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An Improved Wild Horse Optimization algorithm for Reliability Based Optimal DG Planning of Radial Distribution Networks

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Abstract: This paper introduces a novel technique for optimal distribution system (DS) planning with distributed generation (DG) systems. It is being done to see how active and reactive power injections affect the system's voltage profile and energy losses. DG penetration in the power systems is one approach that has several advantages such as peak savings, loss lessening, voltage profile amelioration. It also intends to increase system reliability, stability, and security. The main goal of optimal distributed generation (ODG) is a guarantee to achieve the benefits mentioned previously to increase the overall system efficiency. For extremely vast and complicated systems, analytical approaches are not suitable and insufficient. Therefore, several meta-heuristic techniques are favored to obtain better performance from were convergence and accuracy for large systems. In this paper, an Improved Wild Horse Optimization algorithm (IWHO) is proposed as a novel metaheuristic method for solving optimization issues in electrical power systems. IWHO is devised with inspirations from the social life behavior of wild horses. The suggested method is based on the horse's decency. Reliability amelioration is the most things superb as a result of DGs incorporation. Thus, in this research, a customer-side reliability appraisal in the DS that having a DG unit was carried out by a Monte Carlo Simulation (MCS) approach to construct an artificial history for each ingredient across simulation duration. For load flow calculations, the backward Forward Sweep (BFS) technique has been employed as a simulation tool to assess the network performance considering the power handling restrictions. The proposed IWHO method has been measured on IEEE 33 and 69 buses to ascertain the network performing in the presence of the optimal DG and the potential benefits of the suggested technique for enhancing the tools used by operators and planners to maintain system reliability and efficiency. The results proved that IWHO is an optimization method with lofty performance regarding the exploration-exploitation balance and convergence speed, as it successfully handles complicated problems.

Keywords: Radial Distribution Network, Distributed Generation, BFS Algorithm, Improved wild horse optimization algorithm, Reliability assessment, Monte Carlo simulation.

1. Introduction

Nowadays, there is a global unanimity that incorporating renewable energy sources (RESs) as distributed generators (DG) is crucial to facing the rising electricity need and reducing the overall carbon dioxide footprint. It is one of the most successful and realistic planning methods for enhancing the network's reliability and power quality as demand increases. The DG penetration strategy in the DS is becoming more common as demand load increases, pollutant emissions are reduced, and the electrical power market is deregulated [1]. The leverage of DG performance is more closely related to the types, locations, and sizes of the DG units used, where the best choice will maximize the benefits of the DG units while avoiding their downsides for the system, such as voltage volatility, increased system loss and increased operating costs [2, 3]. The effects of including DG units into the system vary depending on whether the system is in steady-state or transient mode. Some issues occur in the steady-state, such as extreme energy losses, reverse current flow, fluctuations in voltage, managing reactive power, malfunction in the protective system, and weak power quality. [4–6]. The consequences in the transitional state are, on the other hand, caused by the separating DG units and the unexpected outputs of the DG units, such as fluctuations in wind speed and solar radiation. [7]. The acuity of these effects is based on the placement of DG units, the DG penetration levels, and the sort of DG. Furthermore, owing to the nature of renewable DG units, simultaneous fluctuations in DG generation for providing the demand load might lead to a down or overvoltage. The implications of such events may be altered by the placement of DG units and weather conditions, as mentioned previously [8]. Additionally, the system performance is enhanced at the particular penetration levels of the DG units, while the system was in contrast degraded by substation and feeder load, voltage deviations, and higher power losses beyond this level. As a result, the ODG allocation problem has recently piqued the interest of many researchers to achieve various goals, including minimizing real power loss, enhancing voltage profile, boosting power quality, and mounting the distribution system's reliability and efficiency. As a result, many ways to addressing these issues have been proposed in the literature. A mixing of analytical approach and heuristic search has been suggested for optimal placement of DGs in the DS for minimizing power loss in [9]. An efficient analysis (EA) approach to properly deploy multiple DG units is presented to reduce power loss in distribution systems[10]. A novel approach for determining the optimum size and the location of DG was presented in [11] to reduce the power loss and ensure the system's voltage stability. In [12], the authors used an enhanced gravitational search algorithm to learn the location and dimensions of photovoltaics (PV) based DGs to reduce overall expenditures. In[13], the authors presented a technique that would increase the global seeking ability, called Quasi-Oppositional Chaotic Symbiotic Organisms Search (QOCSOS). The

goal of this work is to curb the power loss, enhance the voltage profile, and raise the voltage stability in the radial distribution networks (RDNs). Mixed-integer nonlinear programming (MINLP) technique has been utilized in [14] to identify the best size and position of DGs with power loss curtailment. In [15], the Electrostatic Discharge Algorithm (ESDA) was utilized to resolve the problem of DG assignment to augment the voltage stability and limit the power losses. To optimize the allocation of DGs in the DS concerning reducing annum power losses, the authors are introduced an artificial ecosystem-based technique [16]. To decrease power loss in DS, a simplified analytical technique was presented for optimum DG amalgamation in [17]. The aim of [18] is for an ODG allocation in the typical IEEE 33-bus system to promote voltage stability and minify total power loss. This is based on the Gray Wolf optimization method with loss sensitivities. The Ant Lion Optimization Algorithm (ALOA) is presented in [19] for ODG allocation of RDG sources in diverse RDNs. In [20], the authors offer a hybrid approach based on the combined power loss sensitivity (CPLS) and Salp Swarm Algorithm (SSA) to merge PV and wind turbines (WT) in the DS for boosting voltage, reducing losses, and expanding system capacity. The purpose of [21] is to resolve the best allocation of the DGs in a RDN, diminish the overall operational costs and voltage indexes variations, and ensure a more flexible solution of the hybrid fuzzy logic controller technique and the particle swarm optimization (PSO) with the ALOA. The authors utilized the LSF in [22, 23] to locate the elected bus. To mend the voltage profile and decrease the power loss of the RDN, simulated annealing (SA) and PSO were used to set the optimal position and size of DG. The SAPSO approach to banning the SA & PSO shortage by two methods was introduced and produced the finest solutions in a short time. This article [24] provides an application for optimal sizing and positioning of RDGs including WT, PV, and biomass in DS using a new metaheuristic rider optimization algorithm (ROA).

To epitomize, an improved wild horse optimization algorithm (IWHO) is suggested as a novel population-based algorithm to compete with state-of-the-art and neoteric optimization algorithms. It should be evident that the intended algorithm provides the poise between exploration and exploitation. This feature enables IWHO to solve a complicated optimization issue with multiple locally optimal solutions because it retains several answers and explores a broad area to pinpoint the global solution. Finally, the IWHO is the greatest and most innovative approach for optimizing problems because of loud fineness and soft calculations. To sum up, this research's key contributions are:

1. Introduce for the first time in the power system a devise approach called an improved wild horse optimization algorithm (IWHO) to augment search quality and shun an early convergence to a local minimum.
2. Proposed the optimal option of the ODG allocation (size & position) considering the constraints of the RDN. Standard IEEE 33 & 69 bus networks are hired to check the leverage of the suggested algorithm.

Demonstrated the efficacy of the outcomes of this approach in terms of lowering losses and meliorative the voltage profile.

Verified the performance of the methodology proposed using typical test systems to detect its superiority for handling the problems and compared to other published approaches.

An artificial history for each component in the test system is generated using MCS instead of an analytical method for highly efficient reliability assessment.

This paper was structured as follows: Section 2 depicts the BFS algorithm. The mathematical description of the optimization problem is described in Section 3. Section 4 focuses on the IWHO algorithm. Section 5 transact with the simulation results for the test systems and discussion. Finally, in Section 6, the suggested work's inference is provided.

2. Backward Forward Sweep Algorithm

Load flow is a crucial tool for the design, and operation of power systems to guarantee reliability, stability, and economy. Classical methods as gauss-seidel (GS) and newton raphson (NR) might be inappropriate for the DS and diverge because of [23]:

- Radial formation.
- R/X value is higher.
- Running lopsided.
- DGs.

Backward/Forward Sweep (BFS) is chosen for fit planning owing to:

- The poor nature of RDS.
- Accurate load flow results rely on convergence, simulation time, and the convergence rate.

This technique is carried out through two phases: rear and front sweep using the demand and streak data as follow:

2.1. Forward Sweep

In essence, a voltage decline is calculated through branch currents. Node voltages are updated from the first bus to the most distant bus. The fore scanning aims to identify the node voltage for all buses starting from the origin node. The primary bus voltage is set to 1pu, and the current in reverse propagation is firm.

2.2. Backward Sweep

It is mainly a voltage upgraded by a load flow computation. It moves from the furthest lines to the head node. In the rear-prevalence count, the updated current flows are achieved utilizing the bus voltage of the previous rounds. It implies that the voltage values obtained are not changed during the rear prevalence computations in the front prevalence.

The BFS algorithm steps are listed below:

- Set the injected current ($I_i = 0$)
- Set all nodes voltage (V_i= 1pu)
- Compute the node current ($I_i = \frac{S_i^*}{V_i^*}$)
- Evaluate current of the lines (backward sweep)

$$I_{(i,i+1)} = I_{i+1} + \sum(\text{branches current at node i} + 1)$$

- Modernizing the voltage of buses ($V_i = V_{i+1} + (Z_{(i,i+1)} * I_{(i,i+1)})$)
- Until the criteria are terminated.

3. Problem Formulation

The main key for a healthy environment is renewable distribution generation (RDG), which plays a main role in power systems. Tentatively, the peril of fuel price swings and political influences should be decreased by incorporating the RDGs and guaranteeing that these do not significantly influence public well-being overall. In such regard, changes to the grid might be necessary due to modify the choices of generating sources, which is caused by a large amalgamation of RDGs. The fluctuation of current and voltage in the network is increased as a result of DG permeation. Increasing DG permeation might therefore have a detrimental or beneficial influence depending on the scale of the system and the sort of the load, necessitating modeling and emulation to evaluate its action. If not adequately striped, this may result in an unforeseen rise in power flow, leading to network crowding and higher network losses. DGs offer significant advantages for terminus consumers and their technical assistance through increased reliability, power quality, and cost dilution. Cost cuts and the pressing requirement to fuse DGs maybe drive energy demand. Therefore, good system planning is significant for the good running of the entire system. This concerns the development of convenient mathematical models and algorithms that allow for optimum positioning and size of DGs in the system; this is the issue handled in this study.

3.1. Objective Function (OF)

Its major aim is to identify the best localization and sizing of DGs to constrict the total losses in light of equity and inequality restrictions., which can be described as follow:

$$OF = min(P_{loss}) = min \sum_{i=1}^{L} R_i \left(\frac{P_i^2 + Q_i^2}{V_i^2}\right) \quad (1)$$

3.2. Constraints

The limits ensuring the superior performance of the RDGs technology are split into operating and technological restrictions as see:

3.2.1. Operational constraints

These are called the equality restriction and apportioned into:

- Power balance constraints

$$P_i = |V_i| \sum_{j=1}^{N} |V_j| \times |Y_{ij}| \times \cos\left(\theta_{ij} + \delta_j - \delta_i\right), \forall i \in N \quad (2)$$

$$Q_i = -|V_i| \sum_{j=1}^{N} |V_j| \times |Y_{ij}| \times \sin\left(\theta_{ij} + \delta_j - \delta_i\right), \forall i \in N \quad (3)$$

3.2.2. Technical constraints

These are called the inequality restriction and apportioned into:

- Voltage constraints

$$\left|V_i^{min}\right| \leq |Vi| \leq |V_i^{max}|, \forall i \in N \quad (4)$$

- Current constraints

$$I_{li} \leq I_{li}^{rated}, \forall i \in b \quad (5)$$

- DG size constraints

$$P_{DG}^{min} \leq P_{DG} \leq P_{DG}^{max} \quad (6)$$

$$Q_{DG}^{min} \leq Q_{DG} \leq Q_{DG}^{max} \quad (7)$$

- DG location constraints

$$2 \leq DG_{location} \leq N_{bus} \quad (8)$$

where L is the energized number of branches; N is the number of buses; Y_{ij} is the bus admittance of line i-j; θ_{ij} is the admittance angle of line i-j; $\left|V_i^{min}\right|$; $|V_i^{max}|$ are the limits of the voltage at the bus i; I_{li} is the line current flow of line i; I_{li}^{rated} is the rated line current capacity at line i.

