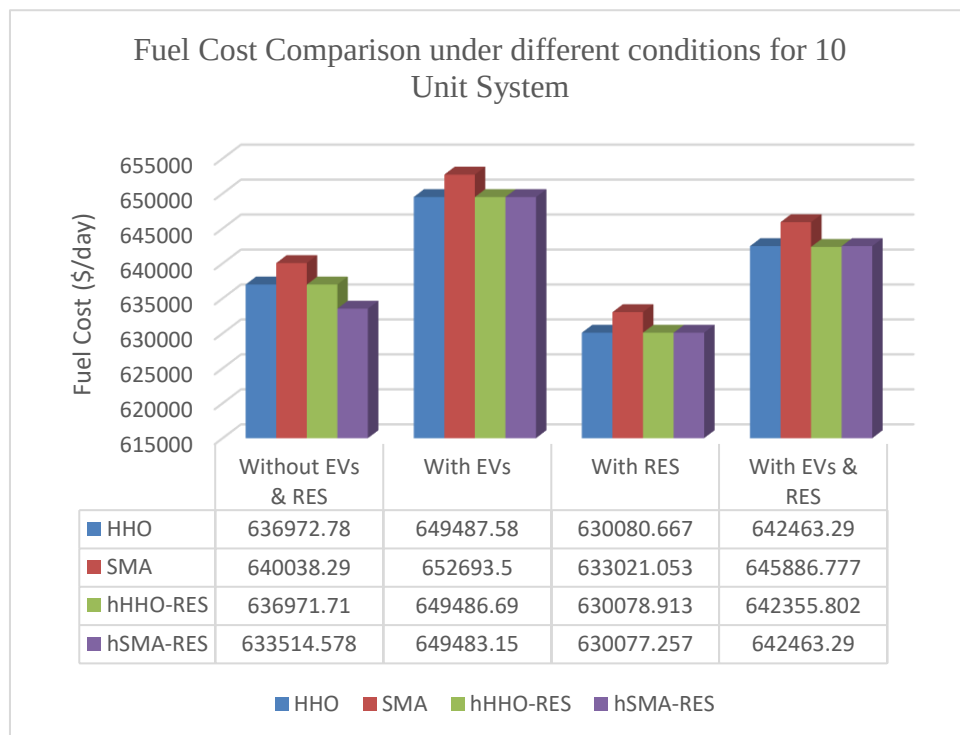


Fig.5.8: Fuel Cost comparison for ten unit generating system

5.8 CONCLUSION

In this chapter the economic load dispatch problem has been considered under three different scenarios using the proposed algorithms. Firstly, the economic load dispatch problem is combined with the renewable energy sources to reduce the fuel cost to a minimum value. Secondly, the impact of electric vehicles on the economic load dispatch has been studied using the proposed algorithms and then the impact of integrating the renewable sources and PEVs/BEVs/BESS with the conventional fossil fuel generating system has been studied using the proposed algorithms. It has been observed that the fuel cost in 6, 7 and 10 generating unit system in an integrated ELD system with HHO is 326621.3 \$/day, 291213.44 \$/day and 642463.29 \$/day respectively but with hHHO-RES it is 326614.182 \$/day, 291213.39 \$/day and 642355.802 \$/day respectively. Similarly, the fuel cost in 6, 7 and 10 generating unit system with SMA 326662.077 \$/day, 291464.95 \$/day, and 645886.777 \$/day respectively while hSMA-RES gives 326614.182 \$/day, 291213.382 \$/day and 642463.29 \$/day respectively. This proves better performance of proposed memetic algorithms in regard to classical methods and other approaches. Further, it is concluded that the generation cost using only conventional sources and adding the load of EVs is more and can be reduced by using renewable sources. The significant outcomes of this chapter showed that depending on the thermal power generation only for supporting electrified transport industry is economically expensive, but utilizing the renewable energy sources along with the PEVs reduces the generation cost. The proper utilization of EVs (G2V/V2G) and their behavior as load and source during charging and discharging mode can significantly reduce the total generation cost and the energy of standalone vehicles can be utilized as battery energy storage system.

CONCLUSIONS AND FUTURE SCOPE

6.1 INTRODUCTION

The increased modernized growth in social, industrial and agriculture sector is the reason for the continuous increase in the demand for electrical energy and there is an imperative need to produce surplus power to satisfy the consumers demand at the most economical cost taking into consideration the environmental issues also. Therefore, the generation and the dispatch of power must be achieved reliably, lucratively and in an ecologically responsible manner.

Globally the major part of electrical energy is produced in thermal power plants by burning coal/ fossil fuels. Due to the unceasing increase in power demand the fuel consumption is also increasing and hence decreasing the limited and irreplaceable existing fuel resources. This encourages the society to be utilize the energy from RESs and have gained desirability other than using conventional thermal power.

Electric vehicles are becoming more popular in motor vehicle market universally and will prove to be a hopeful solution to reduce the pollution in a short time. But the electric vehicles are causing another new challenge to operate & control the power system. To use the generated energy effectively there should be proper use of energy during charging and discharging process and the energy available from the standalone vehicles can be used as battery based energy storage systems (BESSs) for ancillary services. The integrated system considering conventional energy sources, renewable energy sources, electric vehicles or battery energy storage system known as an integrated (RESs-EVs-BESS) problem is accessible in limited land resources and balances the total energy produced and consumed with energy storage systems and optimum load dispatch.

This chapter outlines the most imperative and significant contributions of the research conducted and provided in this thesis with a brief remark on certain research recommendations.

6.2 SIGNIFICANT CONTRIBUTION

The current research focuses on solving and optimizing the ELD problem of an electric power system in order to reduce the overall generation costs while meeting systems physical constraints along with time-varying load demand. In an attempt to find solution for scalar static and dynamic ELD problem of electrical power systems and integrated load dispatch problem with due consideration to PEVs/BEVs/BESS and RESs using HHO, SMA, hHHO-RES and hSMA-RES.

Energy is a fundamental requirement for the nation's socio-economic expansion and scarcity suppression. India's power deficit will persist unless diverse sorts of energy sources for varied categories of customers are explored. There is a necessity to improve transmission and distribution networks to diminish the unused energy generated. The positioning of the advanced plug-in electric vehicles (PEVs) with hybrid and battery electric vehicles (PHEVs/BEVs) and capabilities of V2G technologies provides a feasible solution to this concern. The electrical industry has experienced many changes in the recent years with more focus on RESs and electrifying the transport sector which can reduce the economic and environment issues. The excess energy from standalone vehicles can be utilized as BESSs for ancillary services. These must be optimized for the lowest possible fuel cost while operating under different types of equality and inequality checks imposed by the system and its components.

The ultimate purpose of this research is to find new techniques for defining, extending, and establishing the framework for scalar economic load dispatch problems while taking into account various system and physical constraints by incorporating EVs and renewable energy sources. Different memetic search techniques has been developed and investigated as a solution to different ELD problems. The significant contributions resulted from this study are summarized as follows.

Firstly, memetic optimization algorithms *hHHO-RES* and *hSMA-RES* have been developed by combining the technique based on local search with a recent global search algorithm. These algorithms have been implemented to evaluate the effectiveness on various benchmark functions (F1-F23) and some engineering design problems. The results revealed that the proposed memetic methods are better or in competition with other algorithms.

The scalar ELD problem has been formulated to reduce the fuel cost subjected to different equality-inequality constraints while satisfying the load demand. This complex, non-convex, non-smooth, non-linear optimization has been solved by the proposed memetic optimization algorithms by combining local search algorithm with modern global search algorithms (*hHHO-RES* and *hSMA-RES*). These methods are successfully applied on the scalar ELD problem of power systems considering different IEEE test systems for static and dynamic ELD problems. The static ELD problem test cases has been categorized as small (3,5 and 6 unit systems), medium (10,13,15 and 20 unit system) and large (38 and 40 unit system) scale power systems. Four test systems two with VPLE and two without VPLE are considered under small scale systems. Under medium scale also four test cases are considered with and without VPLE and two test cases are taken for large scale power systems. For dynamic economic load dispatch problem four test cases are considered -5, 6, 7 and 10 generating units with 24 hour load demand.

The proposed memetic algorithms have been implemented to the ELD problem considering renewable energy resources for 6, 7 and 10 generating units systems. The proposed memetic algorithms have also been implemented to ELD problems considering the impact of PEVs/BEVs/BESSs for 6, 7 and 10 generating unit power system. The ELD problem has also been examined with the impact of both renewable energy sources and PEVs/BEVs/BESSs for 6, 7 and 10 generating unit power system. The results of the suggested memetic algorithms are competitive to other well-known evolutionary, heuristic, and meta-heuristic search techniques. It is observed that the proposed memetic algorithms give more feasible solutions as compared to other methods in the literature.

The outcomes of the proposed research are summarized as follows:

- The memetic algorithms hHHO-RES and hSMA-RES proved to have better results in most of the cases and closely competitive in some as compared to original HHO and SMA when tested on various benchmark functions and engineering optimization problems. The results are compared on the basis of best, worst, mean value, median and standard deviation. For statistical significance box plots has been obtained and non-parametric tests like Wilcoxon's Rank sum test and t-test has been performed. The proposed algorithms also proved to have better exploration and exploitation for various test functions.
- The proposed memetic meta-heuristic algorithms are tested on scalar economic load dispatch problem considering static and dynamic ELD systems. It has been observed that in case of static and dynamic ELD problem the fuel cost with proposed memetic algorithms is better in most of the cases as compared to other existing algorithms and simulation time of the proposed memetic HHO is less as compared to memetic SMA methodology.
- The proposed memetic meta-heuristic algorithms are tested on an integrated ELD problem with renewable energy sources and it has been perceived that the fuel cost in 6 generating unit system with HHO is 316495.72 \$/day and with hHHO-RES it is 316486.72 \$/day. Similarly, with SMA 316539.6 \$/day and hSMA-RES gives 316486.716 \$/day which shows the better performance of hSMA-RES algorithm. Also, the fuel cost in 7 generating unit system with HHO is 283632.1 \$/day and with hHHO-RES it is 283631.92 \$/day. Similarly, with SMA 283784.62 \$/day and hSMA-RES gives 283631.91 \$/day which shows the better performance of both hHHO-RES and hSMA-RES algorithm. The fuel cost in 10 generating unit system with renewable energy using HHO is 630080.66 \$/day and with hHHO-RES it is 630078.91 \$/day. Similarly, with SMA 633021.053 \$/day and hSMA-RES gives 630077.257 \$/day which shows the better performance of hSMA-RES algorithm.
- The proposed memetic meta-heuristic algorithms are tested on combined economic load dispatch problem with the load of EVs and it has been observed that the fuel cost in 6 generating unit system with HHO is 397193.21 \$/day and

with hHHO-RES it is 397186.91 \$/day. Similarly, with SMA 397231.67 \$/day and hSMA-RES gives 397186.91\$/day. This also proves better performance of proposed memetic algorithms. In 7 generating unit system the fuel cost outcomes with HHO is 296172.24 \$/day and with hHHO-RES it is 296172.24 \$/day. Similarly, with SMA 295522.05 \$/day and hSMA-RES gives 295334.54 \$/day. This also proves better performance of proposed memetic algorithms in regard to classical methods and memetic SMA performs better among the other methods. In 10 generating unit system the fuel cost outcomes with HHO is 649487.58 \$/day and with hHHO-RES it is 649486.69 \$/day. Similarly, with SMA 652693.5 \$/day and hSMA-RES gives 649483.15 \$/day. This also proves the performance of proposed memetic algorithms is superior to classical methods and memetic SMA performs better among the other methods.

- The proposed memetic meta-heuristic algorithms are tested on combined economic load dispatch problem with renewable energy sources and PEVs/BEV/BESS. It has been observed that the fuel cost in 6 generating unit system with HHO is 326621.3 \$/day and with hHHO-RES it is 326614.1822 \$/day. Similarly, with SMA 326662.08 \$/day and hSMA-RES gives 326614.1824 \$/day. Here, the performance of both memetic algorithms hHHO-RES and hSMA-RES is superior to other approaches. In case of 7 generating unit system the fuel cost outcomes with HHO is 291213.44 \$/day and with hHHO-RES it is 291213.39 \$/day. Similarly, with SMA 291464.95 \$/day and hSMA-RES gives 291213.382 \$/day. This also proves better performance of proposed memetic algorithms in regard to classical methods. In 10 generating unit system the fuel cost outcomes with HHO is 642463.29 \$/day and with hHHO-RES it is 642355.802 \$/day. Similarly, with SMA 645886.777 \$/day and hSMA-RES gives 642463.29 \$/day. This also proves the performance of proposed memetic algorithms is superior to classical methods and memetic algorithms performs better with minimized results.
- It has been concluded that the cost can be minimized by considering the impact of renewable energy sources with conventional sources and approximately 11% savings are possible in fuel cost. After considering the EV load and using the EVs

as BESSs with RESs savings of 17.76% is possible in regard to the cases considered.

- It has also been concluded that the average improvement in results using developed memetic algorithms hSMA-RES and hHHO-RES as compared to other algorithms is 0.8% and has performed better than the conventional SMA and HHO in most of the cases considered.

6.3 SCOPE FOR FUTURE WORK

The scope of research can be extended in following areas in future:

- (i) The scalar ELD problem can be further explored to multi-objective problem, multi-area economic dispatch problems, automatic generation control, optimal power flow, hydrothermal scheduling, unit commitment and other electrical problems using proposed memetic methods.
- (ii) The aforesaid problems can further be explored to integrated problems that can be combined with PEVs/BEVs/RESs for profit based electrical system.
- (iii) The work can be extended considering charging/discharging policies, cost of battery and services for EVs in combined economic load dispatch problem for real time situations.
- (iv) The proposed methods can be implemented to a microgrid/ smart grid problem considering the impact of battery degradation and TOU in distributed energy storage systems and can be compared with linear programming models.
- (v) The work can be extended from active power controls to real time functions considering reactive power balance with voltage and frequency controls using the proposed approaches.
- (vi) The proposed memetic algorithms can further be extended to frame new variants of these methods and implement for cost reduction in electrical power operation and control.

REFERENCES

- [1] G. B. S. Allen J. Wood, Bruce F. Wollenberg, Power Generation, Operation, and Control, 3rd Edition. .
- [2] M. P. Nitin Tyagi , Hari Mohan Dubey, “Economic load dispatch of wind-solar-thermal system using backtracking search algorithm,” *Int. J. Eng. Sci. Technol.*, vol. 8, no. 4, pp. 16–27, 2016.
- [3] P. Aliasghari, B. Mohammadi-ivatloo, M. Alipour, M. Abapour, and K. Zare, “Optimal Scheduling of Plug-in Electric Vehicles and Renewable Micro-grid in Energy and Reserve Markets Considering Demand Response Program,” *J. Clean. Prod.*, 2018, doi: 10.1016/j.jclepro.2018.03.058.
- [4] 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.
- [5] D. P. K. and J. S.Dhillon, Power System Optimization, Second. New Delhi: PHI Learning Private Limited, 2012.
- [6] U. K. Debnath, I. Ahmad, D. Habibi, and A. Y. Saber, “Energy storage model with gridable vehicles for economic load dispatch in the smart grid,” *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 1017–1024, 2015, doi: 10.1016/j.ijepes.2014.09.004.
- [7] S. Freund, S. Hume, and J. Stekli, “Chapter 7 - Energy storage services,” in *Thermal, Mechanical, and Hybrid Chemical Energy Storage Systems*, K. Brun, T. Allison, and R. Dennis, Eds. Academic Press, 2021, pp. 451–462.
- [8] Y. Lin, X. Zhang, S. Yin, J. Wang, and D. Shi, “Real-Time Economic Dispatch for Integrated Energy Microgrid Considering Ancillary Services,” in *2020 IEEE Power Energy Society General Meeting (PESGM)*, Aug. 2020, pp. 1–5, doi: 10.1109/PESGM41954.2020.9281659.
- [9] D. H. Wolpert and W. G. Macready, “No Free Lunch Theorems for Optimization I Introduction,” *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 67–82, 1997, doi: 10.1145/1389095.1389254.
- [10] W. Zhou, P. Wang, A. A. Heidari, M. Wang, and H. Chen, “Multi-core Sine Cosine Optimization : Methods and Inclusive Analysis,” *Expert Syst. Appl.*, p. 113974, 2020, doi: 10.1016/j.eswa.2020.113974.
- [11] K. D. Lee, “R,” H. Vierra. G.D. Nagel R.T. Jenkins, vol. 104, no. 8, pp. 2072–2078, Aug. 1985.
- [12] A. A. El-Keib, H. Ma, and J. L. Hart, “Environmentally constrained economic dispatch using the LaGrangian relaxation method,” *IEEE Trans. Power Syst.*, vol. 9, no. 4, pp. 1723–1729, Nov. 1994, doi: 10.1109/59.331423.
- [13] P. Hota, R. Chakrabarti, and P. K. Chattopadhyay, “Economic emission load dispatch with line flow constraints using sequential quadratic programming technique,” *J. Inst. Eng. Electr. Eng. Div.*, pp. 21–25, Jan. 2000.

