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Optimization Methodologies and Testing on Standard Benchmark Functions of Load Frequency Control for Interconnected Multi Area Power System in Smart Grids

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Abstract: In the recent era, the need for modern smart grid system leads to the selection of optimized analysis and planning for power generation and management. Renewable sources like wind energy play a vital role to support the modern smart grid system. However, it requires a proper commitment for scheduling of generating units, which needs proper load frequency control and unit commitment problem. In this research area, a novel methodology has been suggested, named Harris hawks optimizer (HHO), to solve the frequency constraint issues. The suggested algorithm was tested and examined for several regular benchmark functions like unimodal, multi-modal, and fixed dimension to solve the numerical optimization problem. The comparison was carried out for various existing models and simulation results demonstrate that the projected algorithm illustrates better results towards load frequency control problem of smart grid arrangement as compared with existing optimization models.

Keywords: Harris hawks optimizer; load frequency control; sensitivity analysis; smart grid; particle swarm optimization; genetic algorithm; meta-heuristics

1. Introduction

Optimization shows a critical role in various regions of science and technology. This is the method through which the optimal solution can be found with the help of a wide range of search mechanisms like primary, secondary, and tertiary controls [1]. With recent advancement in technology, novel optimization methodologies are identified as meta-heuristic with concern of mathematical culture. Meta-heuristic algorithms (MA) is a typical technique to get the best outcomes for the issue. It plays a fictional role to find good specifications in an optimization matter [2].

Each real-life optimization problem required procedures which observe the examination zones effectively to find most operative explanations. Moth-flame optimizer (MFO) is newly projected meta-heuristics search algorithmic rule that is inspired by the direction-finding environment of lepidopteron and its convergence in the direction of lightweight. However, like alternative similar strategies, MFO contributes to being stuck into sub-optimal segments, which is mirrored within the procedure effort needed to search out the most effective rate. This case happens due to the developer used for research not performing well to research the find house. In addition, no free lunch theorem encourages planners to promote a new algorithmic rule or to boost the prevailing algorithmic rule.

The modern technology that balances the two-way communication between energy production and consumption and sense the critical behavior of voltage, current, and frequency which makes an electric grid as a smart grid. Smart grid is an opportunity in the growth of the country's economy and environmental health due to efficient electricity transmission, quicker restoration, reduced power cost, and enhanced integration with renewable energy sources, which is possible through optimal gain scheduling and the load frequency control method.

In earlier days, the load frequency control (LFC) problem was explained with respect to conventional dispatching [3], whose objective was to maintain voltages and frequency within prescribed limits. Today, LFC uses advanced numerical optimization techniques to solve constrained combinatorial and diverse number optimization issues. The type of controller [4], its architecture and choice of objective function play a very important role in enhancing achievement of the power system.

In the current scenario, the integral of time multiplied absolute error (ITAE) criteria is observed as an impartial task which is stated as [5]:

$$J = \int_{0}^{t_{sim}} (|\Delta F_1| + |\Delta F_2| + |\Delta P_{tie}|).t.dt., \tag{1}$$

where, ΔF_1, ΔF_2 indicate deviation of the frequency in both areas and the total simulation time (in seconds) is denoted by 't_{sim}' and tie-line interchange [6] assessment is characterized by ΔP_{tie}.

The ITAE is implemented as a detached role to enhance gain of the PI controller in the present investigation. The reduction of the ITAE index with the binary moth flame optimizer (BMFO) algorithm offers augmented constraints of PI controllers which can be subjected to the following restraints [7–9]:
Minimize J,

$$K_i^P \min \leq K^P \leq K_i^P \max, \textit{ and } K_i^{Int.} \min \leq K^{Int.} \leq K_i^{Int.} \textit{ max},$$

where, $K_i^{Int.}$ and K_i^P symbolize fundamental and comparative gain of PI controller of $\mathrm{i_{th}}$ (i = 1, 2) area.

Our contributions in this work are as follows: First, we propose the two variants of binary moth flame optimizers to solve the frequency constraint issues. We implemented two different binary variants for improving performance of the moth flame optimizer (MFO) for discrete optimization problems. In the first variant, i.e., binary moth flame optimizer (BMFO1), coin flipping-based selection probability of binary numbers is used. We used the improved Sigmoid transformation in the second variant called BMFO2. These binary MFO algorithms along with the Harris hawks optimizer (HHO) algorithms are tested and analyzed for various unimodal, multi-modal, and fixed dimension numerical optimization problem. Secondly, Section 2 explores various optimization methodologies, including classical artificial intelligence techniques, modern intelligence techniques, hybrid artificial intelligence techniques, and smart grid technologies which are tested using standard benchmarks and compared with various algorithms. Lastly, in Section 3, all the latest used algorithms are evaluated and compared in terms of standard testing benchmarks in which the proposed HHO model is having improved results in terms of average and standard deviation. Finally, Section 4 concludes the paper.

2. Optimization Methodologies

In order to discover the mathematical design of load frequency control, numerous optimization methodologies are classified into three foremost groups like traditional techniques [10], recent techniques [11], and hybrid techniques [12].

2.1. Traditional Techniques

The traditional methods may be further classified into artificial neural network, fuzzy logic technique [13], and genetic algorithm.

2.1.1. Artificial Neural Network

The architecture of Artificial Neural Network (ANN) as shown in Figure 1 is promptly the emerging zone of investigation, producing attention of predictors from a noble type of scientific field, which gives a deviation of desired output and actual output as an error signal. An error signal acts like a feedback to the neural network, which balances the desired and actual output.

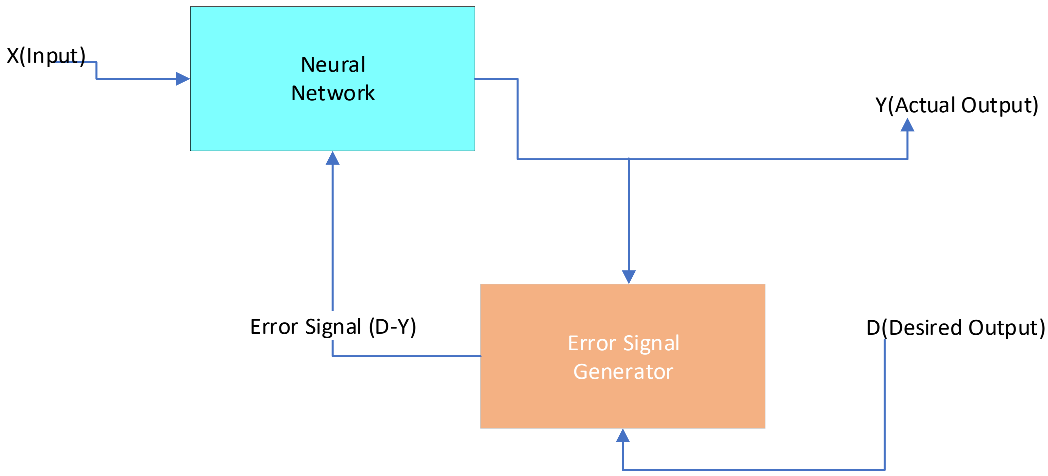


Figure 1. Artificial neural network architecture.

2.1.2. Fuzzy Logic Technique

The essential configuration of the scientific reasoning scheme in which the fuzzification [14] boundary recreates the additional contribution into a fuzzy verbal input, and likewise shows an significant character in the mathematical coherent [15] procedure as actual principles, which are delivered from current sensors, are a forever crisp analytical equivalent as shown in Figure 2.

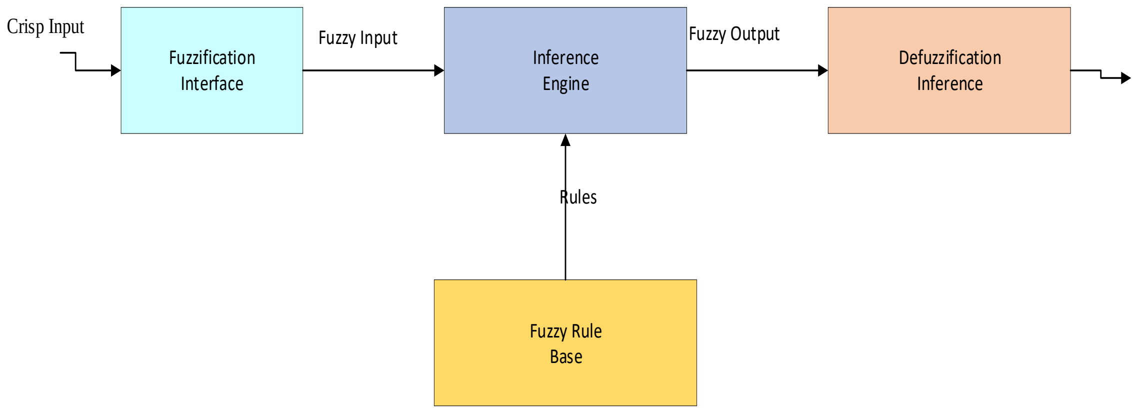


Figure 2. Fuzzy logic system architecture.