3.3. Reliability Assessment for Distribution Systems

The measurement of reliability is a crucial agent for the planning and operation of DS. Based on system configuration and item's reliability data, DS reliability evaluation may forecast the obstruction of a DS at the client end. The primary goal of reliability analysis is to measure, forecast, and compare reliability indicators for multiple network topologies for reliability rising. The reliability evaluation calculates performance at client load points while factoring in the stochastic nature of failures incidence and outage period. The main indicators linked with client points are failure rate (λ), outage time (r), and yearly unavailability (U), which may be computed using equations (9 - 10).

$$\lambda_p = \sum_{i=1}^{N} \lambda_i \left(\frac{f}{yr}\right) \tag{9}$$

$$U_p = \sum_{i=1}^{N} \lambda_i r_i \left(\frac{hr}{yr}\right) \tag{10}$$

$$r_p = \frac{U_p}{\lambda_p} (hr) \tag{11}$$

3.3.1. Monte-Carlo Simulation Approach

Because a power system is uncertain, the Monte-Carlo simulation approach may be used to provide more exact findings when evaluating its reliability. Monte-Carlo simulation can be classified into two types: time-sequential and state sampling methods, but the time-sequential technique is utilized here.

State of the basic distribution equipment such as branches, transformers, and protective components such as disconnecting switches, breakers, and fuses helps for system reliability valuation. In general, line segments and transformers may be depicted by two states seen in figure 1, where the upstate signifies that the portion is operational and the downstate shows that the portion is dud.

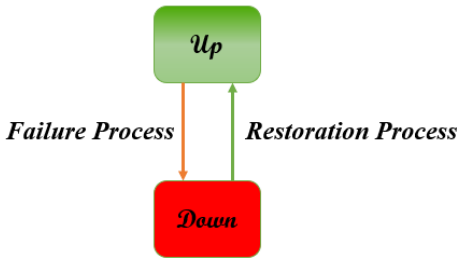


Figure 1. Element state transition diagram

The time to failure is the period that the item persists in the upper (TTF) or failure time(FT), But the period, while an element is down, is called a reconquest time and it might be either the time to repair(TTR) or the time to substitute. The transition from the up to down is the failure operation, while the transition from down to up is the restoration operation. Figure 2 depicts the history of simulated element operation and repair.

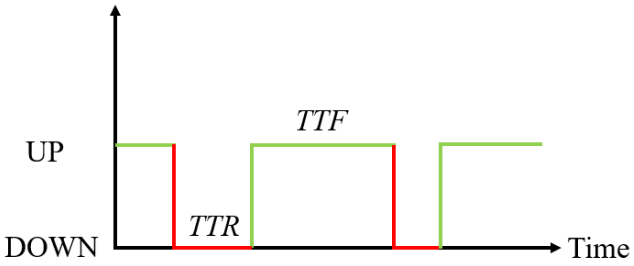


Figure 2. Component Up/Down history

TTF and TTR are randomly generated with potentially varying probabilistic. A universal random number generator can create a uniform distribution direct, and the resulting random numbers are transformed into TTF or TTR using these formulas.

$$TTF = \left(-\log\frac{U}{\lambda}\right) * 8760 \quad (12)$$

$$TTR = -\log U * MTTR \quad (13)$$

where U is a haphazard variable in the range [0, 1].

3.3.1. Load Point Failures identification

The harshest issue in the emulation is to detect the load points influenced by the fiasco of an element. A complicated RDN can be broken down into primary feeders and laterals. The following is the technique for detecting failing load points and their operation/restoration histories [25]:

1. Discover the failure object and its location, as well as the failed elements number and the lost feeder's amount to which the failed element is linked.
2. Identify the impacted load points that are linked to the failing feeder, as well as their failure intervals, based on the setup and protection system of the damaged feeder.
3. Determine the downstream feeders linked to the damaged feeder's sub-feeders and the impact of the damaged component on the load points linked to these sub-feeders.
4. Repeat steps 2 and 3 for every failing sub-feeder till all sub-feeders linked to the failing feeder are identified and analyzed.
5. Find the upstream feeder to which the failing feeder is linked, as well as the impacts of the failure component on the load points in the upstream feeder.
6. Reiterate (2) to (5) until the primary feeder is reached and assessed.

The client obstruction indicators will be used to quantify system reliability; the main indicators are the customer average interruption duration index (CAIDI), the system average interruption frequency index (SAIFI), the system average interruption duration index (SAIDI), the average service availability index (ASAI), and the energy not supplied index (ENS). The following equations are used to compute them [26]:

$$SAIFI = \frac{\sum_{i=1}^{k} \lambda_i N_i}{\sum_{i=1}^{k} N_i} \quad (14)$$

$$SAIDI = \frac{\sum_{i=1}^{k} U_i N_i}{\sum_{i=1}^{k} N_i} \quad (15)$$

$$CAIDI = \frac{\sum_{i=1}^{k} U_i N_i}{\sum_{i=1}^{k} \lambda_i N_i} = \frac{SAIDI}{SAIFI} \quad (16)$$

$$ASAI = \frac{\sum_{i=1}^{k} 8760\ N_i - \sum_{i=1}^{k} U_i N_i}{\sum_{i=1}^{k} 8760\ N_i} \quad (17)$$

$$ENS = \sum_{i=1}^{k} U_i L_i \quad (18)$$

where U_i is the annual outage time, N_i is the number of customers at load point i, λ_i is the failure rate, and "L_i" is the average load connected to load point i and 8760 is the number of hours in a calendar year.

The developed flow chart of the computer program to determine the distribution system reliability indices consists of the following steps:

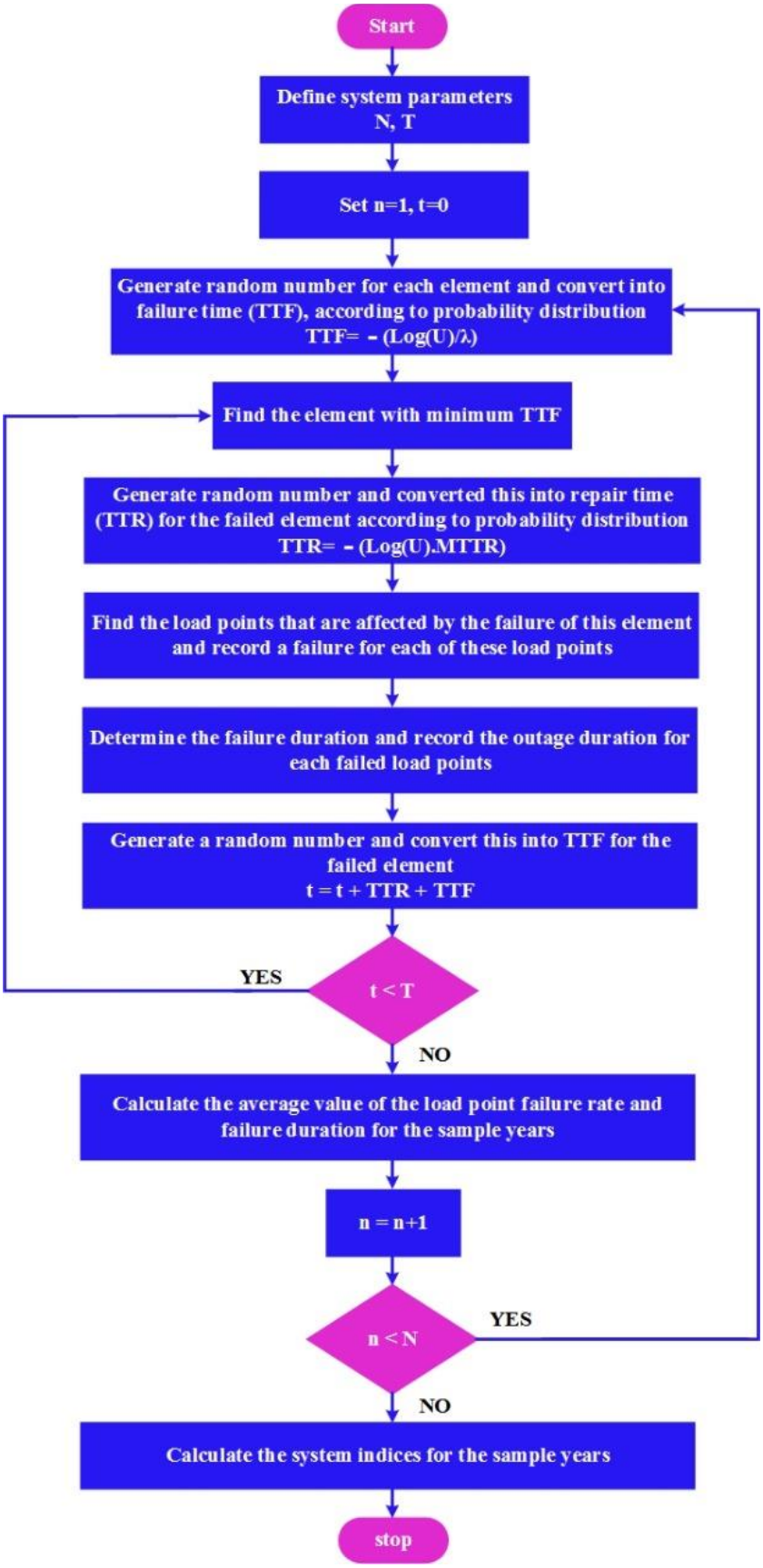


Figure 3. Flowchart for Monte Carlo Simulation

4. Mathematical Model of Optimization Techniques

4.1. Wild horse optimizer (WHO)

For addressing optimization issues, the wild horse optimizer (WHO) technique mathematically simulates and duplicates the social life behavior of these wild horses in nature. [27]. Horses predominately live in herds with a stallion and many foals and mares. They exhibit a variety of behaviors, including mating and grazing, pursuing, dominating, commanding. Five steps for the WHO algorithm are listed below:

4.1.1. Generating an initial population and formation horse groups and choosing leaders

First, the initial population is divided into numerous groups. N is the number of the population and G is the number of groups in the algorithm. Each group has a leader (stallion), so the number of stallions in the algorithm equals G, and (N–G) is the remaining population (Foals and mares) are distributed similarly among these groups. Figure 4 presents how the stallions and foals have been chosen from the initial population to produce various groups.

4.1.2. Grazing behavior

The following equation was proposed to simulate the grazing behavior:

$$X_{i,G}^{j} = 2Z\cos(2\pi RZ) \times \left(Stallion^{j} - X_{i,G}^{j}\right) + Stallion^{j} \quad (19)$$

where $X_{i,G}^{j}$ denotes the current location of the foal or mare group member, $Stallion^{j}$ is the stallion position, R is a uniform stochastic number from the range [-2,2], and Z is the adaptive mechanism calculated from the following equation:

$$P = \overrightarrow{R_1} < TDR; \quad IDX = (P == 0); \quad Z = R_2 \Theta IDX + \overrightarrow{R_3} \Theta (\sim IDX) \quad (20)$$

where P is a vector consisting of 0 to 1, $\overrightarrow{R_1}$ and $\overrightarrow{R_3}$ are a random number from the range [0,1], R_2 is a uniform random number from the range [0,1]. TDR is an adaptive parameter that starts with 1 and decreases until it reaches 0 at the end of the implementation of the algorithm according to the following equation:

$$TDR = 1 - it \times \left(\frac{1}{maxit}\right) \quad (21)$$

where it is the current iteration and $maxit$ is the maximum number of iterations.

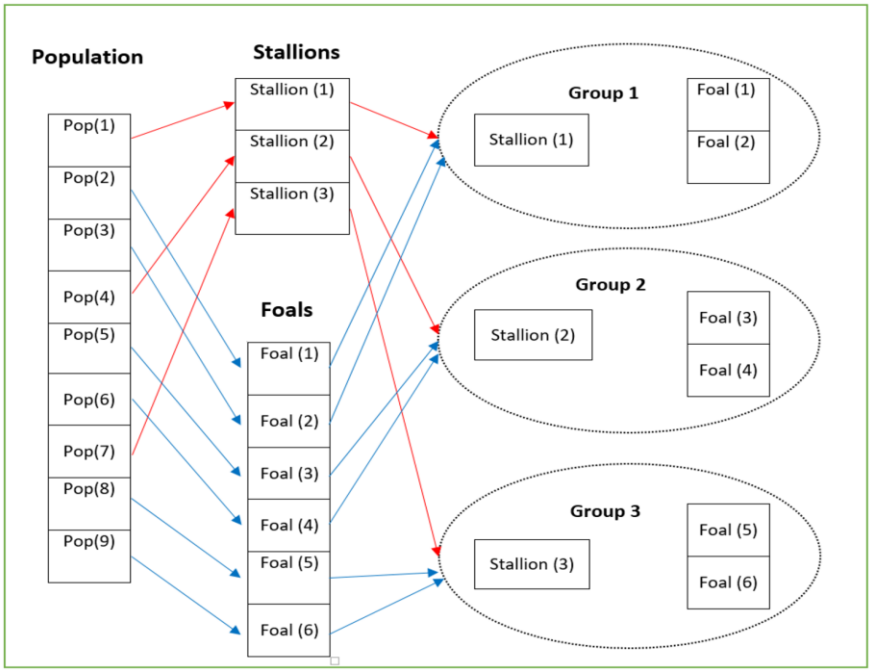


Figure 4. Formation of groups from the original population.