- [14] 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.
- [15] J. Parikh and D. Chattopadhyay, "A multi-area linear programming approach for analysis of economic operation of the Indian power system," *IEEE Trans. Power Syst.*, vol. 11, no. 1, pp. 52–58, 1996.
- [16] Z.-X. Liang and J. D. Glover, "A zoom feature for a dynamic programming solution to economic dispatch including transmission losses," *IEEE Trans. Power Syst.*, vol. 7, no. 2, pp. 544–550, 1992.
- [17] C.-T. Su and C.-T. Lin, "New approach with a Hopfield modeling framework to economic dispatch," *IEEE Trans. Power Syst.*, vol. 15, no. 2, pp. 541–545, 2000, doi: 10.1109/59.867138.
- [18] M. A. Abido, "A niched Pareto genetic algorithm for multiobjective environmental/economic dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 25, no. 2, pp. 97–105, 2003, doi: [https://doi.org/10.1016/S0142-0615\(02\)00027-3](https://doi.org/10.1016/S0142-0615(02)00027-3).
- [19] N. Sinha, R. Chakrabarti, and P. K. Chattopadhyay, "Evolutionary programming techniques for economic load dispatch," *IEEE Trans. Evol. Comput.*, vol. 7, no. 1, pp. 83–94, Feb. 2003, doi: 10.1109/TEVC.2002.806788.
- [20] Z.-L. Gaing, "Gaing, Z.-L.: Particle Swarm Optimization to Solving the Economic Dispatch Considering the Generator Constraints. *IEEE Tans. on Power Syst.* 18(3), 1187-1195," *Power Syst. IEEE Trans.*, vol. 18, pp. 1187–1195, 2003, doi: 10.1109/TPWRS.2003.814889.
- [21] T. K. Abdul Rahman, Z. M. Yasin, and W. N. W. Abdullah, "Artificial-immune-based for solving economic dispatch in power system," in *PECon 2004. Proceedings. National Power and Energy Conference, 2004.*, 2004, pp. 31–35, doi: 10.1109/PECON.2004.1461611.
- [22] T. A. A. Victoire and A. E. Jeyakumar, "Deterministically guided PSO for dynamic dispatch considering valve-point effect," *Electr. Power Syst. Res.*, vol. 73, no. 3, pp. 313–322, 2005, doi: <https://doi.org/10.1016/j.epsr.2004.07.005>.
- [23] C.-L. Chiang, "Improved Genetic Algorithm for Power Economic Dispatch of Units With Valve-Point Effects and Multiple Fuels," *Power Syst. IEEE Trans.*, vol. 20, pp. 1690–1699, 2005, doi: 10.1109/TPWRS.2005.857924.
- [24] M. Sudhakaran, P. A.-D.-V. Raj, and T. G. Palanivelu, "Application of Particle Swarm Optimization for Economic Load Dispatch Problems," in *2007 International Conference on Intelligent Systems Applications to Power Systems*, 2007, pp. 1–7, doi: 10.1109/ISAP.2007.4441694.
- [25] A. L. Devi and O. V. Krishna, "Evolutionary Algorithms-A Case Study," vol. 3, no. 6, pp. 28–35, 2008.
- [26] P. D. I. Musirin, N. Faezaa, M. Kalil, M. Idris, T. K. A. Rahman, and M. R. Adzman, "Ant Colony Optimization (ACO) Technique in Economic Power Dispatch Problems," *Lect. Notes Eng. Comput. Sci.*, vol. 33, 2008, doi:

10.1007/978-1-4020-9532-0_15.

- [27] L. dos S. Coelho and C. S. Lee, "Solving economic load dispatch problems in power systems using chaotic and Gaussian particle swarm optimization approaches," *Int. J. Electr. Power Energy Syst.*, vol. 30, no. 5, pp. 297–307, 2008, doi: 10.1016/j.ijepes.2007.08.001.
- [28] V. Tamilselvan, V. Shanmugasundaram, and S. Naveen, "Economic Dispatch with Valve Point Effect using various PSO Techniques," vol. 2, no. 6, pp. 130–135, 2009.
- [29] L. Singh and J. S. Dhillon, "Cardinal priority ranking based decision making for economic-emission dispatch problem," vol. 1, no. 1, pp. 272–282, 2009.
- [30] E. Sailajamatamyahoocom, "A Fast Computational Genetic Algorithm for Economic Load Dispatch," vol. 1, no. 1, pp. 349–356, 2009.
- [31] K. Chaturvedi, M. Pandit, and L. Srivastava, "Particle swarm optimization with time varying acceleration coefficients for non-convex economic power dispatch," *Int. J. Electr. Power Energy Syst.*, vol. 31, pp. 249–257, 2009, doi: 10.1016/j.ijepes.2009.01.010.
- [32] M. A. Abido, "Multiobjective particle swarm optimization for environmental/economic dispatch problem," *Electr. Power Syst. Res.*, vol. 79, no. 7, pp. 1105–1113, 2009, doi: <https://doi.org/10.1016/j.epsr.2009.02.005>.
- [33] S. Duman, U. Güvenc, and N. Yörükeren, "Gravitational Search Algorithm For Economic Dispatch With Valve-Point Effects," 2010.
- [34] A. Bhattacharya and P. K. Chattopadhyay, "Solving complex economic load dispatch problems using biogeography-based optimization," *Expert Syst. Appl.*, vol. 37, no. 5, pp. 3605–3615, 2010, doi: <https://doi.org/10.1016/j.eswa.2009.10.031>.
- [35] A. Bhattacharya and P. K. Chattopadhyay, "Application of Biogeography-based Optimization for Solving Multi-objective Economic Emission Load Dispatch Problems," *Electr. Power Components Syst.*, vol. 38, no. 3, pp. 340–365, 2010, doi: 10.1080/15325000903273296.
- [36] V. Selvi and D. R. Umarani, "Comparative Analysis of Ant Colony and Particle Swarm Optimization Techniques," *Int. J. Comput. Appl.*, vol. 5, no. 4, pp. 1–6, 2010, doi: 10.5120/908-1286.
- [37] S. Rao Rayapudi, "An intelligent water drop algorithm for solving economic load dispatch problem," *World Acad. Sci. Eng. Technol.*, vol. 82, no. 10, pp. 6–12, 2011.
- [38] V. R. Pandi and B. K. Panigrahi, "Dynamic economic load dispatch using hybrid swarm intelligence based harmony search algorithm," *Expert Syst. Appl.*, vol. 38, no. 7, pp. 8509–8514, 2011, doi: 10.1016/j.eswa.2011.01.050.
- [39] B. Shaw, S. Ghoshal, V. Mukherjee, and S. P. Ghoshal, "Solution of economic load dispatch problems by a novel seeker optimization algorithm," *Int. J. Electr. Eng. Informatics*, vol. 3, no. 1, pp. 26–42, 2011, doi: 10.15676/ijeei.2011.3.1.3.

- [40] N. A. Rahmat and I. Musirin, "Differential Evolution Ant Colony Optimization (DEACO) technique in solving Economic Load Dispatch problem," in 2012 IEEE International Power Engineering and Optimization Conference Melaka, Malaysia, 2012, pp. 263–268, doi: 10.1109/PEOCO.2012.6230872.
- [41] R. K. Swain, N. C. Sahu, and P. K. Hota, "Gravitational Search Algorithm for Optimal Economic Dispatch," *Procedia Technol.*, vol. 6, pp. 411–419, 2012, doi: <https://doi.org/10.1016/j.protcy.2012.10.049>.
- [42] X. Yang, S. Soheil, S. Hosseini, and A. Hossein, "Firefly Algorithm for solving non-convex economic dispatch problems with valve loading effect," *Appl. Soft Comput. J.*, vol. 12, no. 3, pp. 1180–1186, 2012, doi: 10.1016/j.asoc.2011.09.017.
- [43] G. R. Tankasala, "Artificial Bee Colony Optimisation for Economic Load Dispatch of a Modern Power system," vol. 3, no. 1, pp. 1–6, 2012.
- [44] H. Hardiansyah, J. Junaidi, and Y. MS, "Solving Economic Load Dispatch Problem Using Particle Swarm Optimization Technique," *Int. J. Intell. Syst. Appl.*, vol. 4, no. 12, pp. 12–18, 2012, doi: 10.5815/ijisa.2012.12.02.
- [45] R. Subramanian, K. Thanushkodi, and A. Prakash, "An efficient meta heuristic algorithm to solve economic load dispatch problems," *Iran. J. Electr. Electron. Eng.*, vol. 9, no. 4, pp. 246–252, 2013.
- [46] D. Rama Prabha, A. Krishna Prasad Raju, S. Saikumar, R. Mageshvaran, and T. Narendiranath Babu, "Application of Bacterial Foraging and Firefly Optimization Algorithm to Economic Load Dispatch including valve point loading," in 2013 International Conference on Circuits, Power and Computing Technologies (ICCPCT), 2013, pp. 99–106, doi: 10.1109/ICCPCT.2013.6528969.
- [47] K. Thenmalar and A. Allirani, "Solution of firefly algorithm for the economic thermal power dispatch with emission constraint in various generation plants," in 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT), 2013, pp. 1–7, doi: 10.1109/ICCCNT.2013.6726808.
- [48] M. Younes, "A novel hybrid FFA-ACO algorithm for economic power dispatch," *Control Eng. Appl. Informatics*, vol. 15, no. 2, pp. 67–77, 2013.
- [49] A. B. S. Serapião, "Cuckoo Search for Solving Economic Dispatch Load Problem," vol. 2013, no. November, pp. 385–390, 2013.
- [50] L. Wang and L. Li, "An effective differential harmony search algorithm for the solving non-convex economic load dispatch problems," *Int. J. Electr. Power Energy Syst.*, vol. 44, no. 1, pp. 832–843, 2013, doi: <https://doi.org/10.1016/j.ijepes.2012.08.021>.
- [51] H. M. Dubey, M. Pandit, B. K. Panigrahi, and M. Udgir, "Economic Load Dispatch by Hybrid Swarm Intelligence Based Gravitational Search Algorithm," *Int. J. Intell. Syst. Appl.*, vol. 5, no. 8, pp. 21–32, 2013, doi: 10.5815/ijisa.2013.08.03.

- [52] S. Tiwari, A. Kumar, G. S. Chaurasia, G. S. Sirohi, and W. S. Email, "Economic_Load_Dispatch_Using_Particle_Sw," *Int. J. Appl. or Innov. Eng. Manag.*, vol. 2, no. 4, pp. 476–485, 2013.
- [53] R. Effatnejad, H. Aliyari, H. Tadayyoni, and A. Abdollahshirazi, "Novel Optimization Based on the Ant Colony for Economic Dispatch," *Int. J.*, vol. 15, no. 2, pp. 75–80, 2013.
- [54] D. Secui, S. Dzitac, G. Bendea, C. Bendea, and C. Hora, "A Modified Harmony Search Algorithm for the Economic Dispatch Problem," *Stud. Informatics Control*, vol. 23, 2014.
- [55] R. L. Kherfane, M. Younes, N. Kherfane, and F. Khodja, "Solving Economic Dispatch Problem Using Hybrid GA-MGA," *Energy Procedia*, vol. 50, pp. 937–944, 2014, doi: 10.1016/j.egypro.2014.06.112.
- [56] A. Kaur, "Analysis of Economic Load Dispatch Using Genetic Algorithm," 2014.
- [57] S. P. Singh, R. Tyagi, and A. Goel, "Genetic Algorithm for Solving the Economic Load Dispatch," *Int. J. Electron. Electr. Eng.*, vol. 7, no. 5, pp. 523–528, 2014.
- [58] B. Sahu, A. Lall, S. Das, and T. Manoj Kumar Patra, "Economic Load Dispatch in Power System using Genetic Algorithm," *Int. J. Comput. Appl.*, vol. 67, no. 7, pp. 17–22, 2013, doi: 10.5120/11407-6727.
- [59] B. MAHDAD and K. Srairi, "Solving Practical Economic Dispatch Problems Using Improved Artificial Bee Colony Method," *Int. J. Intell. Syst. Appl.*, vol. 6, no. 7, pp. 36–43, 2014, doi: 10.5815/ijisa.2014.07.05.
- [60] N. dutt upadhyay and R. singh, "Soft Computing Technique Based Economic Load Dispatch Using Biogeography-Based Optimization Algorithm," *Int. J. Innov. Res. Sci. Eng. Technol.*, vol. 03, no. 08, pp. 15212–15219, 2014, doi: 10.15680/ijirset.2014.0308021.
- [61] L. I. Wong, M. H. Sulaiman, M. R. Mohamed, and M. S. Hong, "Grey Wolf Optimizer for solving economic dispatch problems," in *2014 IEEE International Conference on Power and Energy (PECon)*, 2014, pp. 150–154, doi: 10.1109/PECON.2014.7062431.
- [62] S. Prakash, J. Jain, S. Hasnat, N. Verma, and Sachin, "Economic Load Dispatch with Valve Point Loading Effect Using Optimization Techniques," in *Proceedings of International Conference on Artificial Intelligence and Applications*, 2021, pp. 407–416.
- [63] S. Sahoo, K. Mahesh Dash, R. C. Prusty, and A. K. Barisal, "Comparative analysis of optimal load dispatch through evolutionary algorithms," *Ain Shams Eng. J.*, vol. 6, no. 1, pp. 107–120, 2015, doi: 10.1016/j.asej.2014.09.002.
- [64] M. M. Nischal and S. Mehta, "Optimal Load Dispatch Using Ant Lion Optimization," *Int. J. Eng. Res. Appl.*, vol. 5, no. 8, pp. 10–19, 2015.
- [65] S. Sharma, S. Mehta, and N. Chopra, "Grey wolf optimization for solving non-

- convex economic load dispatch,” *Eng. Res.*, vol. 3, no. 3, pp. 17–21, 2015.
- [66] D. Prasad Reddy P and M. Suresh, “Economic Load Dispatch Problem With Valve Point Effect Using Firefly Algorithm,” *Int. J. Eng. Sci. Res. Technol.*, vol. 4, pp. 557–560, 2015.
 - [67] C. D. Tran, T. T. Dao, V. S. Vo, and T. T. Nguyen, “Economic Load Dispatch with Multiple Fuel Options and Valve Point Effect Using Cuckoo Search Algorithm with Different Distributions,” *Int. J. Hybrid Inf. Technol.*, vol. 8, no. 1, pp. 305–316, 2015, doi: 10.14257/ijhit.2015.8.1.27.
 - [68] M. Saka, I. Eke, S. S. Tezcan, and M. C. Taplamacioglu, “Analysis of economic load dispatch with a lot of constraints using vortex search algorithm,” *Adv. Sci. Technol. Eng. Syst.*, vol. 2, no. 6, pp. 151–156, 2017, doi: 10.25046/aj020619.
 - [69] J. Lin, C. L. Chen, S. F. Tsai, and C. Yuan, “New intelligent particle swarm optimization algorithm for solving economic dispatch with valve-point effects,” *J. Mar. Sci. Technol.*, vol. 23, no. 1, pp. 44–53, 2015, doi: 10.6119/JMST-013-1231-2.
 - [70] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, “Solution of non-convex economic load dispatch problem using Grey Wolf Optimizer,” *Neural Comput. Appl.*, vol. 27, no. 5, 2016, doi: 10.1007/s00521-015-1934-8.
 - [71] I. N. Trivedi, A. Kumar, A. H. Ranpariya, and P. Jangir, “Economic Load Dispatch problem with ramp rate limits and prohibited operating zones solve using Levy flight Moth-Flame optimizer,” in 2016 International Conference on Energy Efficient Technologies for Sustainability (ICEETS), Apr. 2016, pp. 442–447, doi: 10.1109/ICEETS.2016.7583795.
 - [72] Z. G. Hassan, M. Ezzat, and A. Y. Abdelaziz, “Solving unit commitment and economic load dispatch problems using modern optimization algorithms,” *Int. J. Eng. Sci. Technol.*, vol. 9, no. 4, p. 10, 2017, doi: 10.4314/ijest.v9i4.2.
 - [73] F. X. Rugema, G. Yan, S. Mugemanyi, Q. Jia, S. Zhang, and C. Bananeza, “A Cauchy-Gaussian Quantum-Behaved Bat Algorithm Applied to Solve the Economic Load Dispatch Problem,” *IEEE Access*, vol. 9, pp. 3207–3228, 2020, doi: 10.1109/access.2020.3034730.
 - [74] Q.-G. Wang, M. Yu, and J. Liu, “An integrated solution for optimal generation operation efficiency through dynamic economic dispatch,” *Mater. Today Proc.*, vol. 38, no. xxxx, pp. 639–646, 2021, doi: 10.1016/j.matpr.2020.03.535.
 - [75] R. P. Parouha and P. Verma, “An innovative hybrid algorithm to solve nonconvex economic load dispatch problem with or without valve point effects,” *Int. Trans. Electr. Energy Syst.*, vol. 31, no. 1, p. e12682, 2021, doi: <https://doi.org/10.1002/2050-7038.12682>.
 - [76] S. Deb, D. S. Abdelminaam, M. Said, and E. H. Houssein, “Recent Methodology-Based Gradient-Based Optimizer for Economic Load Dispatch Problem,” *IEEE Access*, vol. 9, pp. 44322–44338, 2021, doi: 10.1109/ACCESS.2021.3066329.