2.1.3. Genetic Algorithm

The overall thoughts were conceived by a European country [16], whereas practicality of persecution of exhausting it to untie innovative concerns was indisputable. It may be a soft computing style, which implements strategies stimulated by usual hereditary knowledge to develop conclusions to matters [17]. Genetic Algorithm (GA) as shown in Figure 3 is refreshed by Darwin's theory concerning progression, which is useful to a vast variety of methodical and industrial problems like optimization, machine learning, and automatic software design [18].

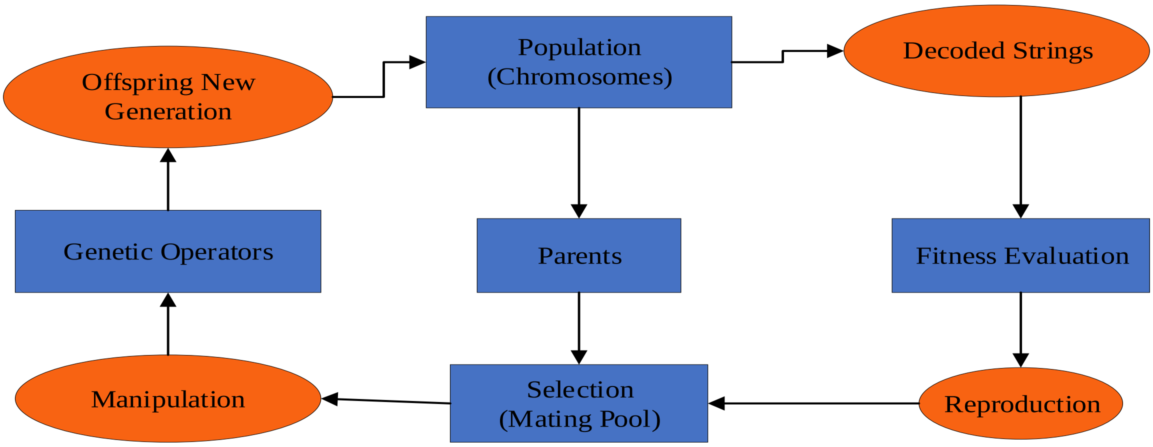


Figure 3. Genetic algorithm architecture.

2.2. *Modern Intelligence Techniques*

To solve the multi-disciplinary optimization problems [14], various modern practices are established by the investigators. The modern intelligence techniques are explored in the following sub-sections.

2.2.1. Differential Evolution Technique

It is a genetic-based algorithm [19] having identical operators corresponding to initialization, mutation, crossover, and selection. In this method, all constraints are expressive in genetic measurable by a genuine measurement [20]. The mathematical formulation of differential evolution is given below:

• **Initialization**

Firstly, whole vector of initial population is assigned any arbitrary assessment [21] starting with its equivalent state:

$$X_{j,i}^{(0)} = X_j^{min} + \mu_j\left(X_j^{max} - X_j^{min}\right), \tag{2}$$

where μ_j represents uniformly dispersed arbitrary numeral initialize with the array of [0, 1], generates novel for all value of X_j^{min} and X_j^{max} are representing the uppermost and lowermost limits of the j^{th} parameter, correspondingly.

• **Mutation**

This operator [22] generates distorted vectors X_i' by disturbing a randomly chosen vector 'X_a' and dissimilarity randomly chosen vectors 'X_b' and 'X_c' as per the following equation:

$$X_i'^{(G)} = X_a'^{(G)} + a\left(X_b^{(G)} + X_c^{(G)}\right)\ i = 1, \ldots..N\,P, \tag{3}$$

where 'X_a','X_b', and 'X_c' represent the randomly selected vectors among set of population, and 'α' represents the scaling constant of the algorithm parameter which is used to regulate the size of the mutation operator and find better results.

• Crossover

Crossover operations [23] create trial vectors X''_i with integration of the parameters of the distorted vectors X'_i with its objective or parent vectors x_i:

$$X''_{j,i}(G) = \begin{cases} X'^{(G)}_{j,i} \ if \ p_j \ \leq \ C_R \ or \ j = q \\ X^{(G)}_{j,i} \ otherwise \end{cases}, \tag{4}$$

where p_j represents consistently discrete unplanned integer [24] between the variety of 0 and 1 and generates an extra for every value of j. q represents the random selected indicator {1, ..., NP} of the trial vector [25] obtain one parameter as a distorted vector. C_R representing the crossover operation constant of algorithm parameters [26] that manage the variety of population and algorithm is run absent as of local minima [27].

• Selection

Selection operator [28] develops the population by choosing the trial and parent vectors (precursor) which presents a best fitness [29]:

$$X^{(G+1)}_i = \begin{cases} X''^{(G)}_i \ if \ f\left(X''^{(G)}_i\right) \leq f\left(X'^{(G)}_i\right) \\ X^{(G)}_i \ otherwise \end{cases} \quad i = 1, \ldots\ldots, N\,P. \tag{5}$$

This optimization procedure is replicate to the number of generations to obtain superior fitness functions because they required optimal values to explore the search space.

2.2.2. Biogeography Based Optimization

Biogeography Based Optimization (BBO) is the investigation of topographical propagation of living classes which is based on mutation and migration procedures [30].

• Migration

The migration process is either leaving or entering the species from an island. Biogeography-based optimization also used a population of candidate solution for optimization similar to partial swarm optimization and another population-based search method [31]. Depiction of all candidate solutions is complete as a vector of actual statistics. Now, all real statistics is considered in the population as suitability index variable (SIV). SIV [32] is similar to the output power of generating components in load frequency control. Few best solutions are the same in the resultant iterations; the migration process arranges to avoid the best solutions from being changed. Emigration rate [33] and immigration rate [34] for habitat contain 'k' species is express as:

$$\lambda_k = I\left(1 - \frac{K}{\eta}\right), \tag{6}$$

$$\mu_k = \frac{Ek}{\eta}, \tag{7}$$

where E represents the emigration rates, I represents the maximum immigration rates, and η represents the maximum number of species, respectively.

• Mutation

The habitat suitability index (HSI) [35] can easily be modified with resultant in the breed calculation to be different from the symmetry value, if a number of catastrophic actions occur. In biogeography-based optimization, this procedure is modeled as SIV mutation and the mutation rates of habitats may be intended to use the species add up probabilities known unexpected modification in weather of one habitat or additional occurrence will cause the unexpected modification in HSI (habitat). This condition is replica in the form of unexpected modification in the value of the suitability index variable in BBO. The probability of some organism [36] is calculated by this equation:

$$P_S = \begin{cases} -(\lambda_S + \mu_S)P_S + \mu_{S+1}P_{S+1} \; S = 0 \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1} + \mu_{S+1}P_{S+1} \; 1 \le S \le S_{max-1} \\ -(\lambda_S + \mu_S)P_S + \lambda_{S-1}P_{S-1} \; S = S_{max} \end{cases}. \tag{8}$$

The own probability of all members is one habitat. If probability of this is too low, and after that, this result has more probability to mutilation [37]. In a similar way, if the probability of a result is more, that result has a small probability to mutate. As a result, solutions with a low suitability index variable and high suitability index variable have a small possibility to grow an improved SIV in the new iteration. Dissimilar low suitability index variable and high suitability index [38] variable solutions, middle HSI solutions have a bigger possibility to grow improved solutions after the mutation process. By the use of equation mutation, all results can be calculated easily:

$$m(s) = m_{max}\left(\frac{1 - P_S}{P_{max}}\right), \tag{9}$$

where $m(s)$ represent the mutation rate.