4.1.3. Horse mating behavior

To implement the mating behavior of horses, a foal goes from group *i* to a temporary group while a foal goes from group j to a temporary group. To simulate the mating behavior of horses, the Crossover operator of the mean type was proposed as follows:

$$X_{G,K}^{P} = Crossover\left(X_{G,i}^{q}, X_{G,j}^{z}\right) i \neq j \neq k, p = q = end, Crossover = Mean \quad (22)$$

4.1.4. Group leadership

In the WHO algorithm, the Stallions (group leaders) lead the group to the water hole. The Stallions compete for this water hole so that the domination group can employ this water hole firstly and then other groups can use the water hole. The following equation was recommended for this step of the algorithm:

$$\overline{Stallion_{G_i}} = \begin{cases} 2Z\cos(2\pi RZ) \times \left(WH - Stallion_{G_i}\right) + WH & if\ R_3 > 0.5 \\ 2Z\cos(2\pi RZ) \times \left(WH - Stallion_{G_i}\right) - WH & if\ R_3 \leq 0.5 \end{cases} \quad (23)$$

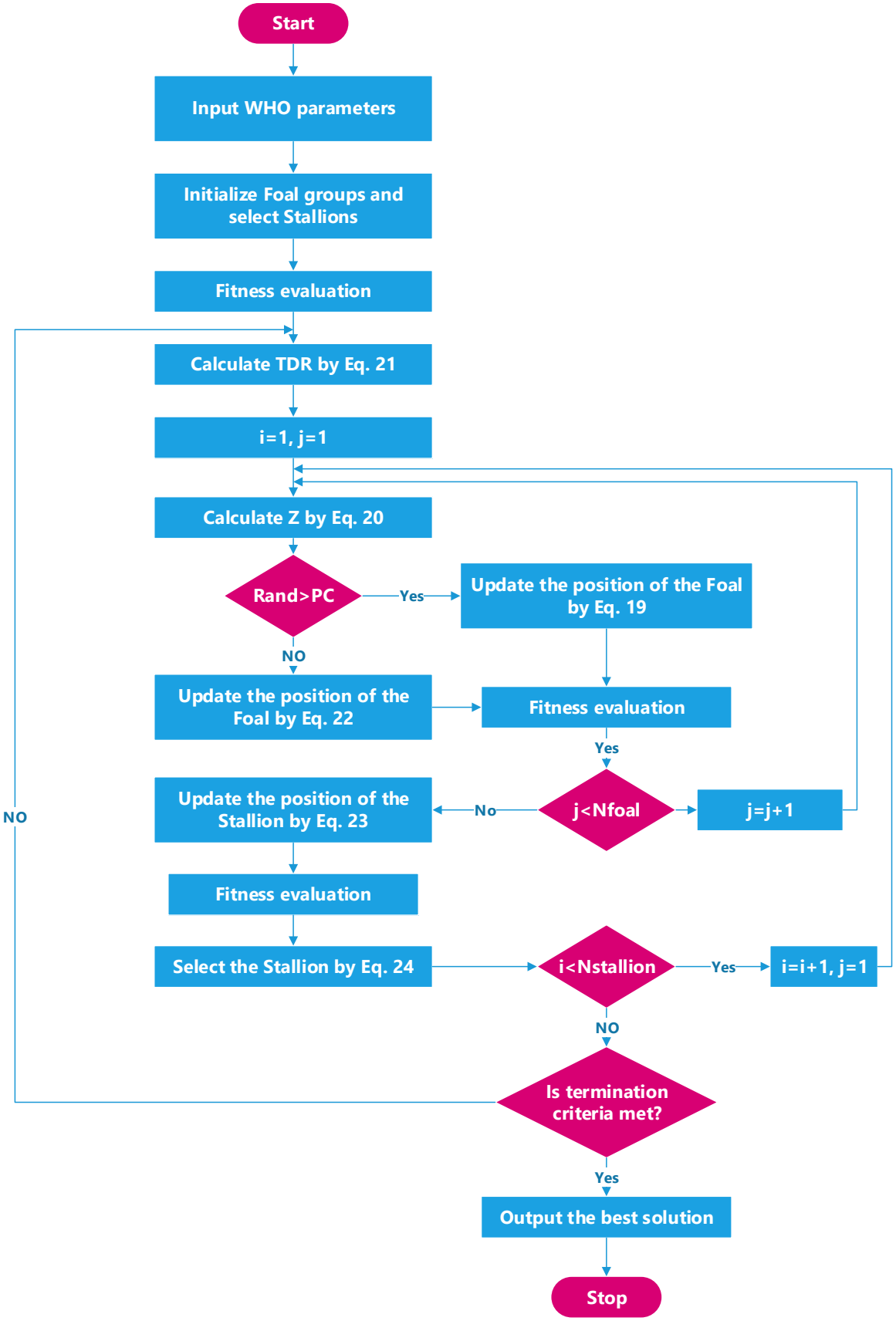
where $\overline{\text{Stallion}_{G_1}}$ is the next position of the leader. WH is the location of the water hole.

4.1.5. Leaders interchange and selection

In the following stages, leaders are chosen according to fitness. The leader position and the relevant member will change based on this equation:

$$\overline{Stallion_{G_i}} = \begin{cases} X_{G,i} \;\; if \;\; \cos t(X_{G,i}) < \cos t(Stallion_{G_i}) \\ Stallion_{G_i} \;\; if \;\; \cos t(X_{G,i}) > \cos t(Stallion_{G_i}) \end{cases} \quad (24)$$

Fig. 5 presents the flow chart of WHO algorithm.



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287 **Figure 5.** The flow chart of WHO algorithm.

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4.2. Improved Wild horse optimizer (IWHO)

The Improved Wild horse optimizer (IWHO) is based on the cuckoo search (CS) algorithm [28]. During the iteration of the proposed algorithm, the new solution is generated using the Levy flight as the following equation:

$$X_{i,G} = X_{i,G} - \gamma\left(X_{i,G} - X_g\right)\oplus Levy(\lambda) = X_{i,G} + \frac{0.01u}{|v|^{1/\lambda}}\left(X_{i,G} - X_g\right) \quad (25)$$

where $X_{i,G}$ is the *i-th* position of the group member, γ denotes the step scaling size, X_g denotes the global gest solution, the ⊕ refers to the process of element-wise multiplications, λ refers to the Levy flight exponent, while u and v are defined as:

$$u \sim N(0, \sigma_u^2) \quad , v \sim N(0, \sigma_v^2) \quad (26)$$

The standard deviations σ_u and σ_v are expressed as:

$$\sigma_u = \left[\frac{\sin\left(\frac{\lambda\pi}{2}\right).\Gamma(1+\lambda)}{2^{(\lambda-1)}\lambda\,.\Gamma(\frac{1+\lambda}{2})}\right]^{1/\lambda} \quad , \sigma_v = 1 \quad (27)$$

where Γ is the Gamma function, then, the new candidate solution is generated, the eq. 21 is applied. The principal advantage of this improvement is the ability of the proposed technique to balance global exploration and local exploitation [29]. Figure 6 shows the flow chart of IWHO algorithm.

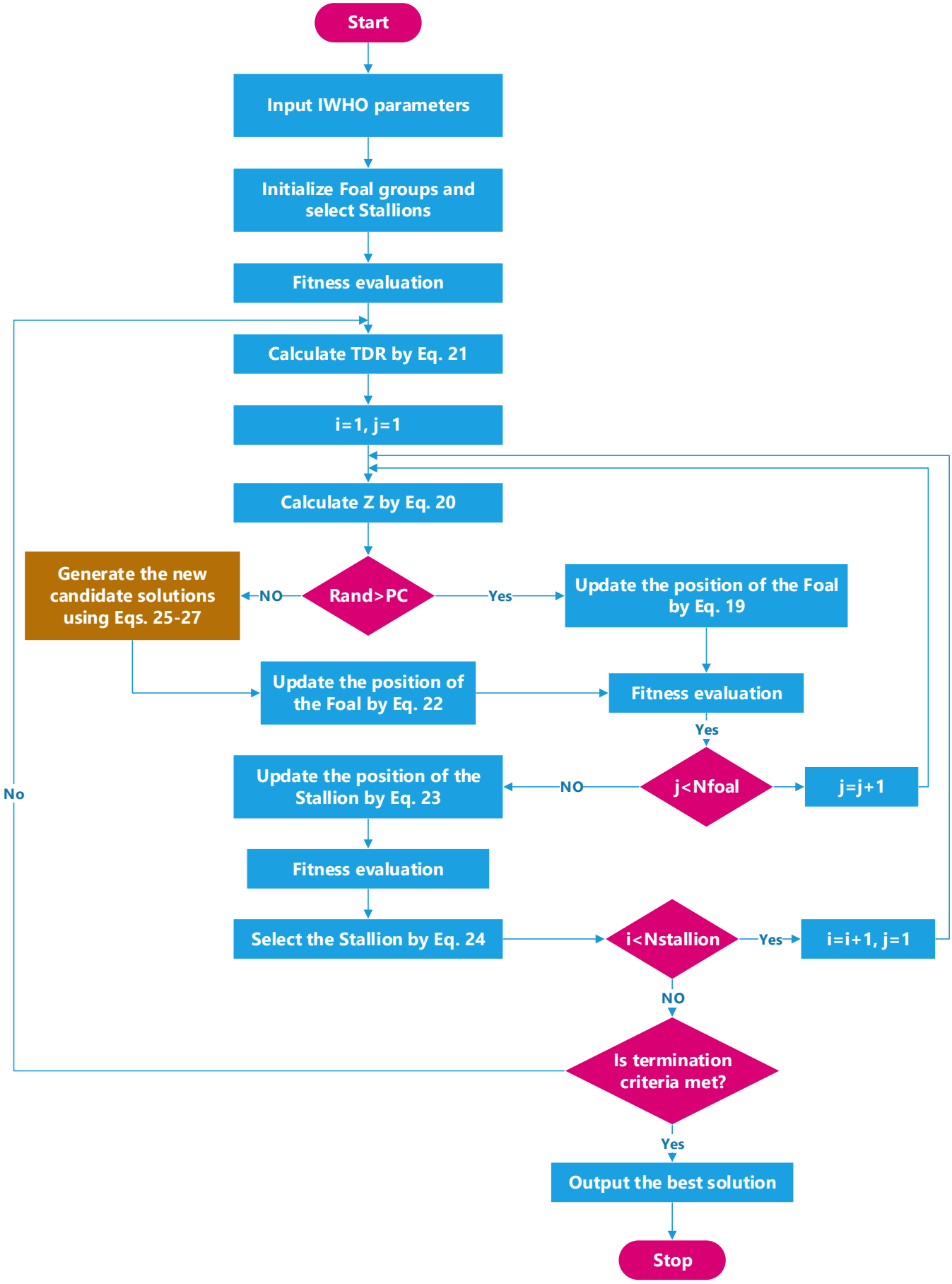
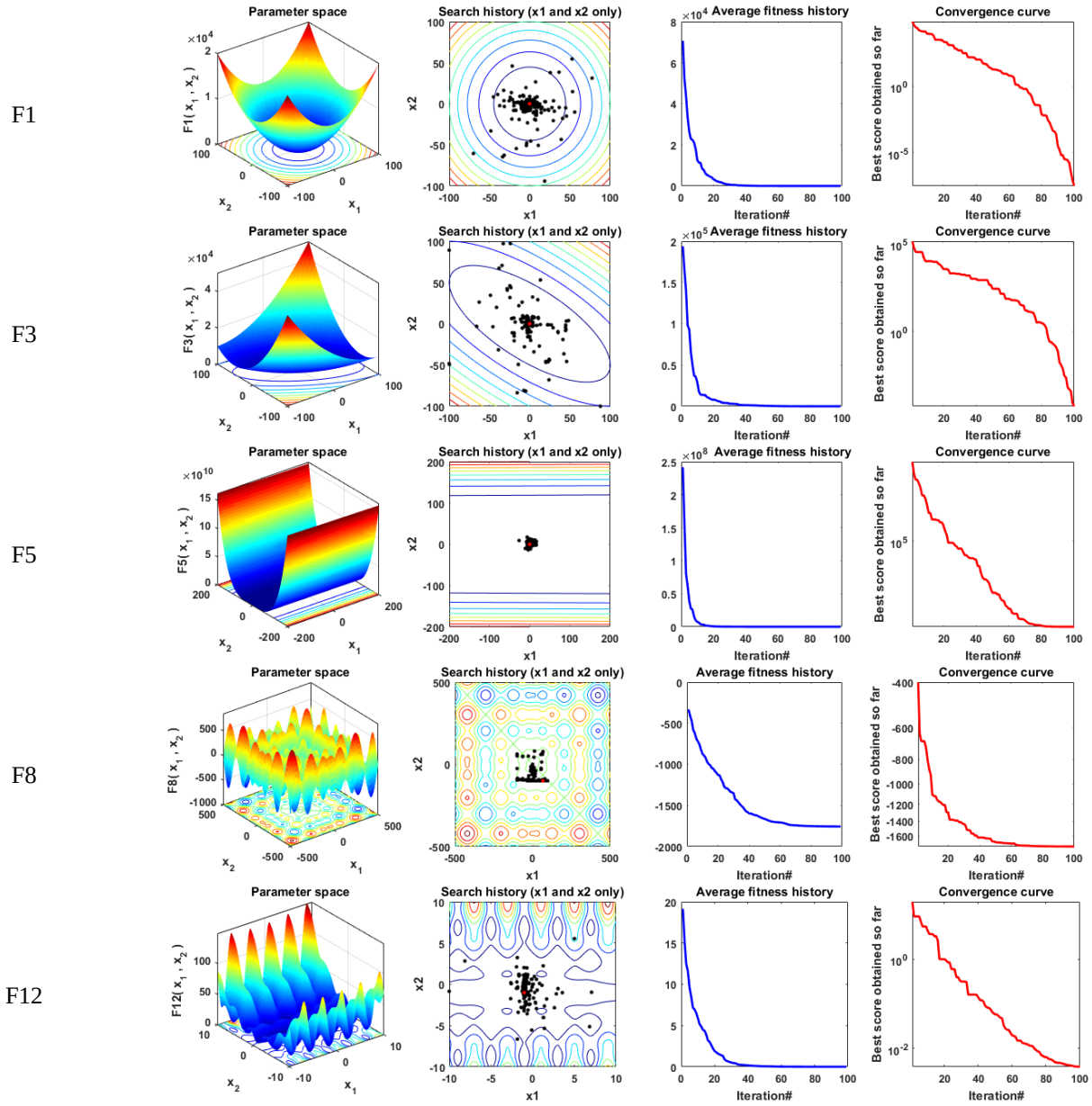


Figure 6. The flow chart of IWHO algorithm.