- [77] A. Kaur, L. Singh, and J. S. Dhillon, "Modified Krill Herd Algorithm for constrained economic load dispatch problem," *Int. J. Ambient Energy*, vol. 0, no. 0, pp. 1–11, 2021, doi: 10.1080/01430750.2021.1888798.
- [78] H. Raj and M. Sharma, "Whale Optimization Algorithm for Static and Dynamic Load Dispatch," in *Advances in Engineering Design*, 2021, pp. 429–440.
- [79] H. Zhong, X. Yan, and Z. Tan, "Real-Time Distributed Economic Dispatch Adapted to General Convex Cost Functions: A Secant Approximation-Based Method," *IEEE Trans. Smart Grid*, vol. 12, no. 3, pp. 2089–2101, 2021, doi: 10.1109/TSG.2020.3049054.
- [80] N. K. Navin, "A Multiagent Fuzzy Reinforcement Learning Approach for Economic Power Dispatch Considering Multiple Plug-In Electric Vehicle Loads," *Arab. J. Sci. Eng.*, vol. 46, no. 2, pp. 1431–1449, 2021, doi: 10.1007/s13369-020-05153-7.
- [81] Allen. J. Bruce F. Wollenberg "Power Generation, Operation and Control", John Wiley & Sons, Technology & Engineering, 7: Wood, 2012.
- [82] D. P. Kothari And J. S. Dhillon, *Power System Optimization*. Phi Learning, 2010.
- [83] P. H. Chen and H. C. Chang, "Large scale economic dispatch by genetic algorithm, *IEEE Transactions on Power Systems*," Vol., vol. 10, no. 4, pp. 1919–1926, 1995.
- [84] C. L. Chiang, "Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels," *IEEE Trans. Power Syst.*, vol. 20, no. 4, pp. 1690–1699, 2005, doi: 10.1109/TPWRS.2005.857924.
- [85] N.-R. H. Amjady N, "Solution of non-convex and non-smooth economic dispatch by a new adaptive real coded genetic algorithm," *Expert Syst. Appl.*, vol. 37, pp. 5239–45, 2010.
- [86] M. A. Swain AK, "A novel hybrid evolutionary programming method for function optimization," in *Proc 2000 Congr Evolut Comput*, 2000, vol. 1, pp. 699–705.
- [87] W. X. Liu W, Li M, "An improved particle swarm optimization algorithm for optimal power flow," in *Power electronics and motion control conference (IPEMC)*, Wuhan, China, pp. 2448–50.
- [88] N. H. Neyestani M, Farsangi MM, "A modified particle swarm optimization for economic dispatch with non-smooth cost functions.," *Eng Appl Artif Int*, vol. 23, pp. 1121–6, 2010.
- [89] A. Srinivasa Reddy and K. Vaisakh, "Shuffled differential evolution for large scale economic dispatch," *Electr. Power Syst. Res.*, vol. 96, no. Complete, pp. 237–245, 2013, doi: 10.1016/j.epsr.2012.11.010.
- [90] A. Bhattacharya and P. K. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems, *IEEE Transactions on Power systems*," Vol., vol. 25, no. 2, pp. 1064–1077, 2010.

- [91] A. Y. Saber and P. O. Box, "Economic Load Dispatch using Bacterial Foraging Technique with Particle Swarm Optimization Biased Evolution," 2008.
- [92] A. Belmadani, L. Benasla, and M. Rahli, "Different Versions of Harmony Search Algorithm to Solve Dynamic Economic-Environmental Dispatch," no. 22, pp. 49–64, 2013.
- [93] K. Y. Lee, A. Sode-yome, and J. H. Park, "Neural Networks for Economic Load Dispatch," vol. 13, no. 2, pp. 519–526, 1998.
- [94] C. S. Affijulla S, "A new intelligence solution for power system economic load dispatch," in 10th International conference on environment and electrical engineering, Rome, 2011, pp. 1–5.
- [95] M. K. Idris, T. Khawa, A. Rahman, S. M. Ieee, and M. R. Adzman, "Ant Colony Optimization (ACO) Technique in Economic Power Dispatch Problems," vol. II, no. 1, pp. 19–21, 2008.
- [96] S. R. Rayapudi, "An Intelligent Water Drop Algorithm For Solving Economic Load Dispatch Problem," Int. J. Electr. Electron. Eng., vol. 5, no. 2, p. 2011, 2011.
- [97] V. Kumar and K. S. K. Bath, "Solution of non-convex economic load dispatch problem using Grey Wolf Optimizer," Neural Comput. Appl., 2015, doi: 10.1007/s00521-015-1934-8.
- [98] T. A. Albert and A. E. Jeyakumar, "Hybrid PSO – SQP for economic dispatch with valve-point effect," vol. 71, pp. 51–59, 2004, doi: 10.1016/j.epsr.2003.12.017.
- [99] E. E. Elattar, "Electrical Power and Energy Systems A hybrid genetic algorithm and bacterial foraging approach for dynamic economic dispatch problem," Int. J. Electr. Power Energy Syst., vol. 69, pp. 18–26, 2015, doi: 10.1016/j.ijepes.2014.12.091.
- [100] H. M. Dubey, M. Pandit, B. K. Panigrahi, and M. Udgir, "A fuzzified improved hybrid PSO-GSA for environmental / economic power dispatch," vol. 6, no. 4, pp. 11–23, 2014.
- [101] V. Kumar, S. K. Bath, and J. S. Dhillon, "Electrical Power and Energy Systems Implementation of hybrid harmony search / random search algorithm for single area unit commitment problem," Int. J. Electr. POWER ENERGY Syst., vol. 77, pp. 228–249, 2016, doi: 10.1016/j.ijepes.2015.11.045.
- [102] N. Chopra and M. Mohsin Ansari, "Golden jackal optimization: A novel nature-inspired optimizer for engineering applications," Expert Syst. Appl., vol. 198, p. 116924, 2022, doi: <https://doi.org/10.1016/j.eswa.2022.116924>.
- [103] J. Zhang, J. Zhang, F. Zhang, M. Chi, and L. Wan, "An Improved Symbiosis Particle Swarm Optimization for Solving Economic Load Dispatch Problem," J. Electr. Comput. Eng., vol. 2021, p. 8869477, 2021, doi: 10.1155/2021/8869477.
- [104] S. V.P., S. M., and S. P.D., "Large-scale economic load dispatch using squirrel

- search algorithm,” *Int. J. Energy Sect. Manag.*, vol. 14, no. 6, pp. 1351–1380, Jan. 2020, doi: 10.1108/IJESM-02-2020-0012.
- [105] M. Gholamghasemi, E. Akbari, M. B. Asadpoor, and M. Ghasemi, “A new solution to the non-convex economic load dispatch problems using phasor particle swarm optimization,” *Appl. Soft Comput.*, vol. 79, pp. 111–124, 2019, doi: <https://doi.org/10.1016/j.asoc.2019.03.038>.
- [106] A. N. A. Iman Niazazari, Oveis Asgari Gashteroodkhani, “A Novel Economic Dispatch in Power Grids Based on Enhanced Firework Algorithm,” *Eur. J. Electr. Comput. Eng.*, vol. 3, no. 4, pp. 1–5, 2019.
- [107] S. A. Muhammad Sulaiman, Masihullah, Zubair Hussain and R. A. K. Wali Khan Mashwani, Muhammad Asif Jan, “Implementation of improved grasshopper optimization algorithm to solve economic load dispatch problems,” *Hacettepe J. Math. Stat.*, vol. XX(x), pp. 1–21, 2019.
- [108] H. R. Hamid Rezaie, M.H. Kazemi-Rahbar, Behrooz Vahidi, “Solution of combined economic and emission dispatch problem using a novel chaotic improved harmony search algorithm,” *J. Comput. Des. Eng.*, vol. 6, pp. 447–467, 2019.
- [109] Q. Zhang, D. Zou, N. Duan, and X. Shen, “An adaptive differential evolutionary algorithm incorporating multiple mutation strategies for the economic load dispatch problem,” *Appl. Soft Comput. J.*, vol. 78, pp. 641–669, 2019, doi: 10.1016/j.asoc.2019.03.019.
- [110] D. Singh and J. S. Dhillon, “Ameliorated Grey Wolf Optimization for Economic Load Dispatch,” *Energy*, 2018, doi: 10.1016/j.energy.2018.11.034.
- [111] M. Nazari-heris, B. Mohammadi-ivatloo, and G. B. Gharehpetian, “A comprehensive review of heuristic optimization algorithms for optimal combined heat and power dispatch from economic and environmental perspectives,” *Renew. Sustain. Energy Rev.*, no. June, pp. 1–16, 2017, doi: 10.1016/j.rser.2017.06.024.
- [112] D. C. Secui, “Large-scale multi-area economic/emission dispatch based on a new symbiotic organisms search algorithm,” *Energy Convers. Manag.*, vol. 154, pp. 203–223, 2017.
- [113] S. Ali, M. Pradhan, P. Kumar, and T. Pal, “Opposition-based krill herd algorithm applied to economic load dispatch problem,” *AIN SHAMS Eng. J.*, 2016, doi: 10.1016/j.asej.2016.02.003.
- [114] M. Singh and J. S. Dhillon, “Multiobjective thermal power dispatch using opposition-based greedy heuristic search,” *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 339–353, 2016, doi: 10.1016/j.ijepes.2016.03.016.
- [115] N. Singh, J. S. Dhillon, and D. P. Kothari, “Synergic predator-prey optimization for economic thermal power dispatch problem,” *Appl. Soft Comput.*, vol. 43, pp. 298–311, 2016, doi: 10.1016/j.asoc.2016.02.042.
- [116] V. K. Kamboj, S. K. Bath, and J. S. Dhillon, “Solution of non-convex economic

- load dispatch problem using Grey Wolf Optimizer,” *Neural Comput. Appl.*, 1934, doi: 10.1007/s00521-015-1934-8.
- [117] R. Arul, S. Velusami, and G. Ravi, “A new algorithm for combined dynamic economic emission dispatch with security constraints,” *Energy*, 2014, doi: 10.1016/j.energy.2014.11.037.
 - [118] A. A. Mousa and E. E. Elattar, “Best Compromise Alternative to EELD Problem using Hybrid Multiobjective Quantum Genetic Algorithm,” vol. 2902, no. 6, pp. 2889–2902, 2014.
 - [119] M. Basu, “Teaching-learning-based optimization algorithm for multi-area economic dispatch,” *Energy*, vol. 68, pp. 21–28, 2014, doi: 10.1016/j.energy.2014.02.064.
 - [120] V. K. Reddy AS, “Shuffled differential evolution for large scale economic dispatch,” *Electr Power Syst Res*, vol. 96, pp. 237–45, 2013.
 - [121] S. Sayah and H. Abdellatif, “A hybrid differential evolution algorithm based on particle swarm optimization for nonconvex economic dispatch problems,” *Appl. Soft Comput.*, vol. 13, pp. 1608–1619, 2013, doi: 10.1016/j.asoc.2012.12.014.
 - [122] Y. M. Hardiansyah, Junaidi, “Solving Economic Load Dispatch Problem Using Particle Swarm Optimization Technique,” *I.J. Intell. Syst. Appl.*, vol. 12, pp. 12–18, 2012.
 - [123] M. Basu, “Economic environmental dispatch using multi-objective differential evolution,” *Appl. Soft Comput. J.*, vol. 11, no. 2, pp. 2845–2853, 2011, doi: 10.1016/j.asoc.2010.11.014.
 - [124] A. Bhattacharya and P. K. Chattopadhyay, “Hybrid differential evolution with biogeography-based optimization algorithm for solution of economic emission load dispatch problems,” *Expert Syst. Appl.*, vol. 38, p. 2011, 2011.
 - [125] H. Lu, P. Sriyanyong, Y. Hua, and T. Dillon, “Electrical Power and Energy Systems Experimental study of a new hybrid PSO with mutation for economic dispatch with non-smooth cost function,” *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 9, pp. 921–935, 2010, doi: 10.1016/j.ijepes.2010.03.001.
 - [126] M. Sharma, M. Pandit, and L. Srivastava, “Multi-area economic dispatch with tie-line constraints employing evolutionary approach,” vol. 2, no. 3, pp. 132–149, 2010.
 - [127] Y. M. Chen and W. S. Wang, “A particle swarm approach to solve environmental/economic dispatch problem,” *Int. J. Ind. Eng. Comput.*, vol. 1, no. 2, pp. 157–172, 2010, doi: 10.5267/j.ijiec.2010.02.005.
 - [128] P. S. Manoharan, P. S. Kannan, S. Baskar, and M. Willjuice Iruthayarajan, “Evolutionary algorithm solution and KKT based optimality verification to multi-area economic dispatch,” *Int. J. Electr. Power Energy Syst.*, vol. 31, no. 7–8, pp. 365–373, 2009, doi: 10.1016/j.ijepes.2009.03.010.
 - [129] M. Younes, M. Rahli, and L. A. Koridak, “Economic Power Dispatch Using

- Evolutionary Algorithm,” vol. 57, no. 4, pp. 211–217, 2006.
- [130] H. Zeynal, Y. Jiazhen, B. Azzopardi, and M. Eidiani, “Flexible economic load dispatch integrating electric vehicles,” *Proc. 2014 IEEE 8th Int. Power Eng. Optim. Conf. PEOCO 2014*, no. March, pp. 520–525, 2014, doi: 10.1109/PEOCO.2014.6814484.
 - [131] V. Gupta, S. R. K. S. Member, R. Kumar, and S. Member, “Multi-Aggregator Collaborative Electric Vehicle Charge Scheduling (CEVCS) Under Variable Energy Purchase and EV Cancellation Events,” vol. 3203, no. c, pp. 1–9, 2017, doi: 10.1109/TII.2017.2778762.
 - [132] B. Qu, B. Qiao, Y. Zhu, J. Liang, and L. Wang, “Dynamic power dispatch considering electric vehicles and wind power using decomposition based multi-objective evolutionary algorithm,” *Energies*, vol. 10, no. 12, 2017, doi: 10.3390/en10121991.
 - [133] Z. Yang, K. Li, A. Foley, and C. Zhang, “Optimal scheduling methods to integrate plug-in electric vehicles with the power system: A review,” *IFAC Proc. Vol.*, vol. 19, pp. 8594–8603, 2014.
 - [134] S. Hu et al., “Optimization strategy for economic power dispatch utilizing retired EV batteries as flexible loads,” *Energies*, vol. 11, no. 7, 2018, doi: 10.3390/en11071657.
 - [135] H. Liu, Y. Ji, H. Zhuang, and H. Wu, “Multi-objective dynamic economic dispatch of microgrid systems including vehicle-to-grid,” *Energies*, vol. 8, no. 5, pp. 4476–4495, 2015, doi: 10.3390/en8054476.
 - [136] P. You, S. Member, Z. Yang, and M. Chow, “Optimal Cooperative Charging Strategy for a Smart Charging Station of Electric Vehicles,” pp. 1–11, 2015.
 - [137] S. Pal, S. Member, R. Kumar, and S. Member, “Electric Vehicle Scheduling Strategy in Residential Demand Response Programs with Neighbor,” vol. 3203, no. c, 2017, doi: 10.1109/TII.2017.2787121.
 - [138] W. Gu, H. Yu, W. Liu, J. Zhu, and X. Xu, “Demand response and economic dispatch of power systems considering large-scale plug-in hybrid electric vehicles/electric vehicles (phevs/evs): A review,” *Energies*, vol. 6, no. 9, pp. 4394–4417, 2013, doi: 10.3390/en6094394.
 - [139] P. Goyal, A. Sharma, S. Vyas, and R. Kumar, “Customer and Aggregator Balanced Dynamic Electric Vehicle Charge Scheduling in a Smart Grid Framework,” pp. 276–283, 2016.
 - [140] 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.
 - [141] K. W. Cheung, S. Member, P. Shamsollahi, D. Sun, J. Milligan, and M. Potishnak, “Energy and Ancillary Service Dispatch for the Interim ISO New England Electricity Market,” vol. 15, no. 3, pp. 968–974, 2000.