2.2.3. Dragonfly Algorithm (DA)

DA [39] is an exceptional optimization process planned by Seyedali. The most important purpose of swarm is durability; thus, all individual must be unfocused outward, and opponents attracted towards nourishment sources. Taking both behaviors in swarms [40], these are five major topographies in position informing procedure of individuals. The numerical model of swarms actions as shown below: The parting procedure [41] in DA informing as in the above equation:

$$S_i = -\sum_{J=1}^{N} X - X_J, \tag{10}$$

where N represents the amount of entities of neighboring, X represents the present situation of specific, X_J indicates the location of J^{th} specific of the adjacent [42].

The orientation procedure in this approach can be rationalized by subsequent expression [43]:

$$A_i = \frac{\sum_{J=1}^{N} V_J}{N}, \tag{11}$$

where V_J represents velocity of J^{th} specific of the adjacent. The unity in DA can be intended by the above evaluation:

$$C_i = \frac{\sum_{J=1}^{N} X_J}{N} - X, \tag{12}$$

where X represents the existing specific point, X_J is the spot of J^{th} specific of the adjacent, and N indicates the amount of areas.

2.3. Hybrid Artificial Intelligence Techniques

2.3.1. Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) Hybridization

The easiest technique to mongrelize PSO and GSA is to implement the strength separately in the successive approach [44].

Particle Swarm Optimization (PSO)

PSO is provoked with keen collective activities [45] accessible by a multiplicity of creatures, such as the group of ants or net of birds. The particle position and velocity both are updated according to the equations:

$$v_i^d(t+1) = w(t)v_i^d(t) + c_1 X r_1 X\left(pbest_i^d - x_i^d\right) + c_2 + r_2, \tag{13}$$

$$x_i^d(t+1) = x_i^d(t+1) + v_i^d(t+1), \tag{14}$$

$$Wt = rand\ X \frac{t}{t_{max}} X(w_{max} - w_{min}) + w_{min}, \tag{15}$$

where $v_i^d(t+1)$ shows velocity of (d^{th}) dimension at (t) reiteration of (i^{th}) particle, $x_i^d(t+1)$ is existing position of (d^{th}) dimensional iteration (t) of (i^{th}) particle; c_1 and c_2 representing the acceleration coefficients [46] which manage the pressure of gbest and pbest on the search procedure, r_1 and r_2 representing the arbitrary statistics in variety [0, 1]; $pbest_i^d$ represents finest point of (i^{th}) element up to now.

Gravitational Search Algorithm (GSA)

GSA is meta-heuristic population-centered approach inspired with directions of attraction and quantity associations [47–49]. In this method, cause is dignified as article encompasses of unlike multitudes and the enactment of this is considered via crowds.

2.3.2. Differential Evolution and Particle Swarm Optimization Hybrids

It is a population-based optimizer [50] alike the genetic algorithm, having identical operatives corresponding to selection, mutation, and crossover. In this method, all constraints are expressive in genetic measurable by a genuine measurement [20,51].

2.3.3. Binary Moth Flame Optimizer (BMFO1)

BMFO is a newly projected meta-heuristics search algorithm proposed by Seyedali Mirjalili [52,53] which is refreshed by direction-finding behavior of moth and its converges near light. Although, moths are having a robust capability to uphold a secure approach with respect to the moon and hold a tolerable erection for nomadic in an orthodox mark for extensive distances. Besides, they are attentive in a fatal/idle curved track over simulated basis of lights.

2.3.4. Modified SIGMOID Transformation (BMFO2)

The binary calibration of constant pursuit house and places of search representatives, resolutions to binary exploration house could be the obligatory method for optimization of binary environmental issues such as LFC. In the proposed research, a modified sigmoidal transfer function is adopted, which has superior performance than another alternatives of sigmoidal transfer function as reported in [54].

2.3.5. Harris Hawks Optimizer

HHO [55] is gradient-free and populations-centered algorithm that comprises exploitative and exploratory stages, which is fortified by astonishment swoop, the fauna of examination of a victim, and diverse stratagems built on violent marvel of Harris hawks.

2.3.6. Smart Grid Applications

The modern smart grid system as shown in Figure 4 consists of various power generating units consisting of thermal, hydro, nuclear, wind, and solar-based power producing elements. The scheduling of every power producing in optimal condition is a tedious task and requires proper commitment schedule of generating units. Further, consideration of solar and wind-based energy sources requires proper load frequency control [56].

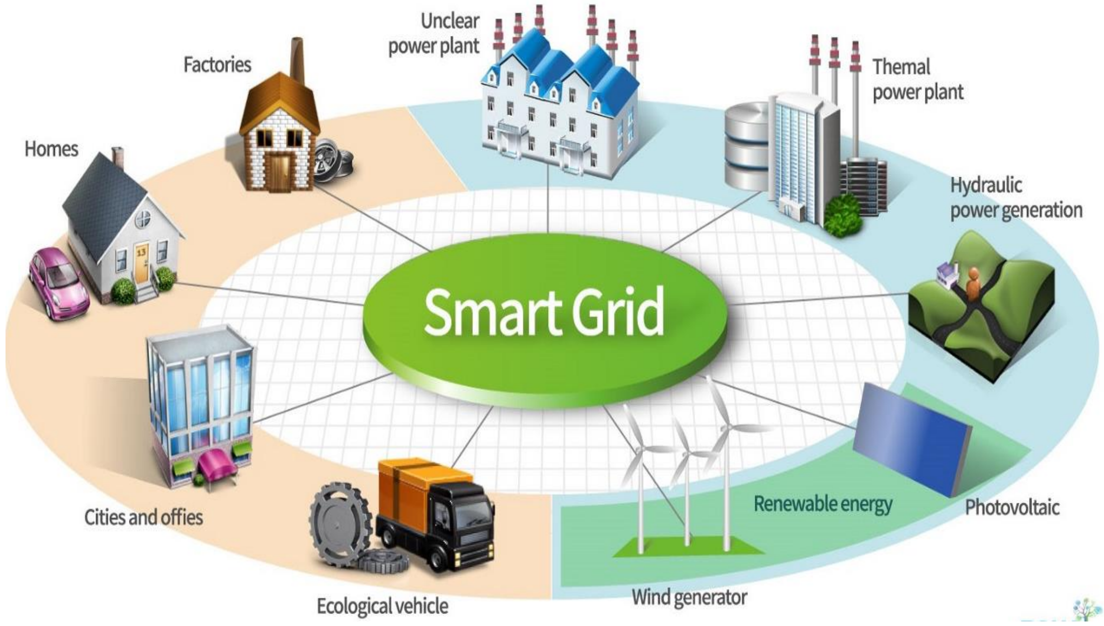


Figure 4. Modern smart grid system with Electric Vehicles (EVs) load demand.

An electric grid can easily be converted into a smart grid by balancing the voltage, current, and frequency which is possible by the load frequency control method [57]. If incoming voltage, current, and frequency is matched with the outgoing voltage, current, and frequency of an electric grid with the help of optimal gain scheduling and load frequency control approach, then steady state error will be near to zero or nil. In the proposed research, load frequency control is tested and validated with various standard benchmarks simultaneously and mathematically depicted in the following sub-sections.

3. Standard Testing Benchmarks

The consequences for various benchmark issues [58] considering the LFC situation are deliberated in the above-mentioned units.

Test System and Standard Benchmark

For confirmation of prospects of deliberate BMFO and HHO algorithms, CEC2005 benchmark functions [59] have been taken into thought, which include unimodal, multi-modal, and fixed dimensions benchmark issues and its mathematical formulation has been represented in Tables 1–3. Table 1 interprets unimodal standard performance, Table 2 portrays multi-modal standard, and Table 3 interprets fixed dimensions standard issues.

To explain the random behavior of the expected BMFO2 logarithmic rule and confirm the consequences, thirty trials were applied with all objective function check for average, variance, best and worst values for justification of output from the probable algorithmic rule, unimodal benchmark work f1, f2, f3, f4, f5, f6, and f7 are used. Table 4 (a) signifies the response of unimodal benchmark function with BMFO1 logarithmic rule, Table 4 (b) characterizes the retort of unimodal benchmark operate function by using the BMFO2 algorithmic rule and Table 4 (c) represents the answer of the fixed dimension benchmark function by using HHO algorithmic instruction.