5. Simulation Results and Discussion

5.1. Mathematical validation

To evaluate the robustness of the suggested IWHO algorithm, it was run separately on all 23 OFs for the maximum iterations number of 1000 and the agents' number of 50. To assess the algorithm's performance, this research uses both quantitative and qualitative measures. Fig.7 shows the qualitative metrics for some the benchmark functions, including 2D views of the functions, search histories, mean fitness histories, and convergence curves.



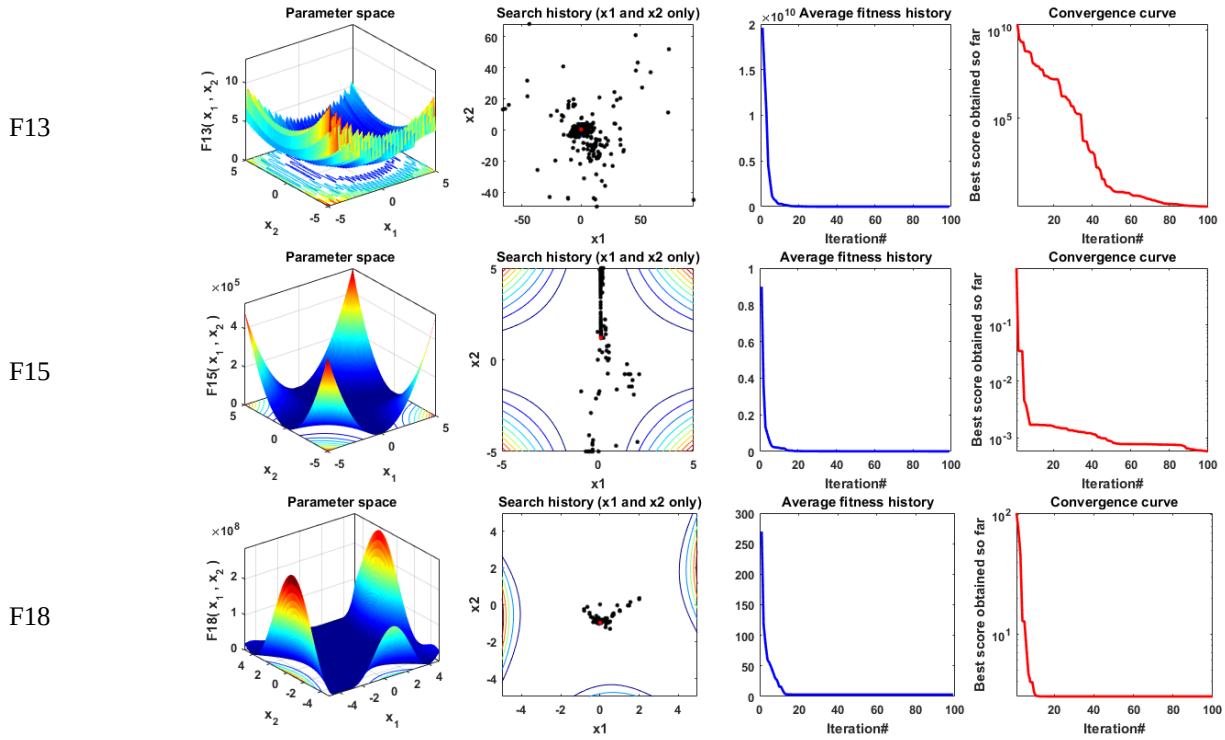


Figure 7. Qualitative metrics on some benchmark functions: 2D views of the functions, search history, mean fitness history, and convergence characteristics curve.

Also, the suggested IWHO was tested for its ability to provide a quasi-suitable solution on a collection of 23 objective functions of various types of unimodal, multi-modal, and fixed-dimensional composite functions [30]. The obtained results are compared with three recent algorithms Grey Wolf Optimizer (GWO) algorithm [31], Tunicate Swarm Algorithm (TSA) [32], and Seagull Optimization Algorithm (SOA) [33], as well as the original WHO. The parameter setting of the chosen algorithms is shown in table 1. Each optimisation technique was executed in 20 independent runs; the optimization results are presented as the best, worst, average, and the standard deviation (std) of the preferable solutions, respectively.

Table 1. Parameter sets of the chosen algorithms.

Algorithms	Parameters setting
Common settings	Population size: nPop=50 Maximum iterations : Max_iter=1000 Number of separate runs: 20
SOA	b=1
IWHO	PS=0.2; % Stallions Percentage
WHO	PC=0.13; % Crossover Percentage

5.1.1. Evaluation of the Objective Functions Findings for Unimodal

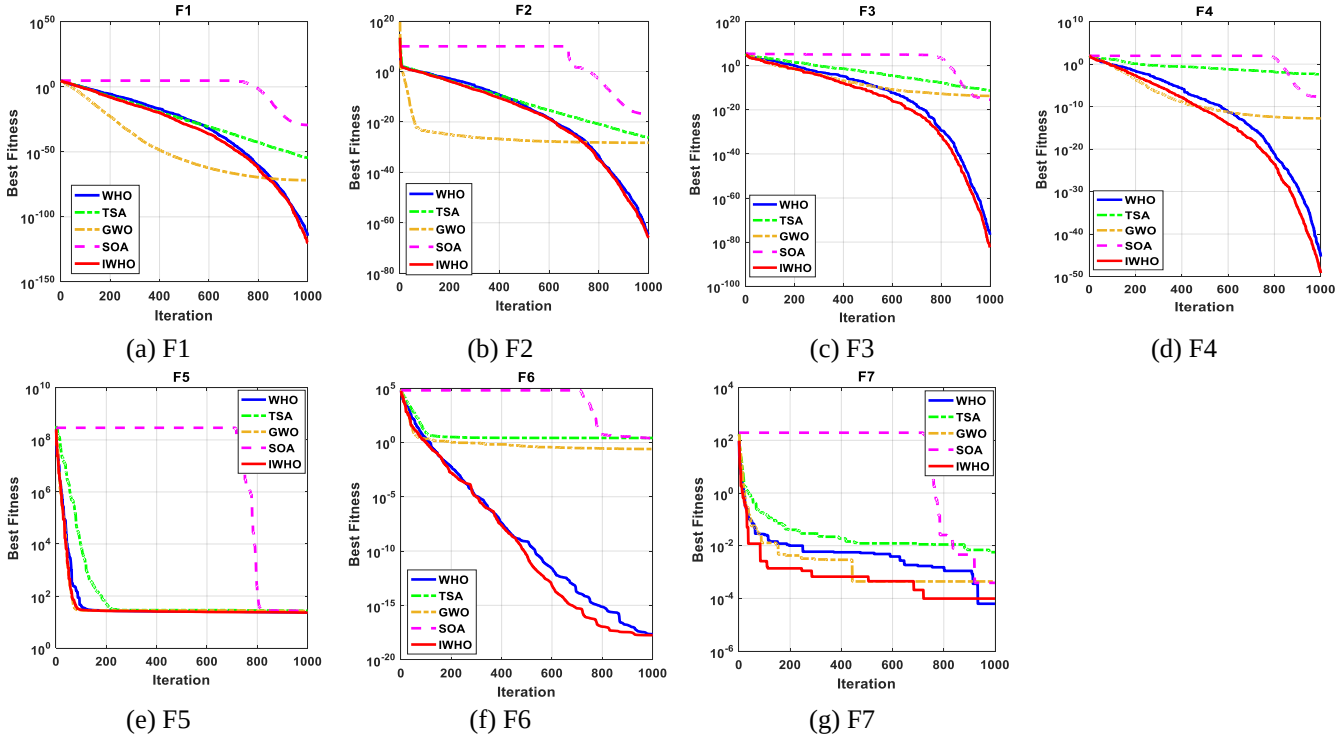
The suggested algorithm's exploitative capacity may be assessed and evaluated using the unimodal test functions. Table 1 displays the best values achieved using the proposed and well-known optimization algorithms for these benchmark functions. It can be noticed that the IWHO technique

provides better results on all unimodal functions except F7 which the original WHO reaches only for the best answer while the proposed algorithm achieves the best values for it in the worst, mean, and std. The suggested IWHO method produces better results than existing approaches for all unimodal test functions. Figure 8 depicts the convergence characteristics curves of the introduced IWHO approach, including well optimization techniques for unimodal benchmark functions. For more analysis to confirm the performance of the recommended technique, a boxplot of outcomes for each technique and OF is demonstrated in Figure 9.

Table 2. Benchmark function outcomes for unimodal.

Function		WHO	IWHO	GWO	TSA	SOA
F1	Best	2.6E-115	**8.2E-121**	1.6E-72	2.82E-55	4.76E-30
	Worst	9.5E-106	**1.4E-108**	3.42E-07	3.45E-17	5.06E-10
	Mean	1.1E-106	**6.9E-110**	1.71E-08	1.72E-18	2.53E-11
	std	2.8E-106	**3.1E-109**	7.65E-08	7.71E-18	1.13E-10
F2	Best	1.53E-65	**1.18E-66**	5.52E-29	6.19E-27	1.3E-17
	Worst	1.03E-59	**2.14E-61**	4.4E-08	7.35E-13	4.26E-08
	Mean	2E-60	**1.49E-62**	2.39E-09	3.68E-14	2.15E-09
	std	3.17E-60	**4.81E-62**	9.81E-09	1.64E-13	9.52E-09
F3	Best	1.95E-77	**3.99E-83**	2.22E-14	6.22E-12	4.12E-16
	Worst	6.75E-64	**3.47E-68**	1.200307	195.9186	0.54897
	Mean	4.99E-65	**1.75E-69**	0.175247	24.31458	0.039322
	std	1.63E-64	**7.76E-69**	0.401434	60.03018	0.124825
F4	Best	4.83E-46	**6.5E-50**	1.7E-13	0.004211	1.88E-08
	Worst	4.2E-41	**1.16E-42**	0.123216	21.22892	1.489819
	Mean	4.68E-42	**7.93E-44**	0.012534	3.538218	0.21736
	std	1.18E-41	**2.63E-43**	0.037861	6.441649	0.523316
F5	Best	23.62242	**23.06539**	26.41102	27.10919	27.20026
	Worst	28.53885	**24.57677**	28.93196	28.92147	28.93044
	Mean	24.46879	**24.07834**	27.85099	28.38438	28.54089
	std	1.000308	**0.415118**	0.799818	0.675004	0.57121
F6	Best	2.19E-18	**1.78E-18**	0.249992	2.596274	2.507228
	Worst	2.92E-14	**2.84E-15**	6.754946	6.30706	6.133702
	Mean	2.04E-15	**4.52E-16**	2.39919	4.176579	4.253747
	std	6.58E-15	**7.79E-16**	1.752866	1.013975	1.034333
F7	Best	**6.26E-05**	9.83E-05	0.000439	0.005675	0.000389
	Worst	0.00123	**0.00078**	0.008863	0.052199	0.024776
	Mean	0.000421	**0.000293**	0.00327	0.014535	0.006081
	std	0.00027	**0.000162**	0.002825	0.010611	0.006765