- [142] Y. Lin, P. Barooah, and J. L. Mathieu, "Ancillary services through demand scheduling and control of commercial buildings," vol. 8950, no. c, pp. 1–12, 2016, doi: 10.1109/TPWRS.2016.2557764.
- [143] G. Singh, K. Dey, K. V. N. P. Kumar, A. Kumar, S. Rehman, and K. Gaur, "Ancillary Services in India- Evolution , Implementation and Benefits," 2016.
- [144] S. Behera, S. Behera, and A. K. Barisal, "Dynamic Economic Load Dispatch with Plug-in Electric Vehicles using Social Spider Algorithm," in 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Mar. 2019, pp. 489–494, doi: 10.1109/ICCMC.2019.8819640.
- [145] F. Tariq, S. Alelyani, G. Abbas, A. Qahmash, and M. R. Hussain, "Solving Renewables-Integrated Economic Load Dispatch Problem by Variant of Metaheuristic Bat-Inspired Algorithm," *Energies*, vol. 13, no. 23, p. 6225, Nov. 2020, doi: 10.3390/en13236225.
- [146] 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.
- [147] 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.
- [148] S. Mirjalili, "The ant lion optimizer," *Adv. Eng. Softw.*, vol. 83, pp. 80–98, 2015, doi: 10.1016/j.advengsoft.2015.01.010.
- [149] A. Yang X-s., "new metaheuristic bat-inspired algorithm," in *Nature inspired cooperative strategies for optimization (NICSO 2010)*, ; p. 65-74: Springer, 2010.
- [150] 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.
- [151] D. Simon, "Biogeography-Based Optimization," *IEEE Trans. Evol. Comput.*, vol. 12, no. 6, pp. 702–713, Dec. 2008.
- [152] S. Das, A. Biswas, S. Dasgupta, and A. Abraham, "Bacterial foraging optimization algorithm: Theoretical foundations, analysis, and applications," *Stud. Comput. Intell.*, vol. 203, pp. 23–55, 2009, doi: 10.1007/978-3-642-01085-9_2.
- [153] X. B. Meng, X. Z. Gao, L. Lu, Y. Liu, and H. Zhang, "A new bio-inspired optimisation algorithm: Bird Swarm Algorithm," *J. Exp. Theor. Artif. Intell.*, vol. 28, no. 4, pp. 673–687, 2016, doi: 10.1080/0952813X.2015.1042530.
- [154] H. C. Kuo and C. H. Lin, "Cultural evolution algorithm for global optimizations and its applications," *J. Appl. Res. Technol.*, vol. 11, no. 4, pp. 510–522, 2013, doi: 10.1016/S1665-6423(13)71558-X.
- [155] 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.
- [156] P. Civicioglu, “Backtracking Search Optimization Algorithm for numerical optimization problems,” *Appl. Math. Comput.*, vol. 219, no. 15, pp. 8121–8144, 2013, doi: 10.1016/j.amc.2013.02.017.
- [157] A. Kaveh and V. R. Mahdavi, “Colliding bodies optimization: Extensions and applications,” *Colliding Bodies Optim. Extensions Appl.*, pp. 1–284, 2015, doi: 10.1007/978-3-319-19659-6.
- [158] 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, Jan. 2013, doi: 10.1007/s00366-011-0241-y.
- [159] 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.
- [160] W. L. Snyder, H. D. Powell, and J. C. Rayburn, “Dynamic programming approach to unit commitment,” *IEEE Trans. Power Syst.*, vol. 2, pp. 339–347, 1987.
- [161] G. G. Wang, S. Deb, and L. D. S. Coelho, “Elephant Herding Optimization,” *Proc. - 2015 3rd Int. Symp. Comput. Bus. Intell. ISCBI 2015*, pp. 1–5, 2016, doi: 10.1109/ISCBI.2015.8.
- [162] 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.
- [163] H. Abedinpourshotorban, S. Mariyam Shamsuddin, Z. Beheshti, and D. N. A. Jawawi, “Electromagnetic field optimization: A physics-inspired metaheuristic optimization algorithm,” *Swarm Evol. Comput.*, vol. 26, pp. 8–22, 2016, doi: 10.1016/j.swevo.2015.07.002.
- [164] G. G. Wang, S. Deb, and L. D. S. Coelho, “Earthworm optimization algorithm: a bio-inspired metaheuristic algorithm for global optimization problems,” *Int. J. Bio-Inspired Comput.*, vol. 1, no. 1, p. 1, 2015, doi: 10.1504/IJBIC.2015.10004283.
- [165] N. Ghorbani and E. Babaei, “Exchange market algorithm,” *Appl. Soft Comput. J.*, vol. 19, no. April, pp. 177–187, 2014, doi: 10.1016/j.asoc.2014.02.006.
- [166] Y. Tan, Y. Tan, and Y. Zhu, “Fireworks Algorithm for Optimization Fireworks Algorithm for Optimization,” no. December, pp. 355–364, 2015, doi: 10.1007/978-3-642-13495-1.
- [167] X. S. Yang, “Firefly algorithm,” *Eng. Optim. pp*, vol. 221, 2010.
- [168] M. Ghaemi and M. R. Feizi-Derakhshi, “Forest optimization algorithm,” *Expert Syst. Appl.*, vol. 41, no. 15, pp. 6676–6687, 2014, doi:

10.1016/j.eswa.2014.05.009.

- [169] Y. X-s., “Flower pollination algorithm for global optimization,” in *Unconventional computation and natural computation*, ; p. 240-9: Springer, 2012.
- [170] 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.
- [171] S. A. Kazarlis, “A genetic algorithm solution to the unit commitment problem, *IEEE Transactions on Power Systems*, pp. 83 -92,” 1996.
- [172] 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.
- [173] V. N. Dieu and W. Ongsakul, “Ramp rate constrained unit commitment by improved priority list and augmented Lagrange Hopfield network,” *Electr. Power Syst. Res.*, vol. 78, no. 3, pp. 291–301, 2008, doi: 10.1016/j.epsr.2007.02.011.
- [174] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, “GSA: a gravitational search algorithm,” *Inf Sci*, vol. 179, p. 2232, 2009.
- [175] C. Dai, W. Chen, L. Ran, Y. Zhang, and Y. Du, “Human Group Optimizer with Local Search,” pp. 310–320, 2011.
- [176] E. Atashpaz-Gargari and C. Lucas, “Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition,” 2007 IEEE Congr. Evol. Comput. CEC 2007, pp. 4661–4667, 2007, doi: 10.1109/CEC.2007.4425083.
- [177] 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.
- [178] S. Karimkashi, S. Member, and A. A. Kishk, “Invasive Weed Optimization and its Features in Electromagnetics,” vol. 58, no. 4, pp. 1269–1278, 2010.
- [179] A. H. Gandomi and A. H. Alavi, “Krill herd: A new bio-inspired optimization algorithm,” *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 12, pp. 4831–4845, 2012, doi: 10.1016/j.cnsns.2012.05.010.
- [180] H. Shareef, A. A. Ibrahim, and A. H. Mutlag, “Lightning search algorithm,” *Appl. Soft Comput. J.*, 2015, doi: 10.1016/j.asoc.2015.07.028.
- [181] 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.*, 2012, doi: 10.1016/j.asoc.2012.11.026.
- [182] 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.

- [183] G. G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," *Neural Comput. Appl.*, 2015, doi: 10.1007/s00521-015-1923-y.
- [184] S. Mirjalili, "Knowledge-Based Systems 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.
- [185] 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.
- [186] C. Dai, Y. Zhu, W. Chen, and C. Engineering, "Seeker Optimization Algorithm," pp. 167–176, 2007.
- [187] A. Husseinzadeh Kashan, "A new metaheuristic for optimization: Optics inspired optimization (OIO)," *Comput. Oper. Res.*, vol. 55, pp. 99–125, 2014, doi: 10.1016/j.cor.2014.10.011.
- [188] J. Kennedy and (1995) Eberhart R. C., "Particle Swarm Optimization," in *Proceedings of the IEEE International Conference on Neural Networks*, pp. 1942–1948.
- [189] S. Gupta and K. Deep, "A novel Random Walk Grey Wolf Optimizer," *Swarm Evol. Comput.*, Jan. 2018, doi: 10.1016/j.swevo.2018.01.001.
- [190] F. Merrikh-Bayat, "The runner-root algorithm: A metaheuristic for solving unimodal and multimodal optimization problems inspired by runners and roots of plants in nature," *Appl. Soft Comput. J.*, vol. 33, pp. 292–303, 2015, doi: 10.1016/j.asoc.2015.04.048.
- [191] 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.
- [192] 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.
- [193] 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.
- [194] M. S. Gonçalves, R. H. Lopez, L. Fleck, and F. Miguel, "Search group algorithm : A new metaheuristic method for the optimization of truss structures," vol. 153, pp. 165–184, 2015, doi: 10.1016/j.compstruc.2015.03.003.
- [195] J. M. Anita and I. J. Raglend, "Shuffled Frog Leaping Algorithm," *Int. Conf. Comput. Electron. Electr. Technol.*, pp. 109–115, 2012.
- [196] 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.
- [197] F. Glover, “Tabu search—Part I,” *ORSA J. Comput.*, vol. 1, p. 190, 1989.
- [198] S. C. Satapathy, A. Naik, and K. Parvathi, “A teaching learning based optimization based on orthogonal design for solving global optimization problems,” pp. 1–12, 2013.
- [199] A. Baykasoğlu and Ş. Akpinar, “Weighted Superposition Attraction (WSA): A swarm intelligence algorithm for optimization problems – Part 1: Unconstrained optimization,” *Appl. Soft Comput. J.*, vol. 56, pp. 520–540, 2017, doi: 10.1016/j.asoc.2015.10.036.
- [200] 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.
- [201] Z. Bayraktar, M. Komurcu, and D. H. Werner, “Wind Driven Optimization (WDO): A Novel Nature-Inspired Optimization Algorithm and its Application to Electromagnetics (1),” no. 1, pp. 0–3, 2010.
- [202] M. D. Li, H. Zhao, X. W. Weng, and T. Han, “Advances in Engineering Software A novel nature-inspired algorithm for optimization : Virus colony search,” *Adv. Eng. Softw.*, vol. 92, pp. 65–88, 2016, doi: 10.1016/j.advengsoft.2015.11.004.
- [203] Y. J. Zheng, “Water wave optimization: A new nature-inspired metaheuristic,” *Comput. Oper. Res.*, vol. 55, pp. 1–11, 2015, doi: 10.1016/j.cor.2014.10.008.
- [204] 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.
- [205] 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.*, vol. 111, pp. 300–323, 2020, doi: <https://doi.org/10.1016/j.future.2020.03.055>.
- [206] P. Niu, S. Niu, N. liu, and L. Chang, “The defect of the Grey Wolf optimization algorithm and its verification method,” *Knowledge-Based Syst.*, vol. 171, pp. 37–43, 2019, doi: 10.1016/j.knosys.2019.01.018.
- [207] M. Clerc, “Particle Swarm Optimization,” *Part. Swarm Optim.*, pp. 507–520, 2010, doi: 10.1002/9780470612163.
- [208] 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.
- [209] R. Tang, S. Fong, and S. Deb, “Wolf Search Algorithm with Ephemeral Memory,” pp. 165–172, 2012.

- [210] 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.
- [211] 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.
- [212] 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.
- [213] 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.
- [214] 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.
- [215] Z. Yang, K. Li, Y. Guo, S. Feng, Q. Niu, and Y. Xue, "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.
- [216] 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.
- [217] S. Mirjalili and A. Lewis, "Advances in Engineering Software The Whale Optimization Algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016, doi: 10.1016/j.advengsoft.2016.01.008.
- [218] and O. R. S. A. Pereira-Neto, C. Unsihuay, "Efficient evolutionary strategy optimisation procedure to solve the nonconvex economic dispatch problem with generator constraints," *IEE Proceedings-Generation, Transm. Distrib.*, vol. 152, pp. 653–660, 2005.
- [219] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowledge-Based Syst.*, vol. 191, p. 105190, 2020, doi: 10.1016/j.knosys.2019.105190.
- [220] 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.
- [221] F. A. Hashim, K. Hussain, E. H. Houssein, M. S. Mabrouk, and W. Al-Atabany, "Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems," *Appl. Intell.*, vol. 51, no. 3, pp. 1531–1551, 2021, doi: 10.1007/s10489-020-01893-z.
- [222] R. V. Rao, V. J. Savsani, and D. P. Vakharia, "Teaching-Learning-Based

- Optimization: An optimization method for continuous non-linear large scale problems,” *Inf. Sci. (Ny)*, vol. 183, no. 1, pp. 1–15, 2012, doi: 10.1016/j.ins.2011.08.006.
- [223] Q. Askari, I. Younas, and M. Saeed, “Political Optimizer: A novel socio-inspired meta-heuristic for global optimization,” *Knowledge-Based Syst.*, 2020, doi: 10.1016/j.knosys.2020.105709.
 - [224] Z. Yiying and A. Chi, “Group teaching optimization algorithm with information sharing for numerical optimization and engineering optimization,” *J. Intell. Manuf.*, Nov. 2021, doi: 10.1007/s10845-021-01872-2.
 - [225] M. El-Shorbagy, “Chaotic Fruit Fly Algorithm for Solving Engineering Design Problems,” *Complexity*, vol. 2022, pp. 1–19, Apr. 2022, doi: 10.1155/2022/6627409.
 - [226] V. Kansal and J. S. Dhillon, “Emended salp swarm algorithm for multiobjective electric power dispatch problem,” *Appl. Soft Comput.*, vol. 90, p. 106172, 2020, doi: <https://doi.org/10.1016/j.asoc.2020.106172>.
 - [227] A. Seyyedabbasi and F. Kiani, “I-GWO and Ex-GWO: improved algorithms of the Grey Wolf Optimizer to solve global optimization problems,” *Eng. Comput.*, no. 0123456789, 2019, doi: 10.1007/s00366-019-00837-7.
 - [228] 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.
 - [229] 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.
 - [230] 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.
 - [231] 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.
 - [232] 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.
 - [233] 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.
 - [234] 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.
- [235] 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.
- [236] 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.
- [237] 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.
- [238] 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.
- [239] 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.
- [240] 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.
- [241] 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.
- [242] H. Chen, A. Asghar, 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.
- [243] 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.
- [244] 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.
- [245] 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.
- [246] 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.
- [247] 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.
- [248] 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.
- [249] 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.
- [250] 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.
- [251] 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.
- [252] 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.
- [253] M. Houburken, 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.
- [254] 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.
- [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] D. İzci and S. Ekinici, “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.
- [257] X. -s. Yang, “A new metaheuristic bat-inspired algorithm, in: *Nature Inspired*

- Cooperative Strategies for Optimization (NISCO 2010),” Springer pp, vol. 65, 2010.
- [258] 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.
 - [259] 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.
 - [260] X. Yao, Y. Liu, and G. Lin, “Evolutionary programming made faster,” *IEEE Trans Evol Comput*, vol. 3, p. 82, 1999.
 - [261] 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.
 - [262] X. Yang, S. Deb, and A. C. B. Behaviour, “Cuckoo Search via Levy Flights,” pp. 210–214, 2009.
 - [263] H. John, Holland, adaptation in natural and artificial systems. Cambridge: MIT Press, 1992.
 - [264] 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.
 - [265] E. Cuevas, A. Echavarra, and M. A. Ramirez-Ortega, “An optimization algorithm inspired by the States of Matter that improves the balance between exploration and exploitation,” *Appl Intel*, vol. 40, p. 256, 2014.
 - [266] Y. X-s and S. Deb, “Cuckoo search via Levy flights,” *World Congr. Nat. Biol. inspired Comput.*, vol. 2009, 2009.
 - [267] Y. X. F. algorithm, “Levy flights and global optimization,” in *Research and development in intelligent systems XXVI*, ; pp 209, vol.18: Springer, 2010.
 - [268] “X.-S,” ang,M.Karamanoglu,X.He,Flowerpollinationalgorithm:anovelapproachformultiobjectiveoptimization,Eng.Optim., vol. 4612, 2014.
 - [269] 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.
 - [270] H. Nezamabadi-Pour, M. Rostami-Sharbabaki, and M. Maghfoori-Farsangi, “Binary Particle Swarm Optimization: Challenges and New Solutions,” *J. Comput. Soc. Iran (CSI) Comput. Sci. Eng.*, vol. 6, no. 1, pp. 21–32, 2008.
 - [271] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, “Multi-Verse Optimizer: a nature-inspired algorithm for global optimization,” no. 30, 2015, doi: 10.1007/s00521-015-1870-7.
 - [272] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: Algorithm and applications,” *Futur. Gener.*