Table 1. Unimodal benchmark.

Function	Dim	Range	$f_{\min}$
$f_1(x) = \sum_{i=1}^{n} x_i^2$	30	[−100, 100]	0
$f_2(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	30	[−10,10]	0
$f_3(x) = \sum_{i=1}^{n} \left(\sum_{j-1}^{i} x_j\right)^2$	30	[−100, 100]	0
$f_4(x) = max_i\{\lvert x_i \rvert, 1 \le i \le n\}$	30	[−100, 100]	0
$f_5(x) = \sum_{i=1}^{n-1}\left[100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right]$	30	[−30, 30]	0
$f_6(x) = \sum_{i=1}^{n} ([x_i + 0.5])^2$	30	[−100, 100]	0
$f_7(x) = \sum_{i=1}^{n} ix_i^4 + \text{random } [0,\ 1]$	30	[−1.28, 1.28]	0

Table 2. Multimodal benchmark.

Function	Dim	Range	$f_{\min}$
$f_8(x) = \sum_{i=1}^{n} -x_i \sin(\sqrt{\lvert x_i \rvert})$	30	[−500, 500]	−418.98
$f_9(x) = \sum_{i=1}^{n}\left[x_i^2 - 10\,cos(2\Pi x_i) + 10\right]$	30	[−5.12, 5.12]	0
$f_{10}(x) = -20\exp(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\Pi x)_i + 20 + c$	30	[−32, 32]	0
$f_{11}(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}}) + 1$	30	[−600, 600]	0
$f_{12}(x) = \frac{\Pi}{n}\left\{10\sin(\Pi y_1) + \sum_{i=1}^{n-1}(y_i - 1)^2\left[1 + 10sin^2(\Pi y_{i+1}) + (y_n - 1)^2\right]\right\} +$ $\sum_{i=1}^{n} u(x_i, 10, 100, 4)$ where $y_i = 1 + \frac{x_{i+1}}{4}$ $u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m, & x_i > a \\ 0, & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$	30	[−50, 50]	0
$f_{13}(x) =$ $0.1\{sin^2(3\Pi x_i) + \sum_{i=1}^{n}(x_i - 1)^2\left[1 + sin^2(3\Pi x_i + 1\right] + (x_m - 1)^2\left[1 + sin^2(2\Pi x_m)\right]\} +$ $\sum_{i=1}^{n} u(x_i, 5, 100, 4)$	30	[−50, 50]	0
$f_{14}(x) = -\sum_{i=1}^{n}\sin(x_i).\left(\sin\left(\frac{ix_i^2}{\Pi}\right)\right)^{2m},\ m = 10$	30	[0, π]	−4.687
$f_{15}(x) = \left[e - \sum_{i=1}^{n}(x_i/\beta)^{2m} - 2e - \sum_{i=1}^{n} x_i^2\right] - \prod_{i=1}^{n} cos^2 x_i, m = 5$	30	[−20, 20]	−1
$f_{16}(x) = \left\{\sum_{i=1}^{n} sin^2(x_i) - exp\left(-\sum_{i=1}^{n} x_i^2\right)\right\}.exp\left[-\sum_{i=1}^{n} sin^2\sqrt{\lvert x_i \rvert}\right]$	30	[−10, 10]	−1

It is analyzed from Table 4 that the unimodel benchmark functions f1 to f7 are tested using the modern hybrid algorithms like BMFO 1, BMFO 2, and HHO, and found that Harris hawks optimizer (HHO) produces optimal outcomes in terms of mean, standard deviation, best and worst value for all functions as compared to other algorithms. The convergence curve and trial solutions for BMFO1, BMFO2, and HHO for f1 to f7 unimodal benchmark functions are presented in Figure 5.

Table 3. Fixed dimension benchmark.

Function	Dim	Range	$f_{\min}$
$f_{14}(x) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j+\sum_{i=1}^{2}\left(x_i - a_{ij}\right)^6}\right)^{-1}$	2	[−65, 65]	1
$f_{15}(x) = \sum_{i=11}^{11}\left[a_i - \frac{x_i\left(b_i^2 + b_i x_2\right)}{b_i^2 + b_i x_3 + x_4}\right]^2$	4	[−5, 5]	0.00030
$f_{16}(x) = 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4$	2	[−5, 5]	−1.0316
$f_{17}(x) = \left(x_2 - \frac{5.1}{4\Pi^2}x_1^2 + \frac{5}{\Pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\Pi}\right)cosx_i + 10$	2	[−5, 5]	0.398
$f_{18}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)]\ X\ [30 + (2x_1 - 3x_2)^2 X\ (18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$	2	[−2, 2]	3
$f_{19}(x) = -\sum_{i=1}^{4} c_i exp\left(-\sum_{j=1}^{3} a_{ij}\left(x_j - p_{ij}\right)^2\right)$	3	[1, 3]	−3.32
$f_{20}(x) = -\sum_{i=1}^{4} c_i exp\left(-\sum_{j=1}^{6} a_{ij}\left(x_j - p_{ij}\right)^2\right)$	6	[0, 1]	−3.32
$f_{21}(x) = -\sum_{i=1}^{5}\left[(x - a_i)(x - a_i)^T + c_i\right]^{-1}$	4	[0, 10]	−10.1532
$f_{22}(x) = -\sum_{i=1}^{7}\left[(x - a_i)(x - a_i)^T + c_i\right]^{-1}$	4	[0, 10]	−10.4028
$f_{23}(x) = -\sum_{i=1}^{10}\left[(x - a_i)(x - a_i)^T + c_i\right]^{-1}$	4	[0, 10]	−10.5363

Table 4. (**a**) Outcomes of the BMFO1 algorithm. (**b**) Outcomes of the BMFO2 algorithm. (**c**) Outcomes of the HHO algorithm.

Benchmark Functions	Parameters				
	Mean Value	**SD**	**Worst Value**	**Best Value**	***p*-Value**
			(**a**)		
f1	5.75×10^{-34}	2.55×10^{-33}	1.40×10^{-32}	0	3.79×10^{-60}
f2	1.48×10^{-20}	2.24×10^{-20}	1.14×10^{-19}	0	3.79×10^{-60}
f3	3.87×10^{-10}	1.61×10^{-9}	8.70×10^{-9}	0	2.56×10^{-60}
f4	0.03831	0.08819	0.4401	0	2.56×10^{-60}
f5	3.14461	2.21914	6.01278	0	2.56×10^{-60}
f6	1.27×10^{32}	1.60×10^{-32}	8.32×10^{-32}	0	7.23×10^{-60}
f7	1.00564	1.00438	1.01652	0	1.74×10^{-60}
			(**b**)		
f1	3.64×10^{-34}	1.05×10^{-33}	4.50×10^{-33}	0	2.56×10^{-60}
f2	6.08×10^{-20}	1.30×10^{-19}	6.12×10^{-19}	0	2.56×10^{-60}
f3	7.64×10^{-11}	3.00×10^{-10}	1.65×10^{-9}	9.46×10^{-15}	1.73×10^{-60}
f4	0.04709	0.09997	0.47495	0	2.56×10^{-60}
f5	3.4591	2.2489	6.2531	0.00064	1.73×10^{-60}
f6	2.85×10^{-32}	5.78×10^{-32}	3.08×10^{-31}	0	1.61×10^{-50}
f7	1.00499	1.00387	1.01831	0.00032	1.74×10^{-60}
			(**c**)		
f1	1.0634×10^{-90}	5.82468×10^{-90}	3.19×10^{-89}	8.7×10^{-112}	1.734×10^{-6}
f2	6.9187×10^{-51}	2.46844×10^{-50}	1.31×10^{-49}	1.71×10^{-60}	1.734×10^{-6}
f3	1.251×10^{-80}	6.62663×10^{-80}	3.632×10^{-79}	8.3×10^{-99}	1.734×10^{-6}
f4	4.4615×10^{-48}	1.70307×10^{-47}	8.676×10^{-47}	2.45×10^{-59}	1.734×10^{-6}
f5	0.01500185	0.023472777	0.0874276	1×10^{-5}	1.734×10^{-6}
f6	0.00011487	0.00015409	0.0007119	4.17×10^{-7}	1.734×10^{-6}
f7	0.00015829	0.000224928	0.001202	2.87×10^{-6}	1.734×10^{-6}