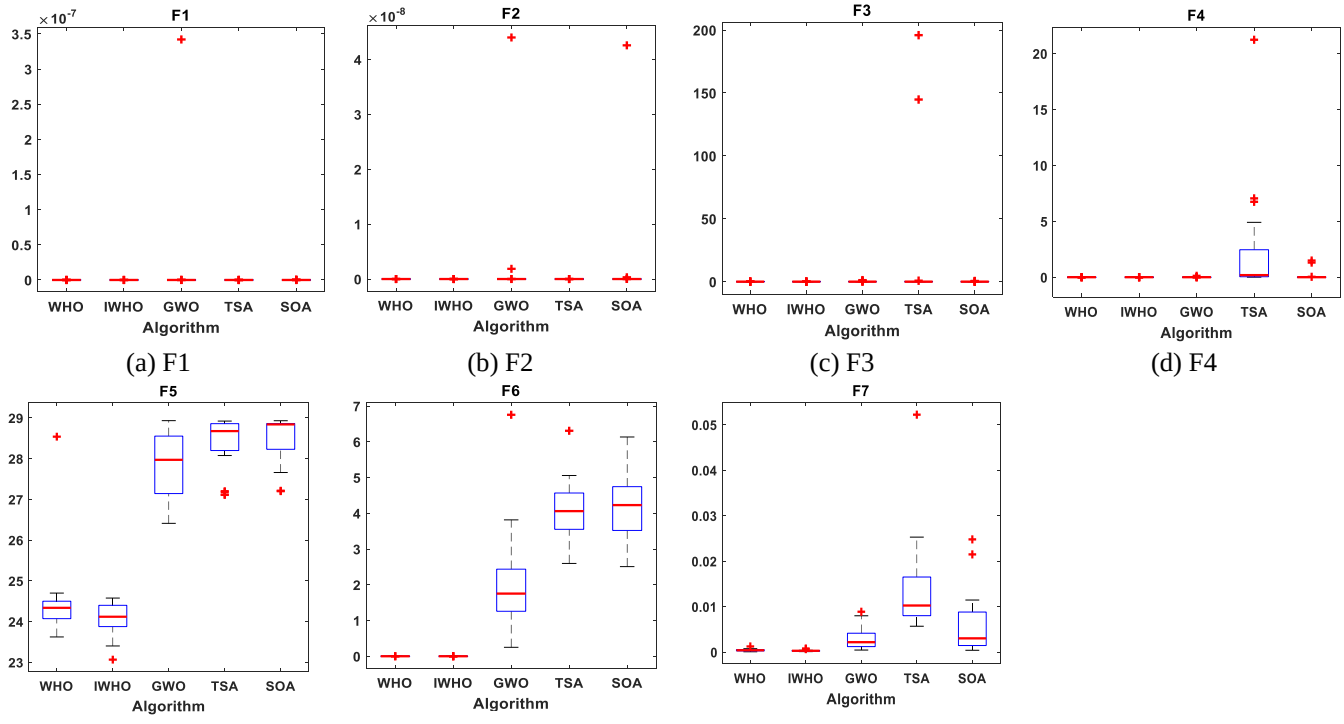
The best values obtained are in bold



(a) F1 (b) F2 (c) F3 (d) F4

(e) F5 (f) F6 (g) F7

Figure 8. The convergence curves of all algorithms for unimodal benchmark functions.



(a) F1 (b) F2 (c) F3 (d) F4

(e) F5 (f) F6 (g) F7

Figure 9. Boxplots for all algorithms for unimodal benchmark functions.

5.1.2. Evaluation of the Objective Functions Findings for multi-modal

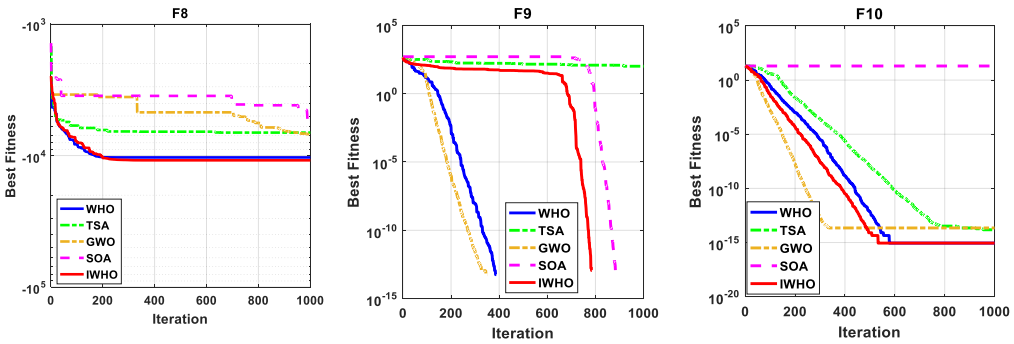
Six objective functions of multi-modal functions, including F8 to F13, were chosen to evaluate the performance of the proposed IWHO technique in presenting the best solutions. The results of the implementation of the IWHO algorithm and three other optimization algorithms as well as the con-

ventional WHO algorithm on this type of objective function, are displayed in Table 2. The emulation results prove that the IWHO performs better and more competitively in tackling this sort of optimization issue. Fig. 10 displays the convergence curves of IWHO and other rival methods. Fig. 11 presents the box plot for the proposed IWHO and other concurrent algorithms on multi-modal functions. According to the results, the proposed IWHO technique is the greatest optimization technique for the majority of the evaluation metrics.

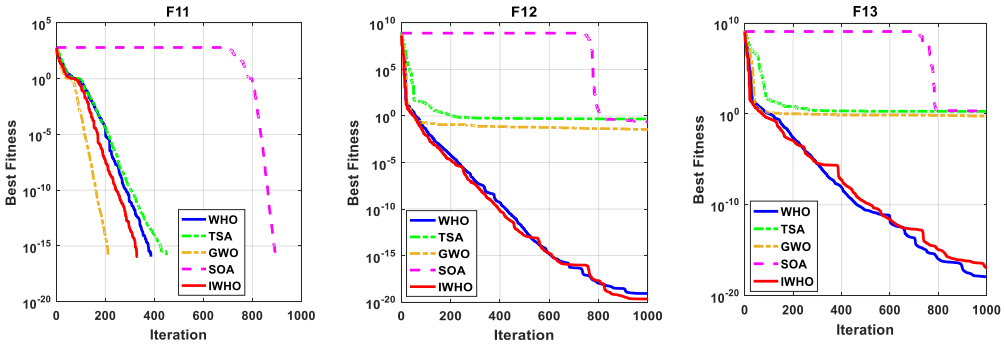
Table 3. Benchmark function outcomes for multi-modal.

Function		WHO	IWHO	GWO	TSA	SOA
F8	Best	-10331.3	**-10867.3**	-6876.85	-6687.08	-5688.53
	Worst	-8811.26	**-8909.96**	-2040.64	-3353.87	-3025.17
	Mean	-9512.65	**-9654.44**	-5363.86	-5404.01	-4662.31
	std	**377.1542**	469.3701	1298.089	964.0392	721.2641
F9	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	101.0783	**0.00E+00**
	Worst	**0.00E+00**	**0.00E+00**	10.64299	312.5106	19.6612
	Mean	**0.00E+00**	**0.00E+00**	1.088214	196.4102	2.489027
	std	**0.00E+00**	**0.00E+00**	2.989658	51.77915	5.370562
F10	Best	**8.88E-16**	**8.88E-16**	2.22E-14	1.51E-14	19.95954
	Worst	**4.44E-15**	**4.44E-15**	4.94E-07	2.891204	19.96677
	Mean	3.2E-15	**3.02E-15**	2.56E-08	0.545612	19.96242
	std	**1.74E-15**	1.79E-15	1.1E-07	1.123192	0.001919
F11	Best	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**	**0.00E+00**
	Worst	**0.00E+00**	**0.00E+00**	0.034439	0.151418	0.11477
	Mean	**0.00E+00**	**0.00E+00**	0.003728	0.029085	0.013796
	std	**0.00E+00**	**0.00E+00**	0.009503	0.052147	0.033163
F12	Best	8.23E-20	**2.12E-20**	0.035117	0.478781	0.237936
	Worst	**0.103669**	0.207317	1.373427	18.46794	1.633411
	Mean	**0.010367**	0.020732	0.253217	6.960091	0.619033
	std	**0.031909**	0.063811	0.394467	5.091209	0.411038
F13	Best	**1.2E-18**	1.1E-17	0.569956	1.889159	1.854413
	Worst	**0.109867**	0.175786	2.764004	3.467599	2.898385
	Mean	**0.019212**	0.034458	1.354047	2.824032	2.29935
	std	**0.028468**	0.050856	0.672746	0.437644	0.298225

The best values obtained are in bold

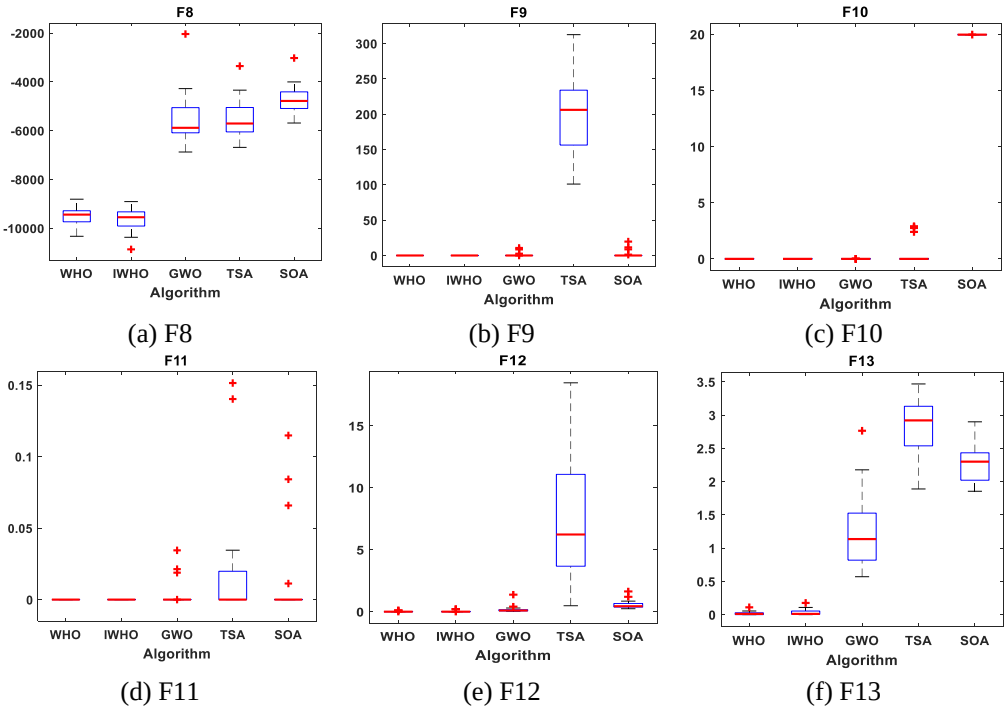


(a) F8 (b) F9 (c) F10



(d) F11 (e) F12 (f) F13

Figure 10. The convergence curves of all algorithms for multi-modal benchmark functions.



(a) F8 (b) F9 (c) F10

(d) F11 (e) F12 (f) F13

Figure 11. Boxplots for all algorithms for multi-modal benchmark functions.

5.1.3. Evaluation Results on composite Objective Functions

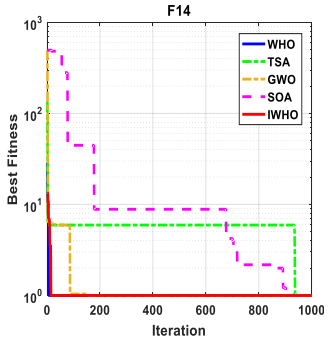
Ten objective functions of composite functions, including F14 to F23, were chosen to assess the performance of the proposed IWHO in providing optimal solutions. Table 3 presents the best optimum solutions found by all algorithms, including the best, worst, average, and STD. Fig. 12 displays the convergence curves of the proposed IWHO technique and other techniques achieved in the multiple benchmark functions. Fig. 13 displays the boxplots for F14 to F23. It can be seen that the boxplots of the proposed IWHO when compared to other techniques, are highly tight for the majority of these functions with the lowest values.

Table 4. Results of composite benchmark functions.