- Comput. Syst., 2019, doi: 10.1016/j.future.2019.02.028.
- [273] D. Simon, "Biogeography-based optimization," IEEE Trans. Evol. Comput., vol. 12, no. 6, pp. 702–713, 2008, doi: 10.1109/TEVC.2008.919004.
 - [274] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," Adv Eng Softw, vol. 69, p. 46, 2014.
 - [275] T. M. Shami, D. Grace, A. Burr, and P. D. Mitchell, "Single candidate optimizer: a novel optimization algorithm," Evol. Intell., 2022, doi: 10.1007/s12065-022-00762-7.
 - [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] X.-S. Yang, "Bat Algorithm for Multi-objective Optimisation," pp. 1–12, 2012, [Online]. Available: <http://arxiv.org/abs/1203.6571>.
 - [278] S. Mirjalili, A. H. Gandomi, S. Zahra, and S. Saremi, "Salp Swarm Algorithm : A bio-inspired optimizer for engineering design problems," Adv. Eng. Softw., vol. 0, pp. 1–29, 2017, doi: 10.1016/j.advengsoft.2017.07.002.
 - [279] 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.
 - [280] G. Dhiman and V. Kumar, "Spotted hyena optimizer: A novel bio-inspired based metaheuristic technique for engineering applications," Adv. Eng. Softw., vol. 114, pp. 48–70, 2017, doi: 10.1016/j.advengsoft.2017.05.014.
 - [281] R. V Rao, V. J. Savsani, and D. P. Vakharia, "Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems," Comput. Des., vol. 43, no. 3, pp. 303–315, 2011, doi: <https://doi.org/10.1016/j.cad.2010.12.015>.
 - [282] S. Sen Gupta, R. Tiwari, and S. B. Nair, "Multi-objective design optimisation of rolling bearings using genetic algorithms," Mech. Mach. Theory, vol. 42, pp. 1418–1443, 2007.
 - [283] K. Deb and A. Srinivasan, "Innovization: Innovating design principles through optimization," in GECCO 2006 - Genetic and Evolutionary Computation Conference, 2006, vol. 2, pp. 1629–1636, doi: 10.1145/1143997.1144266.
 - [284] 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.
 - [285] H. C. G. H. Chickermane, "Structural Optimization Using A New Local Approximation Method," Int. J. Numer. Meth. Engng, vol. 39, pp. 829–846., 1996.
 - [286] G. G. Wang, "Adaptive Response Surface Method Using Inherited Latin Hypercube Design Points ," J. Mech. Des., vol. 125, no. 2, pp. 210–220, 2003,

doi: 10.1115/1.1561044.

- [287] S. Khamsawang, C. Boonseng, and S. Pothiya, "Solving the economic dispatch problem with tabu search algorithm," in 2002 IEEE International Conference on Industrial Technology, 2002. IEEE ICIT '02., 2002, vol. 1, pp. 274–278 vol.1, doi: 10.1109/ICIT.2002.1189906.
- [288] R. Balamurugan and S. Subramanian, "Differential evolution-based dynamic economic dispatch of generating units with valve-point effects," *Electr. Power Components Syst.*, vol. 36, no. 8, pp. 828–843, 2008, doi: 10.1080/15325000801911427.
- [289] S. Hemamalini and S. P. Simon, "Artificial bee colony algorithm for economic load dispatch problem with non-smooth cost functions," *Electr. Power Components Syst.*, vol. 38, no. 7, pp. 786–803, 2010, doi: 10.1080/15325000903489710.
- [290] D. Zou, S. Li, G. G. Wang, Z. Li, and H. Ouyang, "An improved differential evolution algorithm for the economic load dispatch problems with or without valve-point effects," *Appl. Energy*, vol. 181, pp. 375–390, 2016, doi: 10.1016/j.apenergy.2016.08.067.
- [291] N. Jayakumar, S. Subramanian, S. Ganesan, and E. B. Elanchezhian, "Grey wolf optimization for combined heat and power dispatch with cogeneration systems," *Int. J. Electr. Power Energy Syst.*, vol. 74, pp. 252–264, Jan. 2016, doi: 10.1016/J.IJEPES.2015.07.031.
- [292] 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.
- [293] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, "Harris hawks optimization: Algorithm and applications Harris hawks optimization: Algorithm and applications," no. March, 2019, doi: 10.1016/j.future.2019.02.028.
- [294] J. Cai, Q. Li, L. Li, H. Peng, and Y. Yang, "A hybrid CPSO-SQP method for economic dispatch considering the valve-point effects," *Energy Convers. Manag.*, vol. 53, no. 1, pp. 175–181, 2012, doi: 10.1016/j.enconman.2011.08.023.
- [295] B. Mallikarjuna, K. H. Reddy, and O. Hemakeshavulu, "Economic load dispatch with valve - Point result employing a binary bat formula," *Int. J. Electr. Comput. Eng.*, vol. 4, no. 1, pp. 101–107, 2014, doi: 10.11591/ijece.v4i1.4233.
- [296] S. R. Spea, "Solving practical economic load dispatch problem using crow search algorithm," *Int. J. Electr. Comput. Eng.*, vol. 10, no. 4, pp. 3431–3440, 2020, doi: 10.11591/IJECE.V10I4.PP3431-3440.
- [297] A. Victoire and A. E. Jeyakumar, "Hybrid PSO-SQP for economic dispatch with valve-point effect," *Electr. Power Syst. Res.*, vol. 71, pp. 51–59, 2004, doi: 10.1016/j.epsr.2003.12.017.

- [298] A. Y. Saber and G. K. Venayagamoorthy, "Efficient Utilization of Renewable Energy Sources by Gridable Vehicles in Cyber-Physical Energy Systems," *IEEE Syst. J.*, vol. 4, no. 3, pp. 285–294, 2010, doi: 10.1109/JSYST.2010.2059212.
- [299] U. Sharma and B. Moses, "Analysis and optimization of economic load dispatch using soft computing techniques," *Int. Conf. Electr. Electron. Optim. Tech. ICEEOT 2016*, pp. 4035–4040, 2016, doi: 10.1109/ICEEOT.2016.7755472.
- [300] A. Bhattacharya and P. K. Chattopadhyay, "Biogeography-based optimization for different economic load dispatch problems," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1064–1077, 2010, doi: 10.1109/TPWRS.2009.2034525.
- [301] C. C. Kuo, "A novel coding scheme for practical economic dispatch by modified particle swarm approach," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1825–1835, 2008, doi: 10.1109/TPWRS.2008.2002297.
- [302] Z. L. Gaing, "Particle swarm optimization to solving the economic dispatch considering the generator constraints," *IEEE Trans. Power Syst.*, vol. 18, no. 3, pp. 1187–1195, 2003, doi: 10.1109/TPWRS.2003.814889.
- [303] J. Zhang, Y. Wang, R. Wang, and G. Hou, "A new particle swarm optimization solution to nonconvex economic dispatch problem," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 6145 LNCS, no. PART 1, pp. 191–197, 2010, doi: 10.1007/978-3-642-13495-1_24.
- [304] K. T. Chaturvedi, M. Pandit, and L. Srivastava, "Self-organizing hierarchical particle swarm optimization for nonconvex economic dispatch," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1079–1087, 2008, doi: 10.1109/TPWRS.2008.926455.
- [305] United Kingdom Automatic Control Council., Queen's University of Belfast, and Institute of Electrical and Electronics Engineers, *The 2016 UKACC International Conference on Control (UKACC Control 2016): Queen's University Belfast, Belfast, UK, 31 August - 2 September 2016.* .
- [306] S. K. Nayak, K. R. Krishnanand, B. K. Panigrahi, and P. K. Rout, "Application of artificial bee colony to economic load dispatch problem with ramp rate limits and prohibited operating zones," *2009 World Congr. Nat. Biol. Inspired Comput. NABIC 2009 - Proc.*, pp. 1237–1242, 2009, doi: 10.1109/NABIC.2009.5393751.
- [307] R. Storn and K. Price, "Differential Evolution - A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *J. Glob. Optim.*, 1997, doi: 10.1023/A:1008202821328.
- [308] A. Safari and H. Shayeghi, "Iteration particle swarm optimization procedure for economic load dispatch with generator constraints," *Expert Syst. Appl.*, vol. 38, no. 5, pp. 6043–6048, 2011, doi: 10.1016/j.eswa.2010.11.015.
- [309] J. Xu, F. Yan, K. Yun, L. Su, F. Li, and J. Guan, "Noninferior Solution Grey

- Wolf Optimizer with an Independent Local Search Mechanism for Solving Economic Load Dispatch Problems,” *Energies*, vol. 12, no. 12, 2019, doi: 10.3390/en12122274.
- [310] C. K. Panigrahi, P. K. Chattopadhyay, R. N. Chakrabarti, and M. Basu, “Simulated annealing technique for dynamic economic dispatch,” *Electr. Power Components Syst.*, vol. 34, no. 5, pp. 577–586, 2006, doi: 10.1080/15325000500360843.
- [311] B. K. Panigrahi, V. Ravikumar Pandi, and S. Das, “Adaptive particle swarm optimization approach for static and dynamic economic load dispatch,” *Energy Convers. Manag.*, vol. 49, no. 6, pp. 1407–1415, 2008, doi: 10.1016/j.enconman.2007.12.023.
- [312] 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.
- [313] A. Marongiu, M. Roscher, and D. U. Sauer, “Influence of the vehicle-to-grid strategy on the aging behavior of lithium battery electric vehicles,” *Appl. Energy*, vol. 137, pp. 899–912, Feb. 2015, doi: 10.1016/j.apenergy.2014.06.063.
- [314] A. Esfandyari, B. Norton, M. Conlon, and M. SJ, “Performance of a campus photovoltaic electric vehicle charging station in a temperate climate,” *Sol. Energy*, vol. 177, pp. 762–771, 2019, doi: 10.1016/j.solener.2018.12.005.
- [315] E. A. Ul-Haq, A.; Cecati, C.; Al-Ammar, “Modeling of a Photovoltaic-Powered Electric Vehicle Charging Implementation, Station with Vehicle-to-Grid,” *Energies*, vol. 10, no. 4, 2017.
- [316] M. M. Karmaker, A.K.; Ahmed, M.R.; Hossain, M.A.; Sikder, “Feasibility assessment & design of hybrid renewable energy based electric vehicle charging station in Bangladesh,” *Sustain. Cities Soc.*, vol. 39, pp. 189–202, 2018.
- [317] G. R. Chandra Mouli, P. Bauer, and M. Zeman, “System design for a solar powered electric vehicle charging station for workplaces,” *Appl. Energy*, vol. 168, pp. 434–443, 2016, doi: <https://doi.org/10.1016/j.apenergy.2016.01.110>.
- [318] K. Chaudhari, A. Ukil, K. N. Kumar, U. Manandhar, and S. K. Kollimalla, “Hybrid Optimization for Economic Deployment of ESS in PV-Integrated EV Charging Stations,” *IEEE Trans. Ind. Informatics*, vol. 14, no. 1, pp. 106–116, Jan. 2018, doi: 10.1109/TII.2017.2713481.
- [319] W. H. Yao, L.; Damiran, Z.; Lim, “Optimal Charging and Discharging Scheduling for Electric Vehicles in a Parking Station with Photovoltaic System and Energy Storage System,” *Energies*, vol. 10, p. 550, 2017.
- [320] S. M. Shariff, M. S. Alam, F. Ahmad, Y. Rafat, M. S. J. Asghar, and S. Khan, “System Design and Realization of a Solar-Powered Electric Vehicle Charging Station,” *IEEE Syst. J.*, vol. 14, no. 2, pp. 2748–2758, Jun. 2020, doi:

10.1109/JSYST.2019.2931880.

- [321] A. R. Bhatti et al., “Optimized sizing of photovoltaic grid-connected electric vehicle charging system using particle swarm optimization,” *Int. J. Energy Res.*, vol. 43, no. 1, pp. 500–522, 2019, doi: 10.1002/er.4287.
- [322] M. C. Mercan, M. Ö. Kayalica, G. Kayakutlu, and S. Ercan, “Economic model for an electric vehicle charging station with vehicle-to-grid functionality,” *Int. J. Energy Res.*, vol. 44, no. 8, pp. 6697–6708, 2020, doi: 10.1002/er.5407.
- [323] Q. Dai, Q.; Liu, J.; Wei, “Optimal Photovoltaic/Battery Energy Storage/Electric Vehicle Charging Station Design Based on Multi-Agent Particle Swarm Optimization Algorithm,” *Sustainability*, vol. 11, no. 7, p. 1973, 2019.
- [324] S. You, C. Træholt, and B. Poulsen, “Economic dispatch of electric energy storage with multi-service provision,” *2010 9th Int. Power Energy Conf. IPEC 2010*, pp. 525–531, 2010, doi: 10.1109/IPEC2010.5697052.
- [325] S. Behera, S. Behera, and A. K. Barisal, “Dynamic Combined Economic Emission Dispatch integrating Plug-in Electric Vehicles and Renewable Energy Sources,” *Int. J. Ambient Energy*, vol. 0, no. 0, pp. 1–18, 2021, doi: 10.1080/01430750.2021.1918243.
- [326] S. Behera, S. Behera, A. Kumar Barisal, and S. Pradhan, “Economic Load Dispatch with Renewable Energy Resources and Plug-in Electric Vehicles,” in *2020 International Conference on Renewable Energy Integration into Smart Grids: A Multidisciplinary Approach to Technology Modelling and Simulation (ICREISG)*, Feb. 2020, pp. 22–26, doi: 10.1109/ICREISG49226.2020.9174543.
- [327] C. H. Lo and M. D. Anderson, “Economic dispatch and optimal sizing of battery energy storage systems in utility load-leveling operations,” *IEEE Trans. Energy Convers.*, vol. 14, no. 3, pp. 824–829, 1999, doi: 10.1109/60.790960.
- [328] H. Zeynal, J. Yap, B. Azzopardi, and M. Eidiani, “Flexible Economic Load Dispatch Integrating Electric Vehicles,” 2014, doi: 10.1109/PEOCO.2014.6814484.
- [329] M. Fesanghary and M. M. Ardehali, “A novel meta-heuristic optimization methodology for solving various types of economic dispatch problem,” *Energy*, vol. 34, no. 6, pp. 757–766, 2009, doi: <https://doi.org/10.1016/j.energy.2009.02.007>.
- [330] X. X. W. Gu, H. Yu, W. Liu, J. Zhu, “Demand response and economic dispatch of power systems considering large-scale plug-in hybrid electric vehicles/electric vehicles (phevs/evs): A review,” *Energies*, vol. 6, no. 9, pp. 4394–4417, 2013.
- [331] M. Fanoro, M. Božanić, and S. Sinha, “A Review of the Impact of Battery Degradation on Energy Management Systems with a Special Emphasis on Electric Vehicles,” *Energies*, vol. 15, no. 16, 2022, doi: 10.3390/en15165889.
- [332] I. Marouani et al., “Combined Economic Emission Dispatch with and without

- Consideration of PV and Wind Energy by Using Various Optimization Techniques: A Review,” *Energies*, vol. 15, no. 12, 2022, doi: 10.3390/en15124472.
- [333] A. Y. Saber and G. K. Venayagamoorthy, “Plug-in Vehicles and Renewable Energy Sources for Cost and Emission Reductions,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1229–1238, Apr. 2011, doi: 10.1109/TIE.2010.2047828.
- [334] N. Augustine, S. Suresh, P. Moghe, and K. Sheikh, “Economic dispatch for a microgrid considering renewable energy cost functions,” in *2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*, 2012, pp. 1–7, doi: 10.1109/ISGT.2012.6175747.
- [335] A. Gholami, J. Ansari, M. Jamei, and A. Kazemi, “Environmental/economic dispatch incorporating renewable energy sources and plug-in vehicles,” *IET Gener. Transm. Distrib.*, vol. 8, no. 12, pp. 2183–2198, 2014, doi: 10.1049/iet-gtd.2014.0235.
- [336] Hetzer, John & Yu, David & Bhattarai, Keshav. (2008). An Economic Dispatch Model Incorporating Wind Power. *IEEE Transactions on Energy Conversion*,. 23. 603 - 611. 10.1109/TEC.2007.914171.