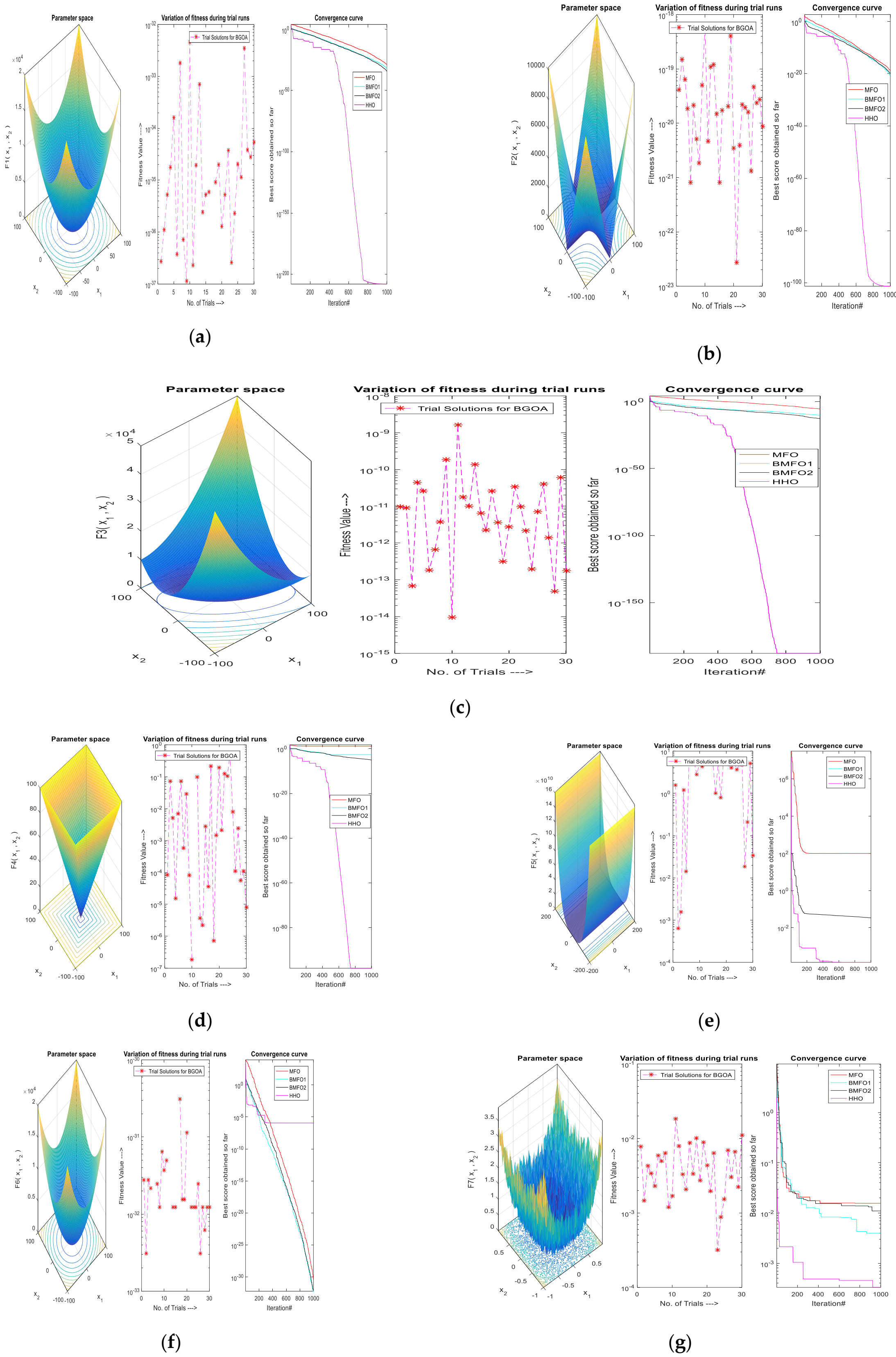


Figure 5. (**a**–**g**) Convergence curve of all algorithms for unimodal benchmark functions.

The convergence curve and trial solutions for BMFO1, BMFO2, and HHO for f1 to f7 unimodal benchmark functions are presented in Figure 5a–g.

The connected upshots for unimodal standard functions [60] have been represented in Table 5, which are correlated with various latest refined algorithms [61] grey wolf optimizer (GWO) [62], PSO [63,64], GSA [8,65], differential evolution (DE) [66,67], fruit fly optimization algorithm (FOA) [68,69], ant lion optimizer (ALO) [70,71], symbiotic organisms search (SOS) [72], bat algorithm (BA) [73], flower pollination algorithm (FPA) [74,75], cuckoo search (CS) [76], firefly algorithm (FA) [52], GA [77], grasshopper optimization algorithm (GOA) [73,78], MFO [79], multiverse optimization algorithm (MVO) [80], DA [81], binary bat optimization algorithm (BBA) [65], BBO [5,82], binary gravitational search algorithm (BGSA) [83,84], sine cosine algorithm (SCA) [85,86], FPA [74,87], salp swarm optimization algorithm (SSA) [88], and whale optimization algorithm (WOA) [89] in lieu of mean and standard deviation.

Table 5. Comparison of unimodal benchmark functions.

Algorithm	Parameter	Uni-Modal Benchmark Functions						
		f1	f2	f3	f4	f5	f6	f7
GWO [62]	Mean	0.02	0	0.01	1.02	26.81	0.82	0
	SD	0	0.03	79.15	1.32	69.9	0	0.1
PSO [63,64]	Mean	0	0.04	70.13	1.09	96.72	0	0.12
	SD	0	0.05	22.12	0.32	60.12	0	0.04
GSA [8,65]	Mean	0	0.06	896.53	7.35	67.54	0	0.09
	SD	0	0.19	318.96	1.74	62.23	0	0.04
DE [66,67]	Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	SD	1.01	1.01	1.01	1.01	1.01	1.01	1.01
FOA [68,69]	Mean	0.05	0.06	0.04	0.4	5.06	0.02	0.14
	SD	0.02	0.02	0.01	1.5	5.87	0	0.35
ALO [70,71]	Mean	0.01	0.01	0	0.01	0.35	0.01	0
	SD	0.01	0	0.01	0.01	0.11	0.01	0.01
SOS [72]	Mean	0.06	0.01	0.96	0.28	0.09	0.13	0
	SD	0.01	0	0.82	0.01	0.14	0.08	0
BA [73]	Mean	1.77	1.33	1.12	1.19	1.33	1.78	1.14
	SD	1.53	4.82	1.77	1.89	1.3	1.67	1.11
FPA [74,75]	Mean	0.01	0.01	0.01	0.01	0.78	0.01	0.01
	SD	0.01	0.01	0.01	0.01	0.37	0.01	0.01
CS [76]	Mean	0	1.21	1.25	0.01	0.01	0.01	0.01
	SD	0	1.04	1.02	0.01	0.01	0.01	0.01
FA [52]	Mean	0.04	0.05	0.05	0.15	2.18	0.06	0
	SD	0.01	0.01	0.02	0.03	1.45	0.01	0
GA [77]	Mean	0.12	0.15	0.14	0.16	0.71	0.17	0.01
	SD	0.13	0.05	0.12	0.86	0.97	0.87	0
GOA [73,78]	Mean	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	SD	0.01	0.01	0.02	0.01	0.01	0.01	0.01
MFO [79]	Mean	0.01	0.01	0.01	0.07	27.87	3.12	0
	SD	0	0	0	0.4	0.76	0.53	0
MVO [80]	Mean	2.09	15.92	453.2	3.12	1272.1	2.29	0.05
	SD	0.65	44.75	177.1	1.58	1479.5	0.63	0.03
DA [81]	Mean	0.01	0.01	0.01	0.01	7.6	0.01	0.01
	SD	0.01	0.01	0.01	0.01	6.79	0.01	0.01
BBA [65]	Mean	1.28	1.06	15.6	1.25	24.7	1.1	1.01
	SD	1.42	1.07	23.8	1.33	35.8	1.14	1.01
BBO [5,82]	Mean	6.52	0.2	16.7	2.8	87.6	7.96	0.01
	SD	2.99	0.05	14.9	1.47	66.9	4.87	0.01
BGSA [83,84]	Mean	85	1.19	458	7.35	3110	109	0.04
	SD	48.7	0.23	275	2.25	2936	77.7	0.06
SCA [85,86]	Mean	0.01	0.01	0.06	0.1	0.01	0.01	0.01
	SD	0.01	0.01	0.14	0.58	0.01	0.01	0.01
SSA [88]	Mean	0.01	0.23	0.01	0.01	0.01	0.01	0.01
	SD	0.01	1	0.01	0.66	0.01	0.01	0.01
WOA [89]	Mean	0.01	0.01	696.73	70.69	139.15	0.01	0.09
	SD	0.01	0.01	188.53	5.28	120.26	0.01	0.05
BMFO1	Mean	0.01	0.01	0.01	0.04	3.14	0.01	0.01
	SD	0.01	0.01	0.01	0.09	2.22	0.01	0.01
BMFO2	Mean	0.01	0.01	0.01	0.05	3.46	0.01	0.01
	SD	0.01	0.01	0.01	0.1	2.25	0.01	0.01
HHO (Proposed)	Mean	1.06×10^{-90}	6.92×10^{-51}	1.25×10^{-80}	4.46×10^{-48}	0.015002	0.000115	0.000158
	SD	5.82×10^{-90}	2.47×10^{-50}	6.63×10^{-80}	1.70×10^{-47}	0.023473	0.000154	0.000225