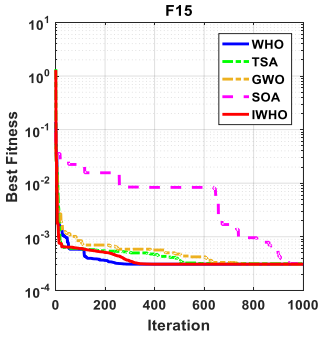
Function		WHO	IWHO	GWO	TSA	SOA
	Best	**0.998004**	**0.998004**	**0.998004**	**0.998004**	**0.998004**
F14	Worst	5.928845	**2.982105**	12.67051	12.67051	12.67051
	Mean	1.294247	**1.14691**	5.686485	7.493557	4.423671

F15	std	1.113224	**0.485651**	4.930301	4.617822	4.324715
	Best	**0.000307**	**0.000307**	0.000308	0.000314	0.000312
	Worst	0.020363	**0.001223**	0.120459	0.088541	0.00143
	Mean	0.001485	**0.000399**	0.007588	0.010089	0.001171
	std	0.004459	**0.000282**	0.026933	0.020407	0.000273
F16	Best	**-1.03163**	**-1.03163**	**-1.03163**	**-1.03163**	**-1.03163**
	Worst	**-1.03163**	**-1.03163**	-0.99999	-0.99999	-1.00018
	Mean	**-1.03163**	**-1.03163**	-1.03002	-1.0253	-1.03005
	std	**1.25E-16**	1.76E-16	0.007069	0.012979	0.007032
F17	Best	**0.397887**	**0.397887**	**0.397887**	**0.397887**	0.397889
	Worst	**0.397887**	**0.397887**	0.39789	0.397983	0.398107
	Mean	**0.397887**	**0.397887**	0.397888	0.397908	0.397927
	std	**0.00E+00**	**0.00E+00**	5.33E-07	2.77E-05	5.14E-05
F18	Best	**3**	**3**	**3**	**3**	**3**
	Worst	**3**	**3**	3.000023	30.00016	3.000026
	Mean	**3**	**3**	3.000004	8.400019	3.000003
	std	6.28E-16	**4.78E-16**	5.43E-06	11.0806	5.99E-06
F19	Best	**-3.86278**	**-3.86278**	**-3.86278**	**-3.86278**	-3.86262
	Worst	**-3.86278**	**-3.86278**	-3.8549	-3.86269	-3.85477
	Mean	**-3.86278**	**-3.86278**	-3.86173	-3.86275	-3.85527
	std	**2.28E-15**	**2.28E-15**	0.002504	2.27E-05	0.001731
F20	Best	**-3.322**	**-3.322**	-3.32199	-3.3214	-3.13591
	Worst	**-3.2031**	**-3.2031**	-3.13491	-2.43163	-2.06108
	Mean	-3.26255	**-3.26849**	-3.24315	-3.19273	-3.00309
	std	0.060991	**0.060685**	0.077104	0.197413	0.227568
F21	Best	**-10.1532**	**-10.1532**	**-10.1532**	-10.1119	-10.1351
	Worst	-2.68286	-2.63047	**-5.05519**	-2.61588	-0.35065
	Mean	-8.89864	-9.14865	**-9.64539**	-7.14247	-4.32683
	std	2.632293	2.494251	**1.562102**	3.341539	4.57182
F22	Best	**-10.4029**	**-10.4029**	**-10.4029**	-10.3678	-10.4004
	Worst	**-10.4029**	-2.7659	-10.4023	-2.70045	-0.90807
	Mean	**-10.4029**	-9.42345	-10.4026	-8.34157	-7.69481
	std	**2.61E-15**	2.423101	0.000173	3.074106	3.963887
F23	Best	**-10.5364**	**-10.5364**	-10.5363	-10.4781	-10.5232
	Worst	-2.87114	-2.87114	**-10.5358**	-2.41561	-0.94448
	Mean	-9.8181	-9.38662	**-10.5361**	-8.56594	-7.46184
	std	2.216446	2.808152	**0.000159**	3.314441	3.716296

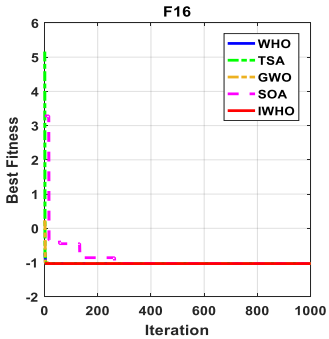
The best values obtained are in bold



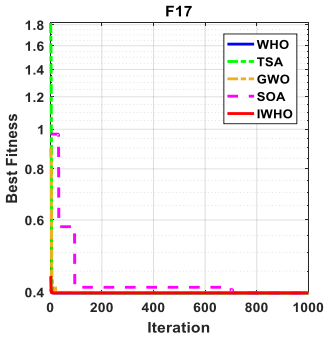
(a) F14



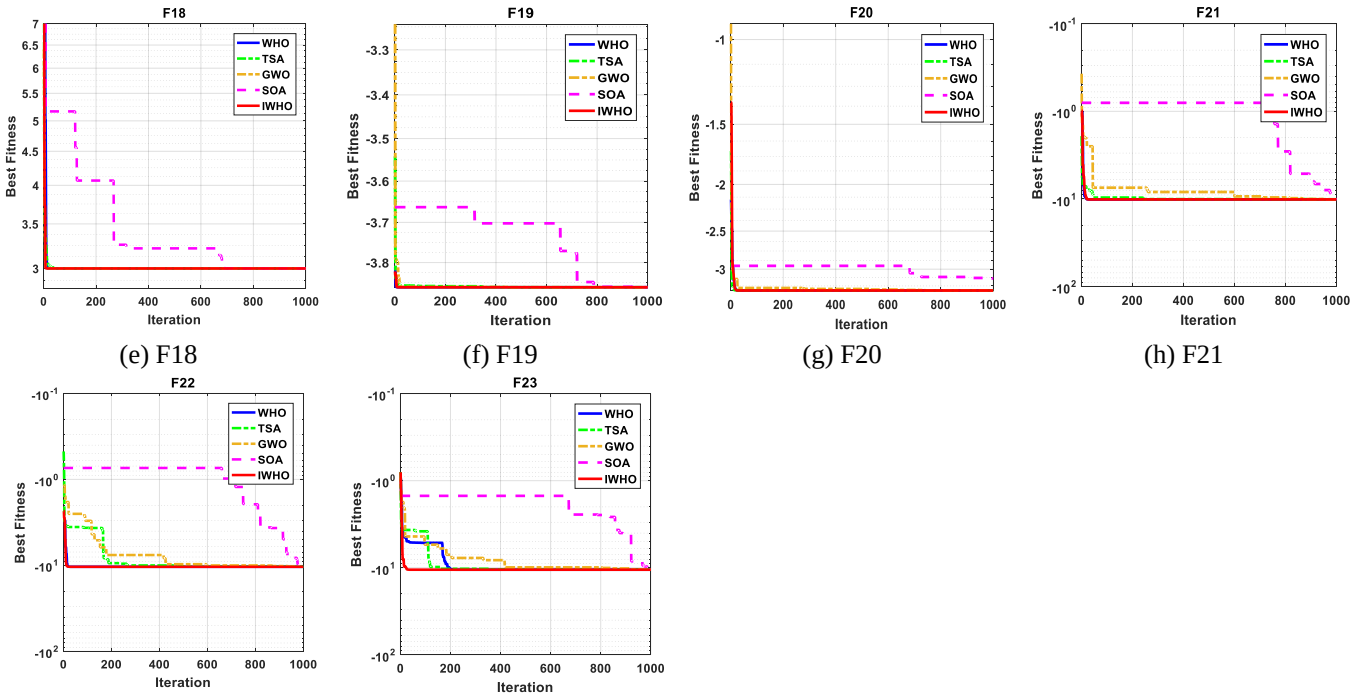
(b) F15



(c) F16



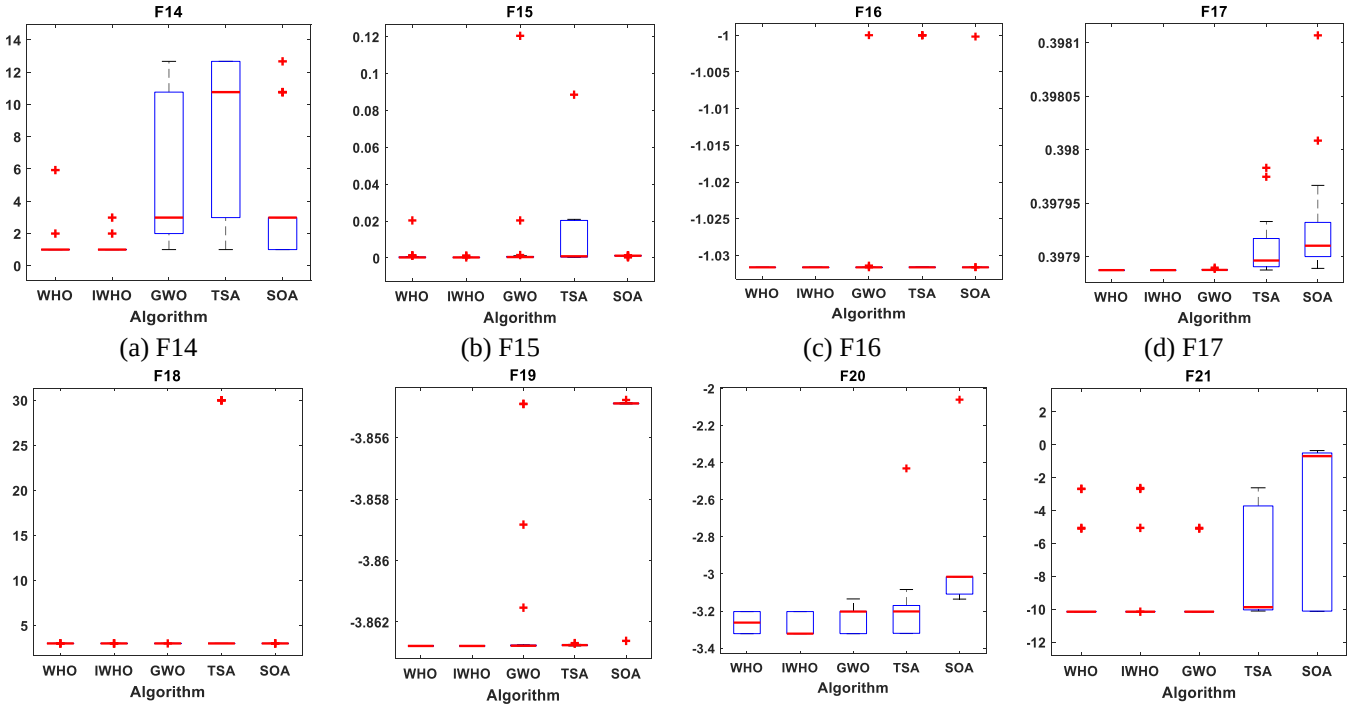
(d) F17



(e) F18 (f) F19 (g) F20 (h) F21

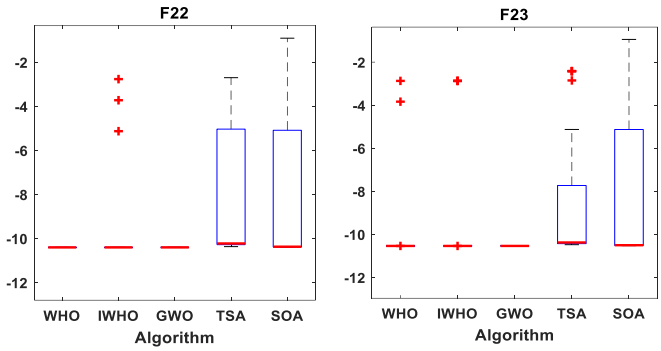
(i) F22 (j) F23

361 **Figure 12.** The convergence curves of all algorithms for composite benchmark functions.



(a) F14 (b) F15 (c) F16 (d) F17

(e) F18 (f) F19 (g) F20 (h) F21



(i) F22 (j) F23

Figure 13. Boxplots for all algorithms for composite benchmark functions.

5.2. Test Systems

The described algorithm was employed and validated on IEEE 33 and 69-bus networks to ensure its usefulness. The starting node voltage is assumed to be 1pu, and all loading buses are considered viable installation options. MATLAB 2020b software was used to perform the suggested technique utilizing Intel(R) Core(TM) i7-8550U CPU @ 1.80GHz 1.99 GHz, 16 GB RAM, 64-bit operation system.

Table 5. The algorithm parameters and operative restrictions

Parameters	**Value**
Number of Population	30
Maximum iteration numbers	100
Stallions Percentage	0.2
Crossover Percentage	0.13
Base MVA	100 MVA
Base kV	12.66 kV
Node system voltage constraints	$0.9pu \leq V_i \leq 1.1$pu
DG's power generation constraints	$0MW \leq P_{DG} \leq 3MW$

Figures 14 and 15 clarify a single-line schematic of these systems [34Real and reactive power consumption for the 33-bus test system are 3715 kW and 2300 KVAR, respectively. The test system's initial power loss is 210.0794 kW, and its minimum voltage is 0.9042 pu. While 69-bus test system's active and reactive power demands are 3802 kW and 2695 KVAR, respectively. The 69-test system's initial power loss is 238.1455 kW, and its minimum voltage is 0.9046 pu.