Appendix A

A.1. Standard Benchmark Functions

Table TA.1: Unimodal Benchmark Function

Test Function	Name	Dim	Range	$f_{\min}$
$f_1(y) = \sum_{i=1}^n y_i^2$	Sphere	30	[-100, 100]	0
$f_2(y) = \sum_{i=1}^{i=n-1} y + \prod_{i=1}^n y_i $	Schwefel Absolute	30	[-10, 10]	0
$f_3(y) = \sum_{i=1}^n \left(\sum_{j=1}^i y_j \right)^2$	Schwefel Double Sum	30	[-100, 100]	0
$f_4(y) = \max_i \{ y_i ; 1 \leq i \leq n \}$	Schwefel maximum	30	[-100, 100]	0
$f_5(y) = \sum_{i=1}^{n-1} [100(y_{i+1} - y_i^2)^2 + (y_i - 1)^2]$	Rosen-brock	30	[-30, 30]	0
$f_6(y) = \sum_{i=1}^n ([y_i + 0.5])^2$	Step	30	[-100, 100]	0
$f_7(y) = \sum_{i=1}^{i=n-1} i y_i^4 + random[0,1]$	Quartic Random	30	[-1.28, 1.28]	0

Table TA.2: Multi-modal (MM) benchmark Function

Test Function	Name	Dim	Limit	$f_{\min}$
$f_8(y) = \sum_{i=1}^n -y_i \sin(\sqrt{ y_i })$	Schwefel Sine	30	[-500, 500]	-418.98295
$f_9(y) = \sum_{i=1}^n [y_i^2 - 10 \cos(2\pi y_i) + 10]$	Rastrigin	30	[-5.12, 5.12]	0
$f_{10}(y) = -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{i=1}^n y_i^2}) - \exp(\frac{1}{n} \sum_{i=1}^n \cos(2\pi y_i)) + 20 + c$	Ackley	30	[-32, 32]	0
$f_{11}(y) = 1 + \sum_{i=1}^n \frac{y_i^2}{4000} - \prod_{i=1}^n \cos \frac{y_i}{\sqrt{i}}$	Griewank	30	[-600, 600]	0
$f_{12}(y) = \frac{\pi}{n} \left\{ 10 \sin(\pi y_1) + \sum_{k=1}^{n-1} (y_k - 1)^2 [1 + 10 \sin^2(\pi z_{k+1})] + (z_n - 1)^2 \right\} + \sum_{k=1}^n u(y_k, 10, 100, 4)$ $z_1 = 1 + \frac{(y_k + 1)}{4};$ $u(y_k, a, l, m) = \begin{cases} l(y_k - a)^m & y_k > a \\ 0 & -a < y_k < a \\ l(-y_k - a)^m & y_k < -a \end{cases}$	Pendlized Penalty# 1	30	[-50, 50]	0
$F_{13}(y) = 0.1 \left\{ \sin^2(3\pi y_1) + \sum_{k=1}^n (y_k - 1)^2 [1 + \sin^2(3\pi y_k + 1)] + \sum_{k=1}^n u(y_k, 5, 100, 4) \right\} + \sum_{k=1}^n (x_k - 1)^2 [1 + \sin^2(2\pi x_k)]$	Levi N. 13	30	[-50, 50]	0

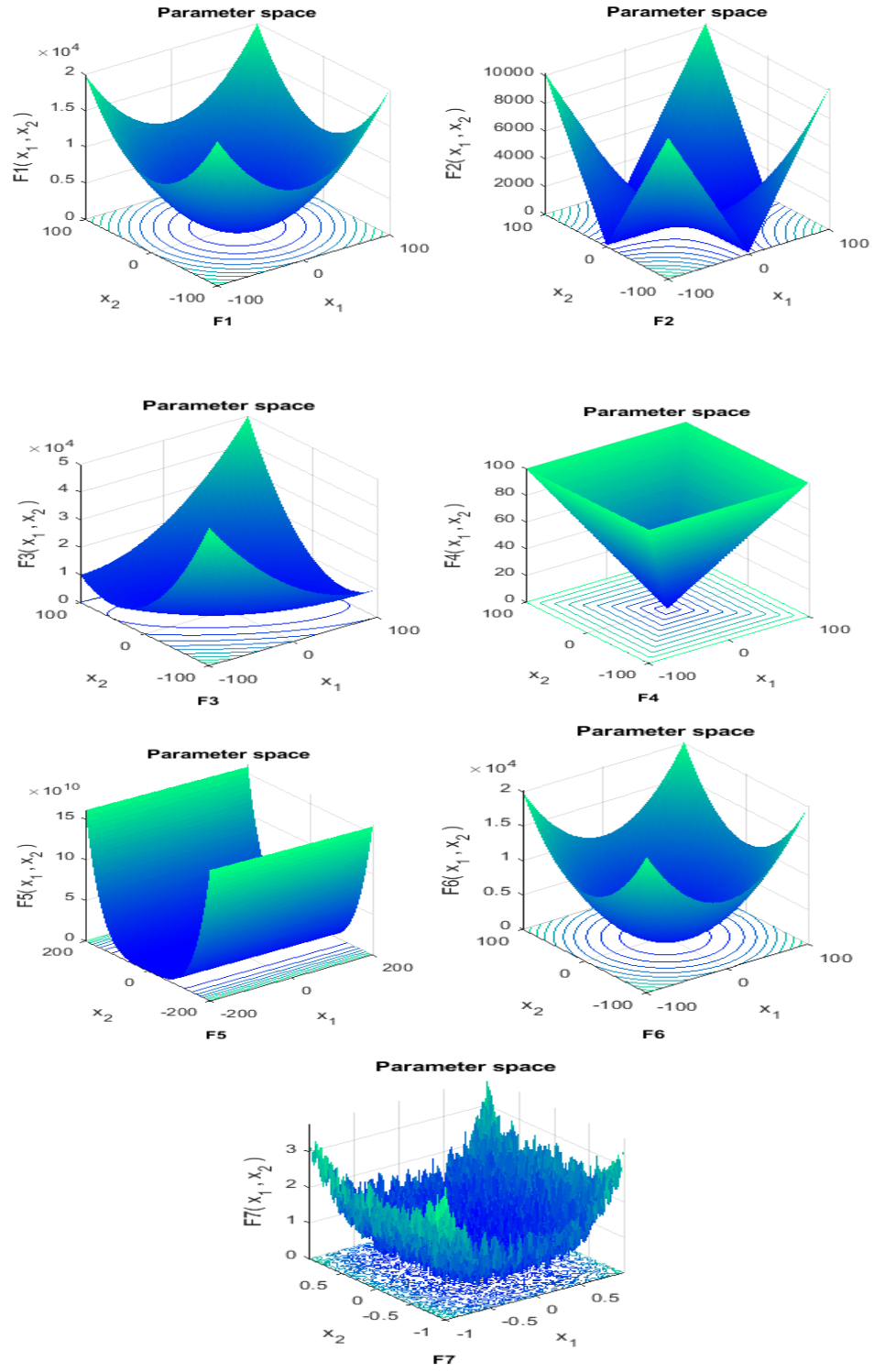


Fig. FA.1: 3D View of unimodal (UM) benchmark function

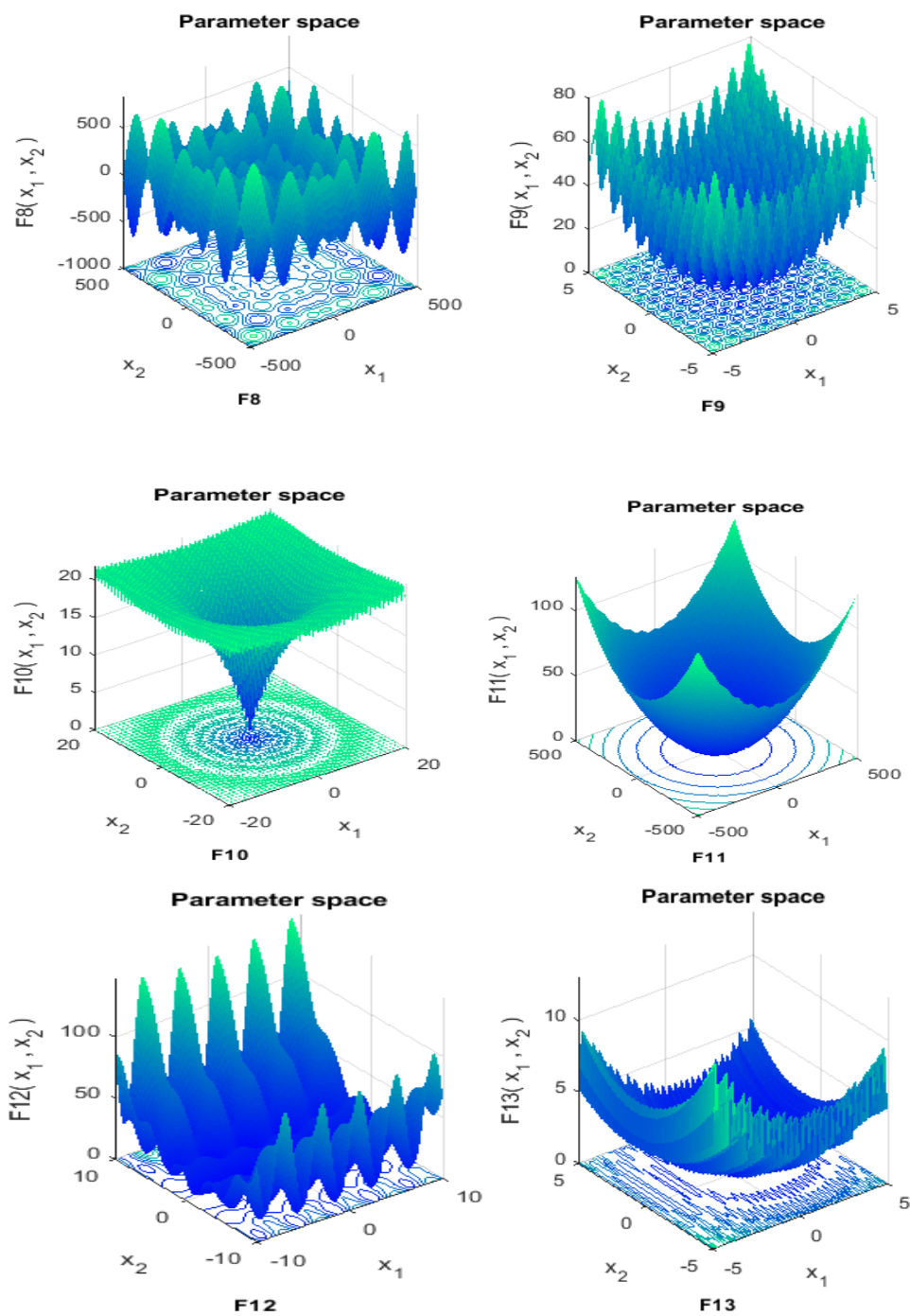


Fig.FA.2: 3D view of multi-modal (MM) benchmark function

Table TA.3: Fixed-Dimension Benchmark Function

FD Test Function	Function Name	Dim	limit	fmin
$f_{14}(y) = \left[\frac{1}{500} + \sum_{j=1}^2 5 \frac{1}{j + \sum_{i=1}^n (y_i - a_i)^6} \right]^{-1}$	Shekel Foxhole Function	2	65.536, 5.536]	1
$f_{15}(y) = \sum_{i=1}^{11} \left[a_i - \frac{y_1(b_i^2 + b_i y_2)}{b_i^2 + b_i y_3 + y_4} \right]^2$	Brad Function	4	[-5, 5]	0.00030
$f_{16}(y) = 4y_1^2 - 2.1y_1^4 + \frac{1}{3}y_1^6 + y_1y_2 - 4y_2^2 + 4y_2^4$	Camel Function-Six Hump	2	[-5, 5]	1.0316
$f_{17}(y) = \left(y_2 - \frac{5.1}{4\pi^2} y_1^2 + \frac{5}{\pi} y_1 - 6 \right)^2 + 10 \left(1 - \frac{1}{8\pi} \right) \cos y_1 + 10$	Branin RCOS Function	2	[-5, 5]	0.398
$f_{18}(y) = \left[\frac{1 + (y_1 + y_2 + 1)^2}{(19 - 14y_1 + 3y_1^2 - 14y_2 + 6y_1y_2 + 3y_2^2)} \right] \times \left[\frac{30 + (2y_1 - 3y_2)^2 \times (18 - 32y_1 + 12y_1^2 + 48y_2)}{-36y_1y_2 + 27y_2^2} \right]$	Goldstein Price Function	2	[-2,2]	3
$f_{19}(y) = -\sum_{i=1}^4 c_i \exp \left(-\sum_{j=1}^3 a_{ij} (y_j - q_{ij})^2 \right)$	Hartman 3 Function	3	[1, 3]	-3.32
$f_{20}(y) = -\sum_{i=1}^4 c_i \exp \left(-\sum_{j=1}^6 a_{ij} (y_j - q_{ij})^2 \right)$	Hartman 6 Function	6	[0, 1]	-3.32
$f_{21}(y) = -\sum_{i=1}^5 \left[\frac{(y - a_i)}{(y - a_i)^T + d_i} \right]^{-1}$	Hybrid Composit Function #1	4	[0,10]	10.1532
$f_{22}(y) = -\sum_{i=1}^7 \left[\frac{(y - a_i)}{(y - a_i)^T + d_i} \right]^{-1}$	Hybrid Composit Function #2	4	[0, 10]	10.4028
$f_{23}(y) = -\sum_{i=1}^{10} \left[\frac{(y - a_i)}{(y - a_i)^T + d_i} \right]^{-1}$	Hybrid composit Function #3	4	[0, 10]	-10.5363

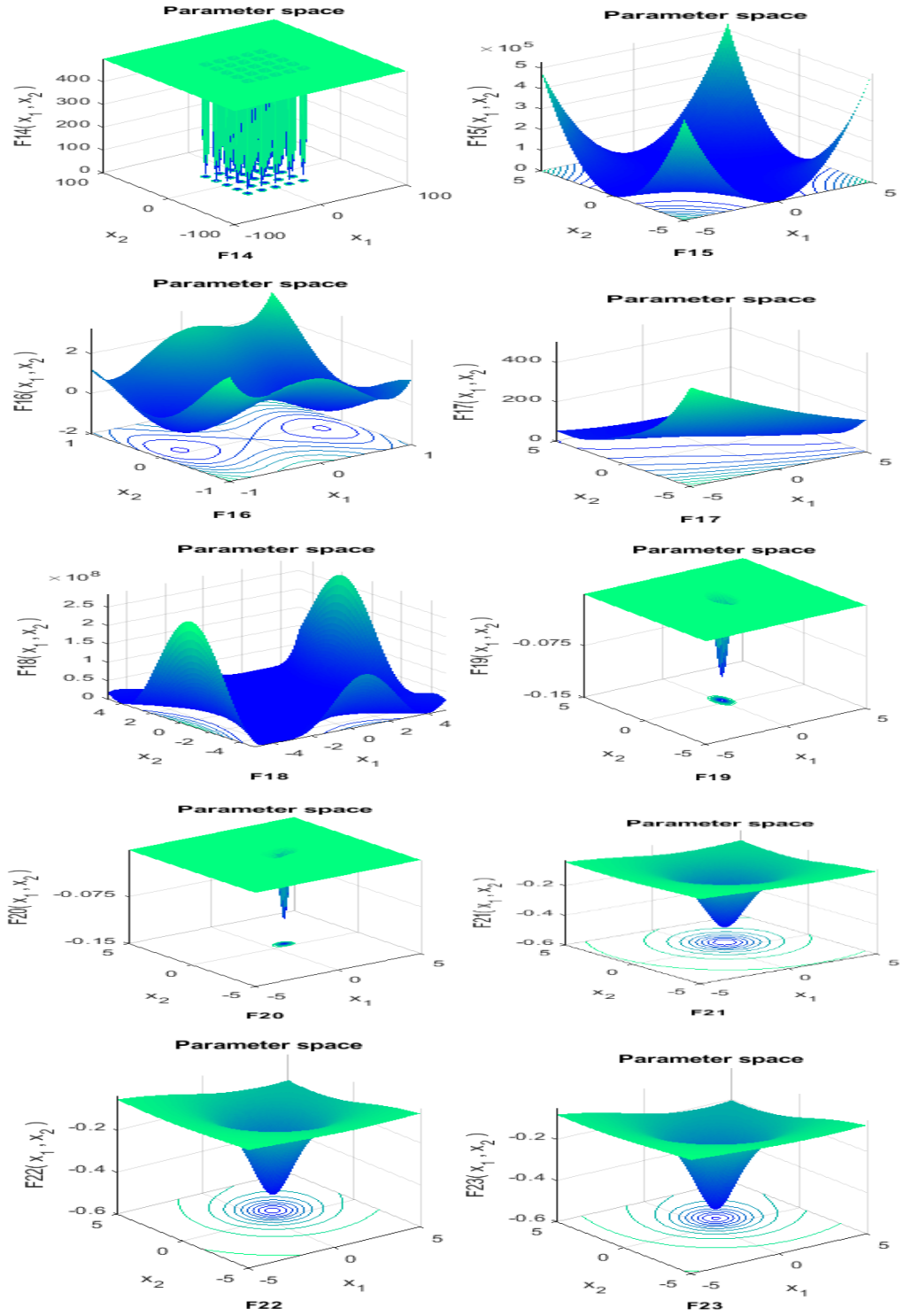


Fig.FA.3: 3D view of Fixed-Dimension (FD) Benchmark Function

A.2 Engineering Design Problems

A.2.1 Three Bar Truss Design Problem (ED1)

Weight minimization is the main objective of ED1- a three bar truss design problem as shown in Fig. FA.4. The various constraints involved in this problem are deflection, warping and stress. The mathematical modelling for 3-Bar Truss are illustrated through equation (EA.1) to equation (EA.2d) subject to various constraints.