To defend the synthesis part of the probable algorithm, multi-modal benchmark functions f8, f9, f10, f11, f12, and f13 are taken with numerous native goals with values rising violently w.r.t magnitude. Table 6 (a) presents clarification of the multimodal benchmark function with the BMFO1 algorithm and Table 6 (b) presents the explanation of the multimodal benchmark function with the BMFO2 algorithm and Table 6 (c) presents the explanation of the multimodal benchmark function with the HHO algorithm.

Table 6. (**a**) Outcomes of the BMFO1 algorithm. (**b**) Outcomes of the BMFO2 algorithm. (**c**) Results of the HHO algorithm.

Benchmark Functions	Parameters				
	Mean Value	SD	Worst Value	Best Value	p-Value
			(**a**)		
f8	−3140.3	290.75	−2641	−4071.4	0
f9	1.63	0.96	2.98	0.01	0
f10	0.04	0.21	1.16	0.01	0
f11	0.01	0.01	0.01	0.01	1
f12	0.01	0.01	0.01	0.01	0.01
f13	0	0	0.01	0	0
			(**b**)		
f8	−3361.2	287.325	−2879.4	−4071.4	1.73×10^{-6}
f9	1.39294	0.72032	2.98488	0	3.89×10^{-6}
f10	4.56×10^{-15}	0	4.56×10^{-15}	4.56×10^{-15}	4.33×10^{-8}
f11	0	0	0	0	1
f12	4.82×10^{-32}	8.59×10^{-34}	5.12×10^{-32}	4.71×10^{-32}	1.56×10^{-6}
f13	0.00256	0.01025	0.05478	1.35×10^{-32}	1.34×10^{-6}
			(**c**)		
f8	−12561.4	40.82419124	−12345.3	−12569.5	1.7344×10^{-6}
f9	0.01	0.01	0.01	0.01	1
f10	8.88×10^{-161}	0.01	8.88×10^{-161}	8.88×10^{-161}	4.3205×10^{-8}
f11	0.01	0.01	0.01	0.01	1
f12	8.92×10^{-6}	1.16218×10^{-5}	4.76×10^{-5}	4.64×10^{-8}	1.7344×10^{-6}
f13	0.000101	0.000132197	0.000612	7.35×10^{-7}	1.7344×10^{-6}

It is analyzed from Table 6 that multi-model benchmark functions f8 to f13 are tested using modern hybrid algorithms like BMFO 1, BMFO 2, and HHO and found that the Harris hawks optimizer (HHO) produces optimal outcomes in terms of mean, standard deviation, best and worst value for all functions as compared to other algorithms.

The convergence curve and trial solutions for BMFO1, BMFO2, and HHO for f8 to f13 multi-modal benchmark functions are presented in Figure 6a–f.

The connected outcomes for multimodal benchmark functions has been signified in Table 7, which are associated with various latest refined meta-heuristics search algorithms like GWO [62], PSO [63,64], GSA [8,65], DE [66,67], FOA [68,69], ALO [70,71], SOS [72], BA [73], FPA [74,75], CS [76], FA [52], GA [77], GOA [73,78], MFO [79], MVO [80], DA [81], BBA [65], BBO [5,82], BGSA [83,84], SCA [85,86], FPA [74,87], SSA [88], and WOA [89] in lieu of average [90] and standard deviation.