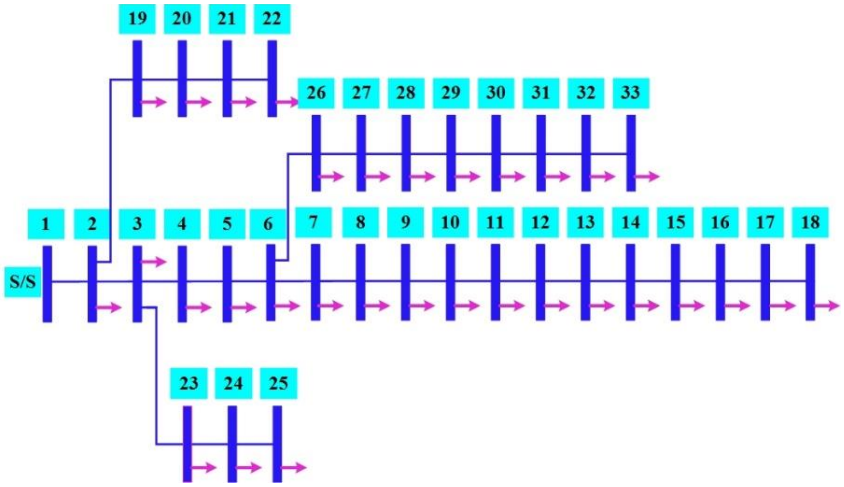


Figure 14. Standard IEEE-33 bus test system

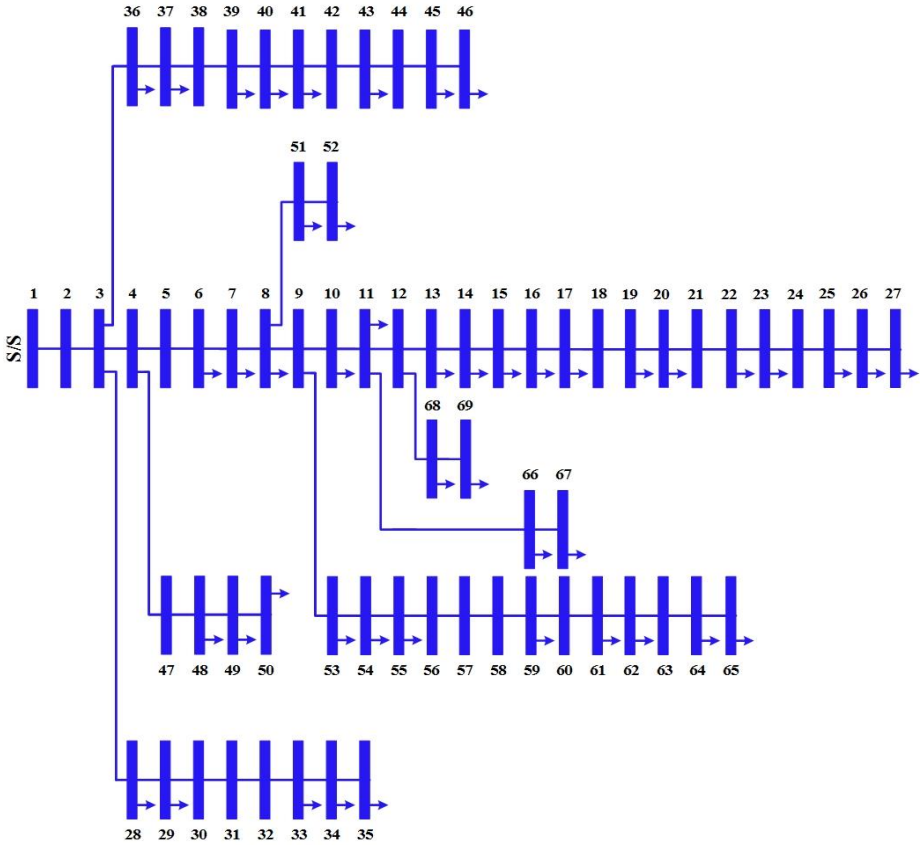


Figure 15. Standard IEEE-69 bus test system

5.2.1 IEEE 33-bus system

Figure 16 depicts the voltage profile before and after DG insertion. Bus 18 is the furthest end-point from the substation; therefore, its voltage is the least in the reference scenario (DG absence), and its value is 0.90421 pu. Without DG, buses 6 to 18 and 26 to 33 have the lowest voltage, whereas introducing DG results in a considerable voltage profile improvement within limitations (approved). Furthermore, the usage of DG yields superior outcomes in terms of power loss alleviation.

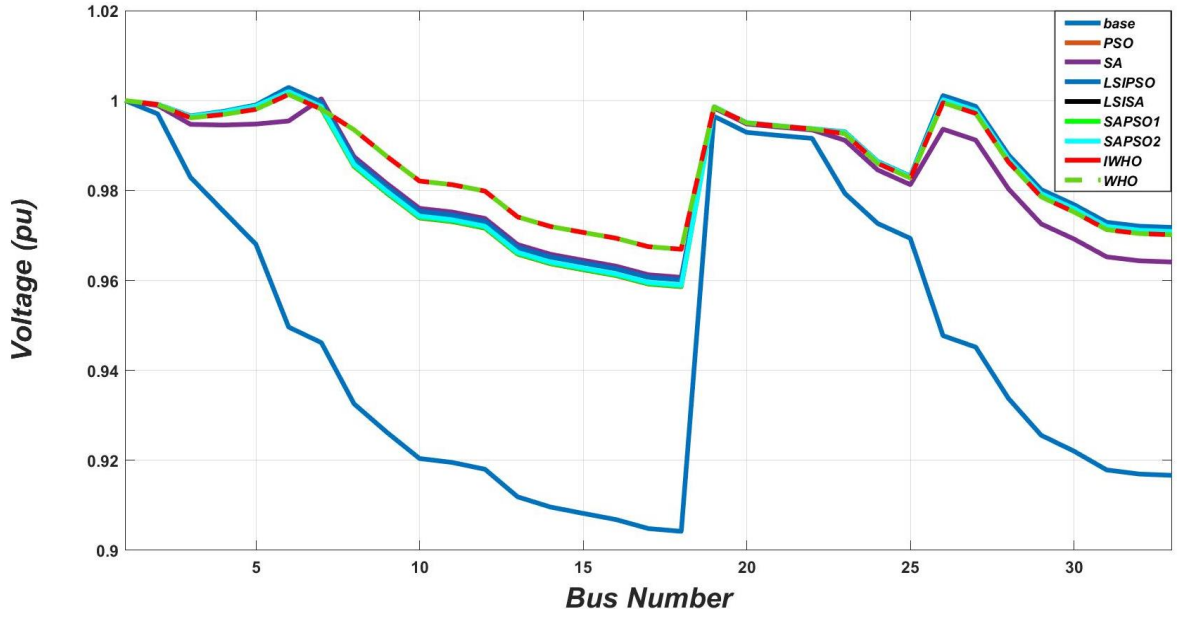


Figure 16. Voltage profile for IEEE-33 bus test system

Table 6 displays the outcomes of the suggested approach for determining the best size, site, and power factor of DG units in a 33-bus system. According to this table, the proportion of power loss depression in the DS is 70.81 percent. Minimum voltages raised from 0.9042 to 0.967 pu as a result.

Table 6. The performance analysis of different algorithms in the IEEE-33 bus test system

Methods	*Power losses (kW)*	*Loss Reduction*	*Min Voltage (pu) & Bus Number*		*DG Location*	*DG Size P (KW) & Q (KVAR)*		*Itr*
Base Case	*210.0794*	-	*0.90421*	*18*	-	-	-	-
SA	*70.1894*	*66.6%*	*0.95904*	*18*	*6*	*2935.6*	*1554.8*	*58*
PSO	*67.8228*	*67.7%*	*0.95862*	*18*	*6*	*2528.3*	*1747.9*	*50*
LSI-SA	*67.8118*	*67.7%*	*0.96041*	*18*	*6*	*2556.7*	*1750.0*	*28*
LSI-PSO	*67.8113*	*67.7%*	*0.96010*	*18*	*6*	*2658.8*	*1619.6*	*33*
SA-PSO1	*67.8123*	*67.7%*	*0.95872*	*18*	*6*	*2557.7*	*1748.4*	*10*
SA-PSO2	*67.8113*	*67.7%*	*0.95896*	*18*	*6*	*2511.9*	*1530.5*	*18*
GA	*72.68*	*64.32%*	-	-	*6*	*2831*	*930.5*	-
SAA	*67.75*	*67.89%*	-	-	*6*	*2540.84*	*1737.19*	-
GWO	*67.87*	*67.86%*	-	-	*6*	*2571.3*	*1794.77*	*20*
BSOA	*82.78*	*60.76%*	*0.9549*	*18*	*8*	*1857.4968*	*1296.54*	-
ALOA	*71.75*	*65.99%*	*0.9528*	*18*	*6*	*1947.756*	*1103.84*	-
HHO	*69.443*	*66.9%*	*0.95579*	*18*	*26*	*2510.01*	*1555.56*	*28*
HGSO	*68.1743*	*67.5%*	*0.9586*	*18*	*6*	*2653.27*	*1644.345*	-
AEO	*68.1698*	*67.55%*	*0.95830*	*18*	*6*	*2637.42*	*1634.526*	-
HSSA	*67.86*	*67.69%*	-	-	*6*	*2547.06*	*1777.858*	-
WOA	*78.4337*	*62.65%*	-	-	*30*	*1746.297*	*845.77*	-
EA	*67.937*	*67.66%*	-	-	*6*	*2528*	*1764.55*	-
Hybrid	*67.9*	*67.82%*	*0.9569*	*18*	*6*	*2482.96*	*1733.11*	-
ROA	*67.83*	*67.83%*	*0.95*	*18*	*6*	*2588.4*	*1785.77*	*17*
IA	*68.157*	*67.82%*	-	-	*6*	*2547.74*	*1778.33*	-

MINLP	*67.854*	*67.7%*	*-*	*-*	*6*	*2558*	*1765.55*	*-*
WHO	*61.3147*	*70.81%*	*0.967*	*18*	*6*	*2541.4727*	*1742.9416*	*15*
IWHO	***61.3147***	***70.81%***	***0.967***	***18***	***6***	***2541.4727***	***1742.9415***	***6***

It is observed that the innovative algorithm results in the least total power loss when compared to those achieved using EA [10], Hybrid approach [9], Hybrid Salp Swarm Algorithm (HSSA) [20], PSO [22], SA [22], Improved Analytical (IA) [14], MINLP [14], Hybrid Loss Sensitivity Index and SA (LSISA) [22], Hybrid Loss Sensitivity Index and PSO (LSIPSO) [22], Hybrid SA and PSO (SAPSO) [22], Rider Optimization Algorithm (ROA) [24], Harris Hawks Optimizer (HHO) [16], Henry gas solubility optimization (HGSO) [16], whale optimization algorithms (WOA) [35], Genetic algorithm (GA) [36], Gray wolf optimizer (GWO) [18], Simplified Analytical Approach (SAA) [17], Backtracking search optimization algorithm (BSOA) [37], ALOA [19] and Artificial ecosystem-based optimization (AEO) [16]. Figure 17 depicts the convergence curves of the two techniques (i.e., WHO and IWHO). The findings demonstrate that the IWHO method smoothly accelerates to a correct decision and has stable faster convergence when compared to the WHO algorithm. The IWHO algorithm's invention and notability have been proved and confirmed by identifying the best choice to attain global minima in a short period.