Consider,

$$\bar{y} = [y_1, y_2] = [A_1, A_2] \quad (\text{EA.1})$$

Minimize,

$$f(\bar{y}) = (2\sqrt{2}y_1 + y_2) * l \quad (\text{EA.2a})$$

Subjected to:

$$g_1(\bar{y}) = \frac{\sqrt{2}y_1 + y_2}{\sqrt{2}y_1^2 + 2y_1y_2} P - \sigma \leq 0 \quad (\text{EA.2b})$$

$$g_2(\bar{y}) = \frac{y_2}{\sqrt{2}y_1^2 + 2y_1y_2} P - \sigma \leq 0 \quad (\text{EA.2c})$$

$$g_3(\bar{y}) = \frac{1}{\sqrt{2}y_2 + y_1} P - \sigma \leq 0 \quad (\text{EA.2d})$$

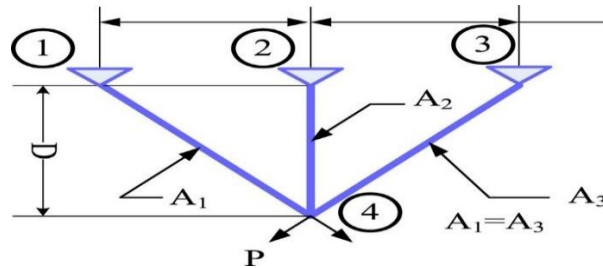


Fig.FA.4: Truss Design (ED1)

A.2.2 Speed Reducer Design Problem (ED2)

The fundamental goal of speed reducer ED 2 is to lessen the weight of the speed reducer to a minimum value. The seven design variables (x_1 to x_7) as shown in Fig. FA.5 to be optimized are width of face, teeth module, pinion teeth, first shaft length and second shaft length, first shaft diameter and second shaft diameter respectively. Mathematically these are formulated as given below:

Minimizing;

$$F(\vec{x}) = 7854 \times 10^{-4} \times x_1 \times x_2 (3.3333 \times x_3^2 + 14.9334 \times x_3 - 43.0934) - 1.508 \times x_1 (x_6^2 + x_7^2) + 7.4777 \times (x_6^3 + x_7^3) + 7854 \times 10^{-4} (x_4 x_6^2 + x_5 x_7^2) \quad (\text{EA.3})$$

Subjected to;

$$r_1(\vec{x}) = \frac{27}{x_1 x_2^2 x_3} - 1 \leq 0 \quad (\text{EA.4a})$$

$$r_2(\vec{x}) = \frac{397.5}{x_1 x_2^2 x_3^2} - 1 \leq 0 \quad (\text{EA.4b})$$

$$r_3(\vec{x}) = \frac{1.93 x_4^3}{x_2 x_3 x_6^4} - 1 \leq 0 \quad (\text{EA.4c})$$

$$r_4(\vec{x}) = \frac{1.93 x_5^3}{x_2 x_3 x_7^4} - 1 \leq 0 \quad (\text{EA.4d})$$

$$r_5(\vec{x}) = \frac{1}{110 x_6^3} \sqrt{\left(\frac{745.0 x_4}{x_2 x_3}\right)^2 + 16.9 \times 10^6} - 1 \leq 0 \quad (\text{EA.4e})$$

$$r_6(\vec{x}) = \frac{1}{85 x_7^3} \sqrt{\left(\frac{745.0 x_5}{x_2 x_3}\right)^2 + 157.5 \times 10^6} - 1 \leq 0 \quad (\text{EA.4f})$$

$$r_7(\vec{x}) = \frac{x_2 x_3}{40} - 1 \leq 0 \quad (\text{EA.4g})$$

$$r_8(\vec{x}) = \frac{5 x_2}{x_1} - 1 \leq 0 \quad (\text{EA.4h})$$

$$r_9(\vec{x}) = \frac{x_1}{12x_2} - 1 \leq 0 \quad (\text{EA.4i})$$

$$r_{10}(\vec{x}) = \frac{1.5x_6 + 1.9}{12x_2} - 1 \leq 0 \quad (\text{EA.4j})$$

$$r_{11}(\vec{x}) = \frac{1.1x_7 + 1.9}{x_5} - 1 \leq 0 \quad (\text{EA.4k})$$

Where

$$2.6 \leq x_1 \leq 3.6; 0.7 \leq x_2 \leq 0.8; 17 \leq x_3 \leq 28; 7.3 \leq x_4 \leq 8.3;$$

$$7.8 \leq x_5 \leq 8.3; 2.9 \leq x_6 \leq 3.9; 5 \leq x_7 \leq 5.5$$

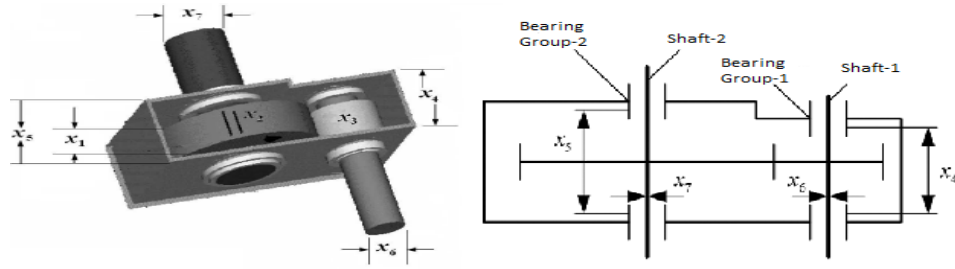


Fig. FA.5: Speed Reducer Design-ED2

A.2.3 Pressure Vessel Design Problem (ED3)

The design specification for ED3 engineering problem is illustrated in Fig FA.6. The four design variables for the pressure vessel are: (i) shell thickness (T_s) (ii) head thickness (T_h) (iii) length of cylindrical unit (L_h) and radius (R). These four variables are modelled as y_1 to y_4 . The mathematical formulation for pressure vessel design problem are given in equation. (EA.5) to equation (EA.6).

Consider:

$$\vec{y} = [y_1 y_2 y_3 y_4] = [T_s T_h R L_h] \quad (\text{EA.5})$$

Minimize;

$$f(\vec{y}) = 0.6224y_1y_3y_4 + 1.7781y_2y_3^2 + 3.1661y_1^2y_4 + 19.84y_1^2y_3 \quad (\text{EA.6a})$$

Subject to:

$$g_1(\vec{y}) = -y_1 + 0.0193y_3 \leq 0 \quad (\text{EA.6b})$$

$$g_2(\vec{y}) = y_3 + 0.00954y_3 \leq 0 \quad (\text{EA.6c})$$

$$g_3(\vec{y}) = -\pi y_3^2 y_4 - \frac{4}{3} \pi y_3^3 + 1296000 \leq 0 \quad (\text{EA.6d})$$

$$g_4(\vec{y}) = y_4 - 240.0 \leq 0 \quad (\text{EA.6e})$$

Range of variables is given as follows:

$$0 \leq y_1 \leq 99; \quad 0 \leq y_2 \leq 99; \quad 10 \leq y_3 \leq 200; \quad 10 \leq y_4 \leq 200;$$

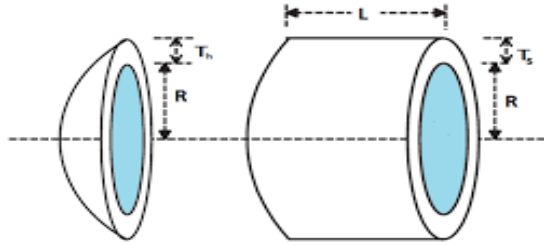


Fig. FA.6: Pressure Vessel Design-ED3

A.2.4 Tension-Compression Spring Design (ED4)

Tension-compression spring design (ED4) is amongst the common mechanical engineering design problem as depicted in Fig FA.7. The primary objective of ED4 is to minimize the spring weight. In ED4 problem three design variables optimized are mean coil diameter (D_m), active coils (N_c) and wire diameter (d_r). This problem is formulated through equation (EA.7) to equation (EA.8).

$$\text{Consider; } \vec{y} = [y_1 y_2 y_3] = [d_r D_m N_c] \quad (\text{EA.7})$$

$$\text{Minimize } f(\vec{y}) = (y_3 + 2)y_2 y_1^2 \quad (\text{EA.8a})$$

$$\text{Subject to: } g_1(\vec{y}) = 1 - \frac{y_2^3 y_3}{71785 y_1^4} \leq 0, \quad (\text{EA.8b})$$

$$g_1(\vec{y}) = 1 - \frac{y_2^3 y_3}{71785 y_1^4} \leq 0, \quad (\text{EA.8c})$$

$$g_1(\vec{y}) = 1 - \frac{y_2^3 y_3}{71785 y_1^4} \leq 0 \quad (\text{EA.8d})$$

$$g_3(\vec{y}) = 1 - \frac{140.45 y_1}{y_2^2 y_3} \leq 0, \quad (\text{EA.8e})$$

$$g_4(\vec{y}) = \frac{y_1 + y_2}{1.5} - 1 \leq 0, \quad (\text{EA.8f})$$

Variables lies in the range as given below:

$$0.005 \leq y_1 \leq 2.00; \quad 0.25 \leq y_2 \leq 1.30; \quad 2.00 \leq y_3 \leq 15.0$$

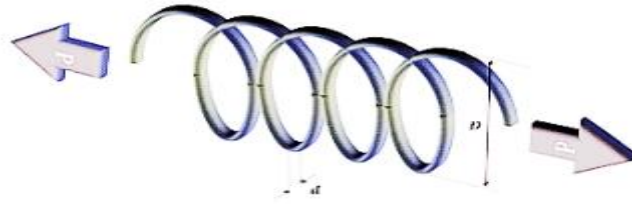


Fig. FA.7: Compression/Tension Spring Design-(ED4)

A.2.5 Welded Beam Design Problem (ED5)

In welded beam design, various parts of molten metal are bonded in order to perform welding process as shown in Fig. FA.8. The primary objective of this problem is to optimize the construction cost of the beam. The variables to be optimized in this design problem are z_1 , z_2 , z_3 and z_4 equivalent to bar thickness, b ; bar length, l ; weld thickness, t and bar height, h ; respectively. These are subjected to constraints like buckling of bar (P_c), Side constraints, End deflection of beam (d), Bending stress of the beam (h) and stress of shear (s). The design problem is modelled through equation (EA.9) through (EA.10).

$$\text{Consider } \vec{Z} = [z_1 z_2 z_3 z_4] = [h l t b] \quad (\text{EA.9})$$

$$\text{Minimize, } f(\vec{Z}) = 1.10471 z_1^2 z_2 + 0.04811 z_3 z_4 (14 + z_2) \quad (\text{EA.10a})$$

Subjected to:

$$g_1(\vec{z}') = \tau(\vec{z}') - \tau'_{\max} \leq 0 \quad (\text{EA.10b})$$

$$g_2(\vec{z}') = \sigma(\vec{z}') - \sigma'_{\max} \leq 0 \quad (\text{EA.10c})$$

$$g_3(\vec{z}') = \delta(\vec{z}') - \delta'_{\max} \leq 0 \quad (\text{EA.10d})$$

$$g_4(\vec{z}') = z_1 - z_4 \leq 0 \quad (\text{EA.10e})$$

$$g_5(\vec{z}') = P_i - P_c(\vec{z}') \leq 0 \quad (\text{EA.10f})$$

$$g_6(\vec{z}') = 0.125 - z_1 \leq 0 \quad (\text{EA.10g})$$

$$g_7(\vec{z}') = 1.10471z_1^2 + 0.04811z_3z_4(14.0 + z_2) - 5.0 \leq 0 \quad (\text{EA.10h})$$

variable ranges between :-

$$0 \leq z_1 \leq 2; 0.1 \leq z_2 \leq 10; 0.1 \leq z_3 \leq 10; 0.1 \leq z_4 \leq 2$$

Where,

$$\tau(\vec{z}) = \sqrt{(\tau')^2 + 2\tau'\tau'' \frac{z_2}{2R} + (\tau'')^2}, \quad (\text{EA.10i})$$

$$\tau' = \frac{P_i}{\sqrt{2z_1z_2}}, \tau'' = \frac{MR}{J}, M = P_i \left(L + \frac{z_2}{2} \right), \quad (\text{EA.10j})$$

$$R = \sqrt{\frac{z_2^2}{4} + \left(\frac{z_1 + z_3}{2} \right)^2}, \quad (\text{EA.10k})$$

$$J = 2 \left\{ \sqrt{2z_1z_2} \left[\frac{z_2^2}{4} + \left(\frac{z_1 + z_3}{2} \right)^2 \right] \right\}, \quad (\text{EA.10l})$$

$$\sigma(\vec{z}) = \frac{6P_iL}{z_4z_3^2}, \delta(\vec{z}) = \frac{6P_iL^3}{Ez_2^2z_4}, \quad (\text{EA.10m})$$

$$P_c(\vec{z}) = \frac{4.013E \sqrt{z_3^2z_4^6}}{L^2} \left(1 - \frac{z_3}{2L} \sqrt{\frac{E}{4G}} \right), \quad (\text{EA.10n})$$

$$P_i = 6000lb; L = 14in; \delta_{\max i} = 0.25in; E = 30 \times 10^6 psi;$$

$$G = 12 \times 10^6 psi; \tau_{\max i} = 13600 psi; \sigma_{\max i} = 3000 psi$$

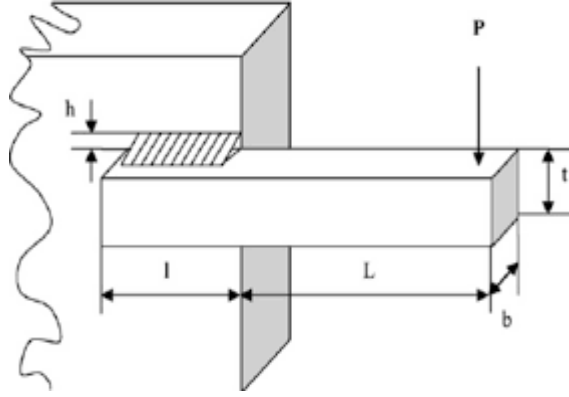


Fig. FA.8: Welded Beam Design-ED5

A.2.6 Rolling Element Bearing Design (ED6)

The primary goal of ED6 design issue is to improve the dynamic load bearing ability of the rolling element as depicted in Fig. FA.9. This ED problem has ten decision variables: ball diameter (DIM_B); pitch diameter (DIM_P); ball numbers (N_b), and raceway curvature coefficients for the outer and inner parts (r_o and r_i). The remaining five factors have a little impact on the internal shape. The following equations explain the mathematical formulation of rolling element bearing design problem for maximizing:

$$\text{If } DIM_p \leq 25.4mm; \text{ then } C_{RB} = f_c N^{2/3} DIM_B^{1.8} \quad (EA.11a)$$