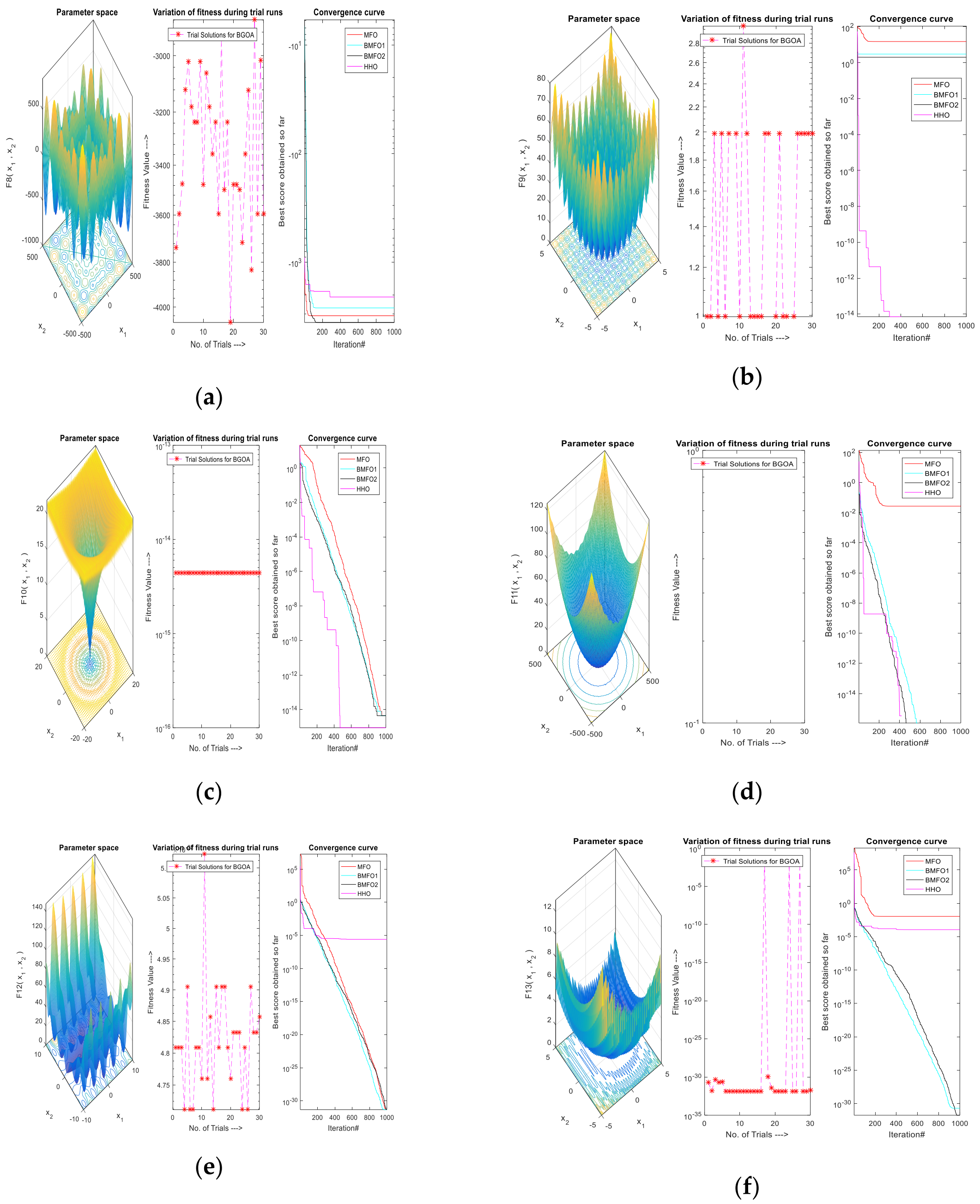


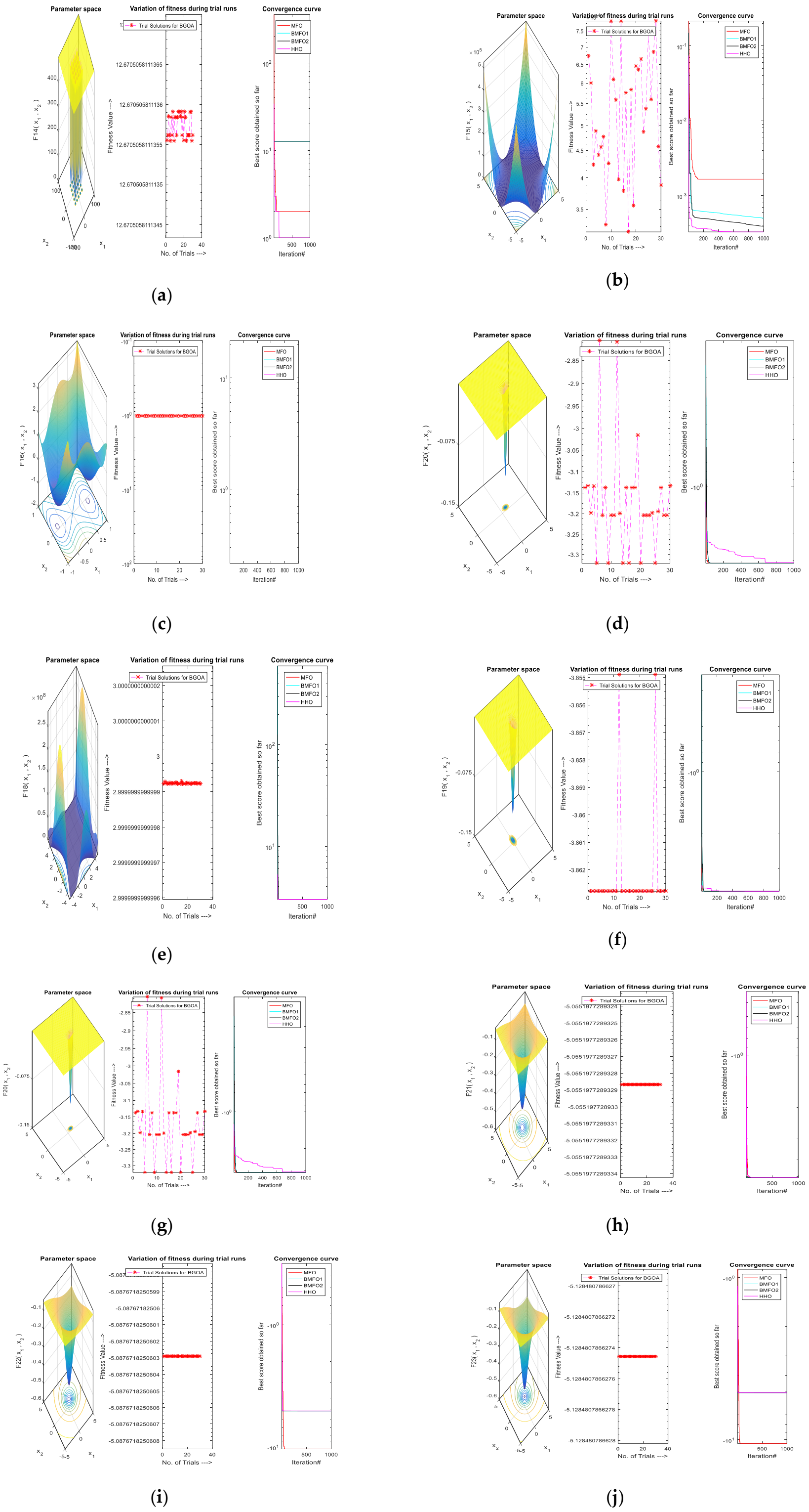
Figure 6. (**a**–**f**) Convergence curve of all algorithms for multi-modal benchmark functions.

The verified consequences for fixed dimension benchmark situations are obtainable in Table 8. It is analyzed from Table 8 that fixed dimension benchmark functions f14 to f23 are tested using modern hybrid algorithms like BMFO 1, BMFO 2, and HHO and found that Harris hawks optimizer (HHO) produces optimal outcomes in terms of mean, standard deviation, best and worst value for all functions as compared to other algorithms.

The convergence curve and trial solutions for BMFO1, BMFO2, and HHO for f14 to f23 fixed dimension benchmark functions are presented in Figure 7a–j.

Table 7. Comparison of multi-modal benchmark functions.

Algorithms	Parameters	Multi-Modal Benchmark Functions					
		f8	**f9**	**f10**	**f11**	**f12**	**f13**
GWO [62]	Mean	−6120	0.31	0	0	0.05	0.65
	SD	−4090	47.4	0.08	0.01	0.02	0
PSO [63,64]	Mean	−4840	46.7	0.28	0.01	0.01	0.01
	SD	1150	11.6	0.51	0.01	0.03	0.01
GSA [8,65]	Mean	−2820	26	0.06	27.7	1.8	8.9
	SD	493	7.47	0.24	5.04	0.95	7.13
DE [66,67]	Mean	−11100	69.2	0	0	0	0
	SD	575	38.8	0	0	0	0
FOA [68,69]	Mean	−12600	0.05	0.02	0.02	0	0
	SD	52.6	0.01	0	0.02	0	0
ALO [70,71]	Mean	−1610	0	0	0.02	0	0
	SD	314	0	0	0.01	0	0
SOS [72]	Mean	−4.21	1.33	0	0.71	0.12	0.01
	SD	0	0.33	0	0.91	0.04	0
BA [73]	Mean	−1070	1.23	0.13	1.45	0.4	0.39
	SD	858	0.69	0.04	0.57	0.99	0.12
FPA [74,75]	Mean	−1840	0.27	0.01	0.09	0	0
	SD	50.4	0.07	0.01	0.04	0	0
CS [76]	Mean	−2090	0.13	0	0.12	0	0
	SD	0.01	0	0	0.05	0	0
FA [52]	Mean	−1250	0.26	0.17	0.1	0.13	0
	SD	353	0.18	0.05	0.02	0.26	0
GA [77]	Mean	−2090	0.66	0.96	0.49	0.11	0.13
	SD	2.47	0.82	0.81	0.22	0	0.07
GOA [73,78]	Mean	1	0	0.1	0	0	0
	SD	0	0	1	0	0	0
MFO [79]	Mean	−5080	0	7.4	0	0.34	1.89
	SD	696	0	9.9	0	0.22	0.27
MVO [80]	Mean	−11700	118	4.07	0.94	2.46	0.22
	SD	937	39.3	5.5	0.06	0.79	0.09
DA [81]	Mean	−2860	16	0.23	0.19	0.03	0
	SD	384	9.48	0.49	0.07	0.1	0
BBA [65]	Mean	−924	1.81	0.39	0.19	0.15	0.04
	SD	65.7	1.05	0.57	0.11	0.45	0.06
BBO [5,82]	Mean	−989	4.83	2.15	0.48	0.41	0.31
	SD	16.7	1.55	0.54	0.13	0.23	0.24
BGSA [83,84]	Mean	−861	10.3	2.79	0.79	9.53	2220
	SD	80.6	3.73	1.19	0.25	6.51	5660
SCA [85,86]	Mean	1	0.01	0.38	0.01	0.01	0.01
	SD	0.01	0.73	1	0.01	0.01	0.01
SSA [88]	Mean	0.06	0.01	0.2	0.01	0.14	0.08
	SD	0.81	0.01	0.15	0.07	0.56	0.71
MFO [79]	Mean	−8500	84.6	1.26	0.02	0.89	0.12
	SD	726	16.2	0.73	0.02	0.88	0.19
BMFO1	Mean	−3140.3	1.63	0.04	0	0	0
	SD	290.75	0.96	0.21	0	0	0
BMFO2	Mean	−3361.2	1.39	0	0	0	0
	SD	287.32	0.72	0	0	0	0.01
HHO (Proposed)	Mean	−12561.38	0	8.88×10^{-16}	0	8.92×10^{-6}	0.000101
	SD	40.82419	0	0	0	1.16×10^{-5}	0.000132



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 7. (**a**–**j**) Convergence curve and trial solution of BMFO2 for fixed dimension benchmark functions.

Table 8. (**a**) Outcomes of the BMFO1 algorithm. (**b**) Outcomes of the BMFO2 algorithm. (**c**) Outcomes of the HHO algorithm.

Benchmark Functions	Parameters				
	Mean Value	SD	Worst Value	Best Value	p-Value
(**a**)					
f14	12.61	1.35	12.67	10.76	0
f15	0	0	0	0	0
f16	−1.03	0	−1.03	−1.03	0
f18	3	0	3	3	0
f19	−3.86	0	−3.85	−3.86	0
f20	−3.16	0.08	−2.86	−3.32	0
f21	−5.06	0	−5.06	−5.06	0
f22	−5.09	0	−5.09	−5.09	0
f23	−5.13	0	−5.13	−5.13	0
(**b**)					
f14	12.67	0	12.67	12.67	0
f15	0	0	0	0	0
f16	−1.03	0	−1.03	−1.03	0
f18	3	0	3	3	0
f19	−3.86	0	−3.85	−3.86	0
f20	−3.17	0.12	−2.81	−3.32	0
f21	−5.06	0	−5.06	−5.06	0
f22	−5.09	0	−5.09	−5.09	0
f23	−5.13	0	−5.13	−5.13	0
(**c**)					
f14	2.361171	1.95204	5.928845	1.998004	1.73×10^{-8}
f15	1.00035	3.2×10^{-5}	0.000433	0.000309	1.73×10^{-8}
f16	−1.03162	2.86×10^{-9}	−1.03162	−1.03162	1.73×10^{-8}
f17	0.397895	1.6×10^{-5}	0.397948	0.397887	1.73×10^{-6}
f18	3.000001	4.94×10^{-6}	3.000027	2	1.73×10^{-8}
f19	−2.85977	1.005195	−3.8354	−3.86274	1.73×10^{-8}
f20	−2.06481	0.136148	−2.74389	−3.26174	1.73×10^{-8}
f21	−4.37397	1.227502	−5.0413	−10.0309	1.73×10^{-6}
f22	−5.08346	0.004672	−5.06481	−5.08765	1.73×10^{-6}
f23	−5.78398	1.712458	−5.1145	−10.3706	1.73×10^{-6}

The comparative outcomes for fixed dimension benchmark [91] functions have been represented in Tables 9 and 10, which are associated with other latest refined met heuristics search algorithms [54,92] GWO [62], PSO [63,64], GSA [8,65], DE [66,67], FOA [68,69], ALO [70,71], SOS [72], BA [73], FPA [74,75], CS [76], FA [52], GA [77], GOA [73,78], MFO [79], MVO [80], DA [81], BBA [65], BBO [5,82], BGSA [83,84], SCA [85,86], FPA [74,87], SSA [88], and WOA [89] in terms of standard deviation [93] and average.

Table 9. Comparison of fixed dimension benchmark functions.

Algorithms	Parameters	Composite Benchmark Functions					
		f14	**f15**	**f16**	**f17**	**f18**	**f19**
GWO [62]	Mean	3.06	0	−1.03	0.4	3	−3.86
	SD	4.25	0	−1.03	0.4	3	−3.86
PSO [63,64]	Mean	3.63	0	−1.03	0.4	3	−3.86
	SD	2.56	0	0	0	0	0
GSA [8,65]	Mean	5.86	0	−1.03	0.4	3	−3.86
	SD	3.83	0	0	0	0	0
DE [66,67]	Mean	1	0	−1.03	0.4	3	NA
	SD	0	0	0	0	0	NA
FOA [68,69]	Mean	1.22	0	−1.03	0.4	3.02	−3.86
	SD	0.56	0	0	0	0.11	0
ALO [70,71]	Mean	0	14.6	175	316	4.4	500
	SD	0	32.2	46.5	13	1.66	0.21
SOS [72]	Mean	776.48	873.8	961	899.86	741	900.5
	SD	0	9.72	67.2	0	0.79	0.84
BA [73]	Mean	182.48	487.2	588.2	756.98	542	818.5
	SD	117.02	161.4	137.8	160.1	220	152.5
FPA [74,75]	Mean	0.34	18.23	224	362.03	10.2	504
	SD	0.24	3.07	50.3	54.02	1.39	1.16
CS [76]	Mean	110	140.6	290	402	213	812
	SD	110.05	92.8	86.1	98.2	206	192
FA [52]	Mean	150.17	314.5	734.5	818.57	134	862.2
	SD	97.16	92.93	204	109.97	216	126
GA [77]	Mean	114.61	95.46	325.4	466.31	90.4	521.2
	SD	26.96	7.16	51.67	29.57	13.7	27.99
GOA [73,78]	Mean	0	0.49	0	0.82	0	0.79
	SD	0.34	0.72	0	1	0.01	0.94
MFO [79]	Mean	2.11	0	−1.03	0.4	3	−3.86
	SD	2.5	0	0	0	0	0
MVO [80]	Mean	10	30.01	50	190.3	161	440
	SD	31.62	48.31	52.7	128.67	158	51.64
DA [81]	Mean	104	193	458	596.66	230	680
	SD	91.2	80.6	165	171.06	185	199
BBA [65]	Mean	1.39	1.02	1.05	1	1.01	1
	SD	1.19	1.07	1.49	1.11	1.01	1.2
BBO [5,82]	Mean	0.06	0	0.2	0	0.14	0.08
	SD	0.81	0	0.15	0.07	0.56	0.71
MFO [79]	Mean	0	66.73	119	345.47	10.4	707
	SD	0	53.23	28.33	43.12	3.75	195
BMFO1	Mean	12.61	0	−1.03	0	3	−3.86
	SD	0.35	0	0	0	0	0
BMFO2	Mean	12.67	0	−1.03	0	3	−3.86
	SD	0	0	0	0	0	0
HHO (Proposed)	Mean	1.361171	0.00035	−1.03163	0.397895	3.000001225	−3.8597664
	SD	0.95204	3.20×10^{-5}	1.86×10^{-9}	1.60×10^{-5}	4.94×10^{-6}	0.00519467

Table 10. Comparison of results for fixed dimension functions.

Algorithms	Parameters	Benchmark Functions			
		f20	**f21**	**f22**	**f23**
GWO [62]	Mean	−2.79	−9.8	−9.9	−9.69
	SD	−2.84	−9.18	−7.55	−7.48
PSO [63,64]	Mean	−2.29	−7.89	−7.49	−8.99
	SD	1.06	3.07	4.08	1.76
GSA [8,65]	Mean	−2.36	−4.99	−8.64	−10.63
	SD	1.02	4.74	2.01	0
DE [66,67]	Mean	0.01	−10.2	−10.4	−10.54
	SD	0.01	0	0	0
FPA [74,75]	Mean	−4.28	−6.56	−6.57	−7.59
	SD	0.08	1.57	2.18	3.18
WOA [84]	Mean	−2.98	−7.05	−8.18	−9.34
	SD	0.38	3.63	3.83	2.41
BMFO1	Mean	−3.16	−5.06	−5.09	−5.13
	SD	0.08	0	0	0
BMFO2	Mean	−3.17	−5.06	−5.09	−5.13
	SD	0.12	0	0	0
HHO (Proposed)	Mean	−3.06481	−5.37397	−5.08346	−5.78398
	SD	0.136148	1.227502	0.004672	1.712458

4. Conclusions

The smart grid process needs a continuing matching of resource and ultimatum in accordance with recognized functioning principles of numerous algorithms. The LFC scheme delivers the consistent action of power structure by constantly balancing the resource of electricity with the response, while also confirming the accessibility of adequate supply volume in upcoming periods. In this paper, binary variations of the moth flame optimizer and HHO have been analyzed and tested to solve twenty-three benchmark problems including unimodel, multi-model, and fixed dimension functions which investigate that the proposed Harris hawks optimizer approach suggestions are offering better results as associated to substitute labeled meta-heuristics search algorithms. In upcoming work, the effectiveness of the HHO technique is deliberate for optimal matching of total generation with total consumption of electrical energy to convert an electric grid to smart grid. So, by using the Harris hawks optimizer, we can easily balance the smart grid elements by matching production and consumption of electrical energy.

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