Else if

$$DIM_p \geq 25.4mm; C_{RB} = 3.647 f_c N^{2/3} DIM_B^{1.4} \quad (EA.11b)$$

Addressing variables r_1 to r_{10} in the following equations

$$r_1(s) = \frac{\theta_0}{2 \sin^{-1} \left(\frac{DIM_B}{DIM_{MAX}} \right)} - N + 1 \geq 0 \quad (EA.12a)$$

$$r_2(s) = 2DIM_B - K_{DIM_{MIN}} (DIM - \dim) \geq 0 \quad (EA.12b)$$

$$r_3(s) = K_{DIM_{MAX}} (DIM - \dim) \geq 0 \quad (EA.12c)$$

$$r_4(s) = \beta B_w - DIM_B \leq 0 \quad (EA.12d)$$

$$r_5(s) = DIM_{MAX} - 0.5 \times (DIM + \dim) \geq 0 \quad (EA.12e)$$

$$r_6(s) = DIM_{MAX} - 0.5 \times (DIM + \dim) \geq 0 \quad (\text{EA.12f})$$

$$r_7(s) = (0.5 + re)(DIM + \dim) \geq 0 \quad (\text{EA.12g})$$

$$r_8(s) = 0.5(DIM - DIM_{MAX} - DIM_B) - \alpha DIM_B \geq 0 \quad (\text{EA.12h})$$

$$r_9(s) = f_I \geq 0.515 \quad (\text{EA.12i})$$

$$r_{10}(s) = f_0 \geq 0.515 \quad (\text{EA.12j})$$

Here,

$$f_c = 37.91 \left[1 + \left\{ 1.04 \left(\frac{1-\varepsilon}{1+\varepsilon} \right)^{1.72} \left(\frac{f_I (2f_0 - 1)}{f_0 (2f_I - 1)} \right)^{0.41} \right\}^{10/3} \right]^{-0.3} \times \left[\frac{\varepsilon^{0.3} (1-\varepsilon)^{1.39}}{(1+\varepsilon)^{1/3}} \right] \left[\frac{2f_I}{2f_I - 1} \right]^{0.41} \quad (\text{EA.13})$$

$$\theta_0 = 2\pi - 2 \cos^{-1} \left(\frac{\left[\left\{ (DIM - \dim) / 2 - 3(t/4) \right\}^2 + (DIM/2 - t/4 - DIM_B)^2 - \left\{ \dim/2 + t/4 \right\}^2 \right]}{2 \left\{ (DIM - \dim) / 2 - 3(t/4) \right\} \left\{ D/2 - t/4 - DIM_B \right\}} \right) \quad (\text{EA.14})$$

$$\text{Here} \quad \varepsilon = \frac{DIM_B}{DIM_{MAX}}; f_I = \frac{R_I}{DIM_B}; f_0 = \frac{R_0}{DIM_B}; t = DIM - \dim - 2DIM_B$$

Different constants and variable ranges are taken as follows:

$$DIM = 160; \dim = 90; B_w = 30; R_I = R_0 = 11.033$$

$$0.5(DIM + \dim) \leq DIM_{MAX} \leq 0.6(DIM + \dim);$$

$$0.15(DIM - \dim) \leq DIM_B \leq 0.45(DIM - \dim);$$

$$4 \leq N \leq 50$$

$$0.515 \leq f_I \quad \text{and} \quad f_0 \leq 0.6$$

$$0.4 \leq K_{DIM_{MIN}} \leq 0.5;$$

$$0.6 \leq K_{DIM_{MAX}} \leq 0.7;$$

$$0.3 \leq re \leq 0.1; 0.02 \leq re \leq 0.1;$$

$$0.6 \leq \beta \leq 0.85$$

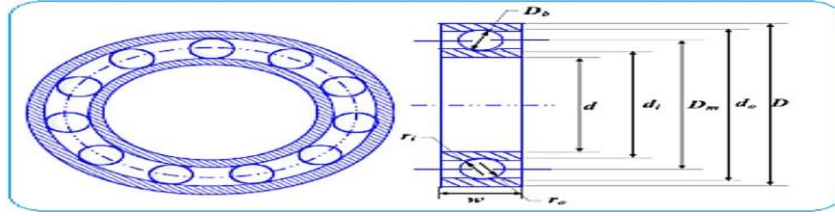


Fig. FA.9: Rolling bearing design Problem-ED6

A.2.7 Cantilever Beam Design Problem (ED7)

This is civil engineering problem concerned with reducing the weight of the beam as shown in Fig. FA.10. In this ED problem five elements l_1, l_2, l_3, l_4 and l_5 are optimized to obtain the optimum beam weight. The displacement of vertical constraint should not interrupt during complete process of the beam for final optimal solution shown by equation (EA.15) and equation (EA.16). The formulation of design is given below:

Consider; $\vec{x} = [l_1 l_2 l_3 l_4 l_5]$, (EA.15)

Minimize, $f(\vec{x}) = 0.6224(l_1 + l_2 + l_3 + l_4 + l_5)$, (EA.16a)

Subject to $g(\vec{x}) = \frac{61}{l_1^3} + \frac{37}{l_2^3} + \frac{19}{l_3^3} + \frac{7}{l_4^3} + \frac{1}{l_5^3} \leq 1$ (EA.16b)

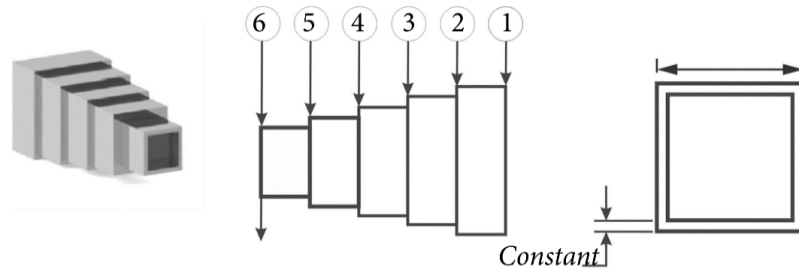


Fig. FA.10: Cantilever Beam Design-ED7

A.2.8 Gear Train Design Problem (ED8)

In ED8 the primary aim is to decrease the scalar value and teeth ratio as shown in Fig. FA.11. The different variables considered to be optimized are g_1, g_2, g_3 , and g_4 Teeth's on each gear depicts the decision variables and this design problem is formulated through

equation (EA.17a) to equation (EA.17b) to attain the optimum values.

$$\text{Consider, } \vec{g} = [g_1 g_2 g_3 g_4] = [M_A M_B M_C M_D] \quad (\text{EA.17a})$$

Minimizing;

$$f(\vec{g}) = \left(\frac{1}{6.931} - \frac{g_3 g_4}{g_1 g_4} \right)^2 \quad (\text{EA.17b})$$

$$\text{Subject to: } 12 \leq g_1, g_2, g_3, g_4 \leq 60 \quad (\text{EA.17c})$$

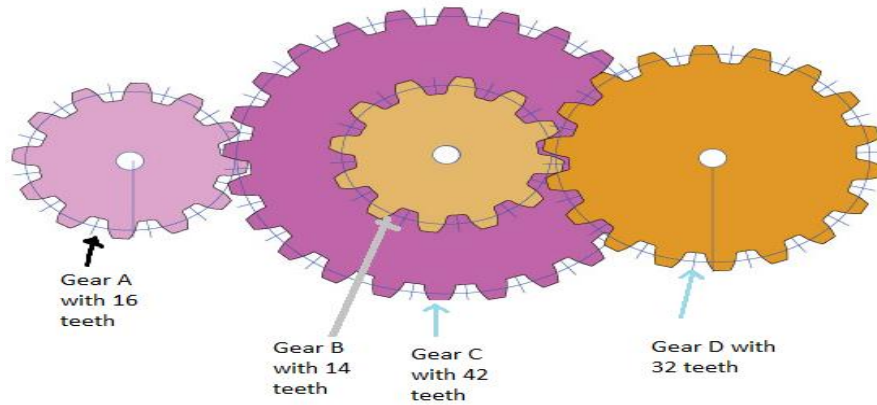


Fig. FA.11: Gear Train Design –ED8

A.2.9 Multi-Plate Disc Clutch Brake (ED10)

Multi- plate disc clutch brake design problem (ED10) is considered as one of the most substantial engineering problem shown in Fig. FA.12. The key goal of this method of optimization aims at decreasing or rising weight, yet it is composed of five discrete variables, such as friction surface number (S_f), disk thickness (T_h), outer surface radius, (D_o), actuating force form (F_{ac}) and inner surface radius (D_{in}). The mathematical formulations for ED10 is illustrated in equations below:

$$f(D_{in}, D_o, S_f, Th) = \pi Th \gamma (D_o^2 - D_{in}^2) (S_f + 1) \quad (\text{EA.18})$$

Where

$$D_{in} \in 60, 61, 62, \dots, 80;$$

$$D_o \in 90, 91, \dots, 110;$$

$$Th \in 1, 1.5, 2, 2.5, 3;$$

$$F_{ac} \in 600, 610, 620, 1000;$$

Subjected to,

$$c_1 = D_0 - D_{in} - \Delta D \geq 0 \quad (\text{EA.19a})$$

$$c_2 = L_{MAX} - (S_f + 1)(Th + \alpha) \geq 0 \quad (\text{EA.19b})$$

$$c_3 = PM_{MAX} - PM_{\pi} \geq 0 \quad (\text{EA.19c})$$

$$c_4 = PM_{MAX} Z_{MAX} + PM_{\pi} Z_{SR} \geq 0 \quad (\text{EA.19d})$$

$$c_5 = Z_{SR_{MAX}} - Z_{SR} \geq 0 \quad (\text{EA.19e})$$

$$c_6 = t_{MAX} - t \geq 0 \quad (\text{EA.19f})$$

$$c_7 = RC_h - RC_f \geq 0 \quad (\text{EA.19g})$$

$$c_8 = t \geq 0 \quad (\text{EA.19h})$$

Here, $PM_{\pi} = \frac{F_{ac}}{\Pi(D_0^2 - D_{in}^2)}$ (EA.20)

$$Z_{SR} = \frac{2\pi n(D_0^3 - D_{in}^3)}{90(D_0^2 - D_{in}^2)} \quad (\text{EA.21})$$

$$t = \frac{i_x \pi n}{30(RC_h + RC_f)} \quad (\text{EA.22})$$

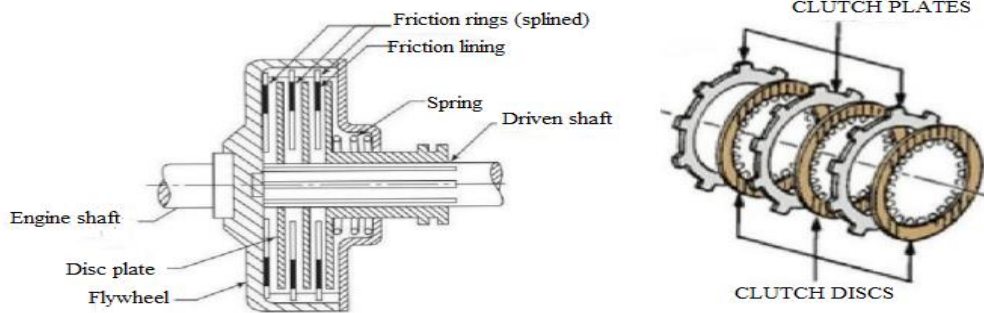


Fig. FA.12: Multi Plate Disc Clutch Break (ED10)

A.2.10 I Beam Design Problem (ED11)

The engineering design problem (ED11) aims to reduce vertical I-beam deviation by using four parameters as shown in Fig. FA.13. The design parameters are beam height (h), flange width (B), flange thickness (r_f) and web thickness (I_w). Mathematical design of I beam structure is shown in equations below.

$$i = [i_1 \ i_2 \ i_3 \ i_4] = [h \ B \ r_f \ I_w]$$

$$f_1(i) = 2i_2i_4 + i_3(i_1 - 2i_4) \quad (\text{EA.23a})$$

$$f_2(i) = \frac{60000}{i_3(i_1 - 2i_4)^3 + 2i_1i_4[4i_4^2 + 3i_1 + (i_1 - 2i_4)]} \quad (\text{EA.23b})$$

Subject to,

$$g(i) = 16 - \frac{180000i_1}{i_3(i_1 - 2i_4)^3 + 2i_1i_4[4i_4^2 + 3i_1 + (i_1 - 2i_4)]} - \frac{15000i_2}{(i_1 - 2i_4)^3 i_3^3 + 2i_4i_2^3} \geq 0 \quad (\text{EA.24})$$

Variable ranges are as follows:

$$10 \leq i_1 \leq 80 \ ; \ 10 \leq i_2 \leq 50; \ 0.9 \leq i_3 \leq 5 \ ; \ 0.9 \leq i_4 \leq 5$$

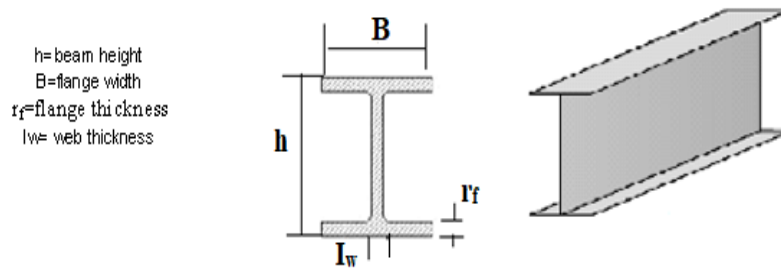


Fig. FA.13: I beam design and structure

LIST OF PUBLICATIONS

Journals Publications

1. Vikram Kumar Kamboj, Ayani Nandi, Ashutosh Bhadoria, Shivani Sehgal, “An intensify Harris Hawks optimizer for numerical and engineering optimization problems”, *Applied Soft Computing*, Volume 89, 2020.
2. Kumari, Ch Leela, Vikram Kumar Kamboj, S. K. Bath, Suman Lata Tripathi, Megha Khatri, and Shivani Sehgal. "A boosted chimp optimizer for numerical and engineering design optimization challenges." *Engineering with Computers* (2022): 1-52.
3. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “Scope of Heuristics, Meta-Heuristics and Nature Inspired Methodologies for Economic Load Dispatch and Bess Based Ancillary Services” *Think India Journal*, Vol-22, Issue-17-September-2019, pp2965-76.
4. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “Economic Load Dispatch Problem for BESS Based Ancillary Services considering Electric Vehicles (PEVs/BEVs) and Renewable Energy Sources” *International Journal of Emerging Technologies and Innovative Research*, ISSN:2349-5162, Vol.6, Issue 1, pp.1366-1377.
5. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj, "A memetic approach to Multi-disciplinary design and numerical optimization problems using Intensify Slime Mould Optimizer" communicated in *Applied intelligence*. [Status: Minor Revision].

International Conferences

1. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “Modelling for Optimal Load Dispatch with Renewable Energy Source/Battery Energy Storage System/Electric Vehicle Charging Station” communicated in *The International Conference on Decision Aid Sciences and Applications, DASA 2020*.

2. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “Memetic Optimal Approach for Economic Load Dispatch Problem with Renewable Energy Source in Realistic Power System” Communicated in International Conference on Advances and Applications of Artificial Intelligence and Machine Learning, ICAAAIML-2020.
3. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “A Cost Effective Memetic Optimal approach for Solution of Economic Load Dispatch Problem in Realistic Power System” communicated in FTNCT-2020 Approved by CCIS, Springer (Indexed by Scopus and DBLP).

Book Chapters

1. Sehgal S., Ganesh A., Kamboj V.K. (2021) Memetic Optimal Approach for Economic Load Dispatch Problem with Renewable Energy Source in Realistic Power System. In: Choudhary A., Agrawal A.P., Logeswaran R., Unhelkar B. (eds) Applications of Artificial Intelligence and Machine Learning. Lecture Notes in Electrical Engineering, vol 778. Springer, Singapore. https://doi.org/10.1007/978-981-16-3067-5_47.
2. Sehgal S., Ganesh A., Kamboj V.K. (2021) A Cost Effective Memetic Optimal Approach for Solution of Economic Load Dispatch Problem in Realistic Power System. In: Singh P.K., Veselov G., Pljonkin A., Kumar Y., Paprzycki M., Zachinyaev Y. (eds) Futuristic Trends in Network and Communication Technologies. FTNCT 2020. Communications in Computer and Information Science, vol 1396. Springer, Singapore. https://doi.org/10.1007/978-981-16-1483-5_5

Communicated Publications

1. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj, “A pattern search inspired Slime mould optimizer to solve hard industrial design challenges and power system optimization problems” communicated in Computers in Industry, Springer Publications [Status: Under Review].

2. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “Random Exploratory Search Inspired Hybrid Slime Mould Optimizer for Engineering Design Optimization and Battery Energy Storage Based Ancillary Services”, communicated in Engineering with computers, Springer Publication [Status: Under Review].
3. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “A Memetic Solution Approach for Economic Load Dispatch Considering Battery Energy Based Ancillary Services and Renewable Energy Sources”, communicated in Neural Computing and Applications, Springer Publication [Status: Under Review].
4. Shivani Sehgal, Aman Ganesh, Vikram Kumar Kamboj “A Memetic SMA-RES based solution approach for dynamic economic load dispatch problem considering impact of electric vehicles and renewable energy sources”, communicated in Electrical Engineering, Springer Publication [Status: Under Review].