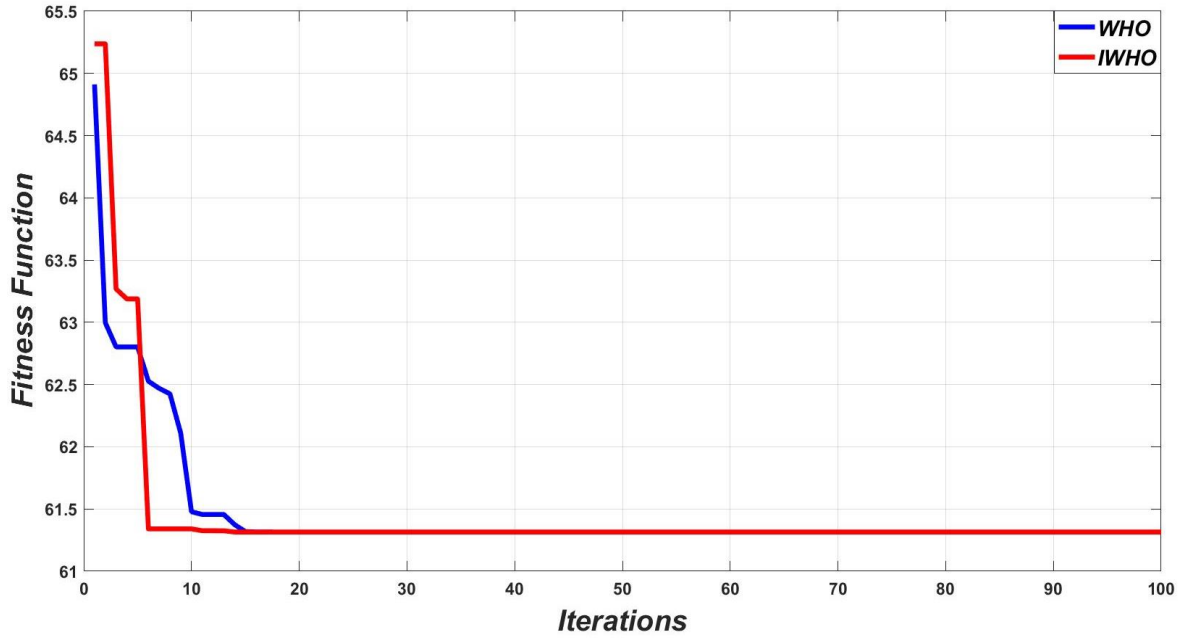
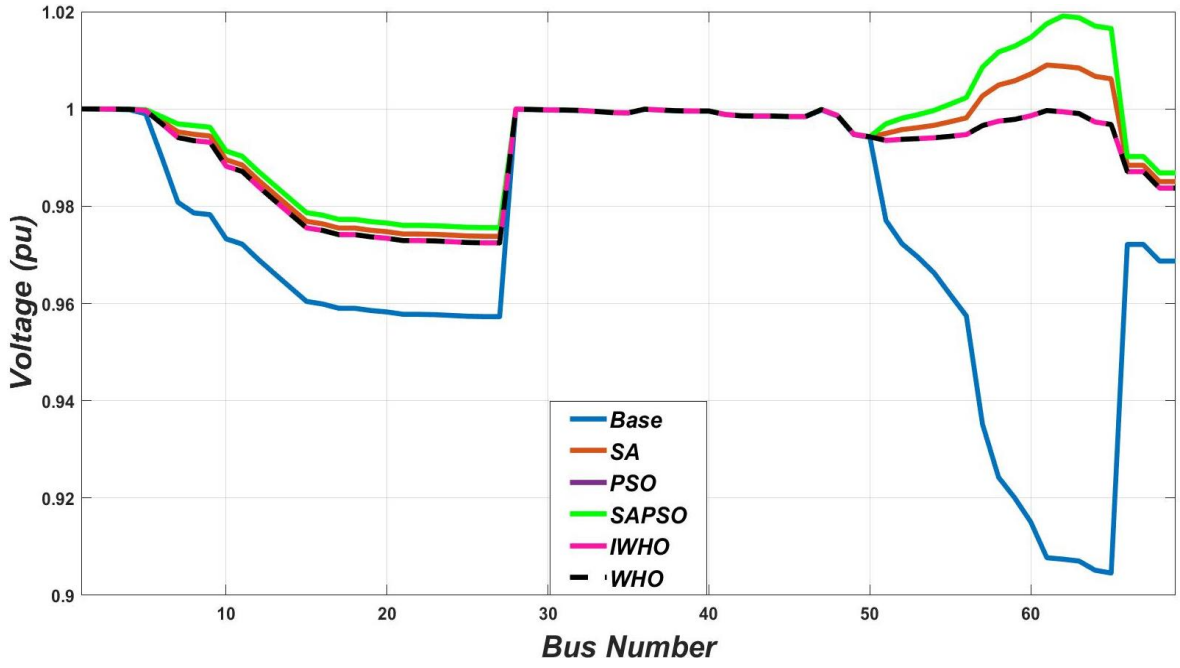


Figure 17. Convergence curve of the IEEE 33-bus system

5.2.2 IEEE 69-bus system

While bus 27 is the furthest end of the 69-bus system from the supply node, bus 65 have the lowest voltage value 0.9046 pu because bus 61, which is linked to it is a strongly loaded point. So, it was chosen as the location for the DG unit. Figure 18 displayed a significant improvement in the voltage profile.



411

412 **Figure 18.** Voltage profile for IEEE-69 bus test system

413 Table 7 shows the outcomes of the suggested approach for determining the best size, site, and
414 power factor of DG units in a 69-bus system. According to this table, the proportion of power loss
415 depression in the DS is 90.26 percent. Minimum voltages raised from 0.9046 to 0.9725 pu as a result.

416

417 **Table 7.** The performance analysis of different algorithms in the IEEE-69 bus test system

Methods	*Power losses (kW)*	*Loss Reduction*	*Min Voltage (pu) & Bus Number*		*DG Location*	*DG Size P (KW) & Q (KVAR)*		*Itr*
Base Case	*238.1455*	-	*0.9046*	*65*	-	-	-	-
SA	*26.2583*	*88.97%*	*0.9727*	*27*	*61*	*1904.7*	*1571.9*	*39*
MPSO	*23.2358*	*90.24%*	*0.9724*	*27*	*61*	*1814.1*	*1293.3*	*77*
SAMPSO	*23.2378*	*90.24%*	*0.9738*	*27*	*61*	*1807.0*	*1295.3*	*3*
GA	*38.458*	*82.9*	-	-	*61*	*2047.82*	*673.085*	-
CSA	*52.6*	*76.6*	-	-	*61*	*2254*	*457.694*	-
SGA	*64.4*	*71.37*	-	-	*61*	*2548*	*517.39*	-
SAA	*23.18*	*89.7*	-	-	*61*	*1818.357*	*1311.74*	-
HHO	*34.65*	*85%*	-	-	*61*	*1879.41*	*1311.83*	*12*
HGSO	*35.71*	*85%*	-	-	*60*	*1695.9*	*1360.589*	*36*
BA	*52.5*	*76.67%*	-	-	*61*	*2100*	*426.42*	*65*
PSO	*52.5*	*76.67%*	-	-	*61*	*2100*	*426.42*	*75*
EA	*23.26*	*90.23%*	-	-	*61*	*2290*	*1598.429*	-
IA	*23.24*	*90.24%*	-	-	*61*	*1839*	*1283.629*	-
Hybrid	*23.19*	*89.7%*	-	-	*61*	*1814.4*	*1313.6*	-
MINLP	*23.31*	*90.21%*	-	-	*61*	*1828*	*1299.698*	-
MODE	*23.20*	*89.7%*	-	-	*61*	*1814.8*	*1290.314*	-

WOA	*27.9649*	*87.57%*	*-*	*-*	*61*	*1995.66*	*966.54*	*-*
ROA	*23.17*	*90.27%*	*-*	*-*	*61*	*1828.47*	*1304.78*	*37*
WHO	*23.178*	*90.26%*	*0.9725*	*27*	*61*	*1814.0767*	*1293.2988*	*10*
IWHO	***23.178***	***90.26%***	***0.9725***	***27***	***61***	***1814.0767***	***1293.2988***	***3***

According to Table 7, the suggested algorithm has the lowest power loss when compared to the Bat Algorithm (BA) [15], EA [10], Hybrid approach [9], HSSA [20], PSO [22], Modified PSO algorithm [23], SA [22], IA [14], Mixed Integer Non- Linear Programming (MINLP) [14], Hybrid SA and MPSO (SAMPSO) [23], Rider Optimization Algorithm (ROA) [24], HHO [16], HGSO [16], WOA [35], GA [36], SAA [17], ALOA [19], Cuckoo Search algorithm (CSA), Standard GA [38] and Multi-objective differential evolution (MODE) [39]. Figure 19 depicts the convergence curves of the two techniques (i.e., WHO and IWHO). The findings demonstrate that the IWHO method smoothly accelerates to a correct selection and has stable faster convergence when compared to the WHO algorithm. The IWHO algorithm's invention and notability have been proved and confirmed by identifying the best option to attain global minima in a short period after 3 iterations.

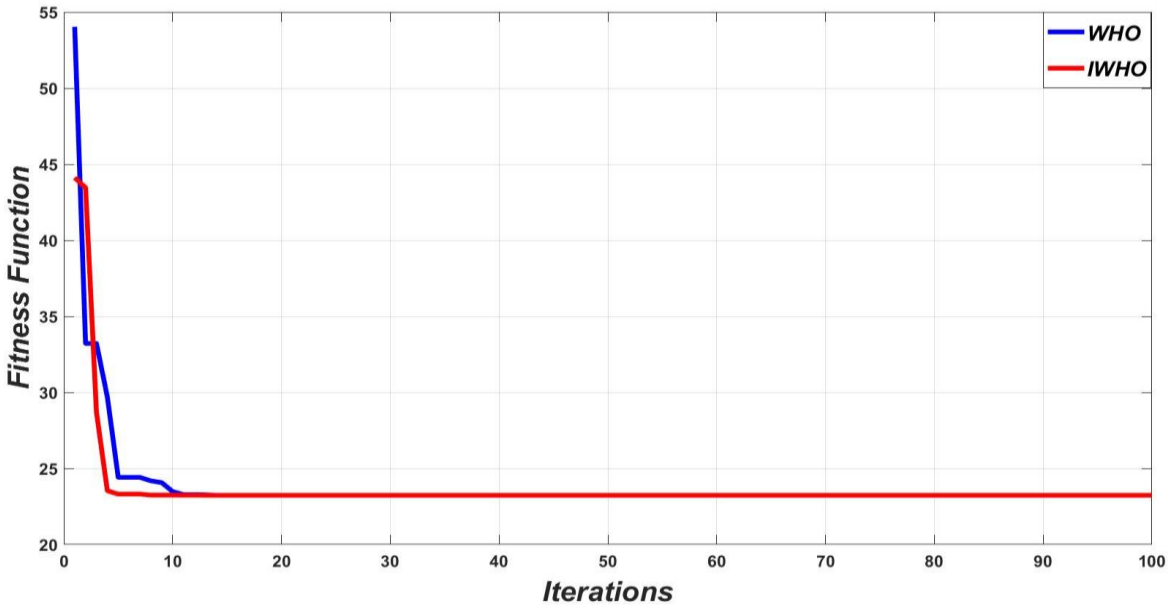


Figure 19. Convergence curve of the IEEE 69-bus system

5.3. Reliability Analysis

The DG incorporation can improve system reliability as DG can be actively involved in system restoration. The reliability improvement can be maximized if DG units are allocated properly with automatic recloser (AR). AR is a safeguard device that can identify a defect and open it for a pre-programmed period before shutting automatically and without the intervention of a human aspect. Figures 20 and 21 show the modified IEEE 33 & 69 bus test models, including DG and AR. Automat-

ic reclosers/CBs must be used when installing a DG in the DS; otherwise, there'd be no avail because the fault would undoubtedly prevent the DG units from connecting during outages.

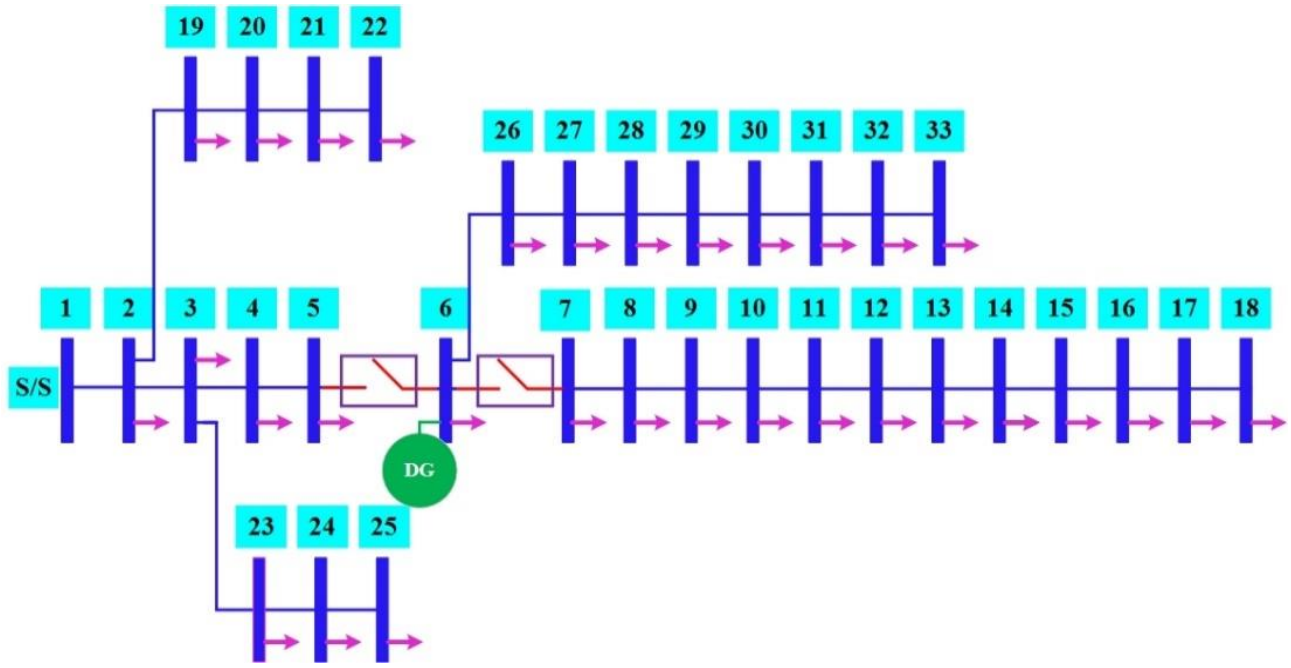


Figure 20. A modified IEEE 33 bus test

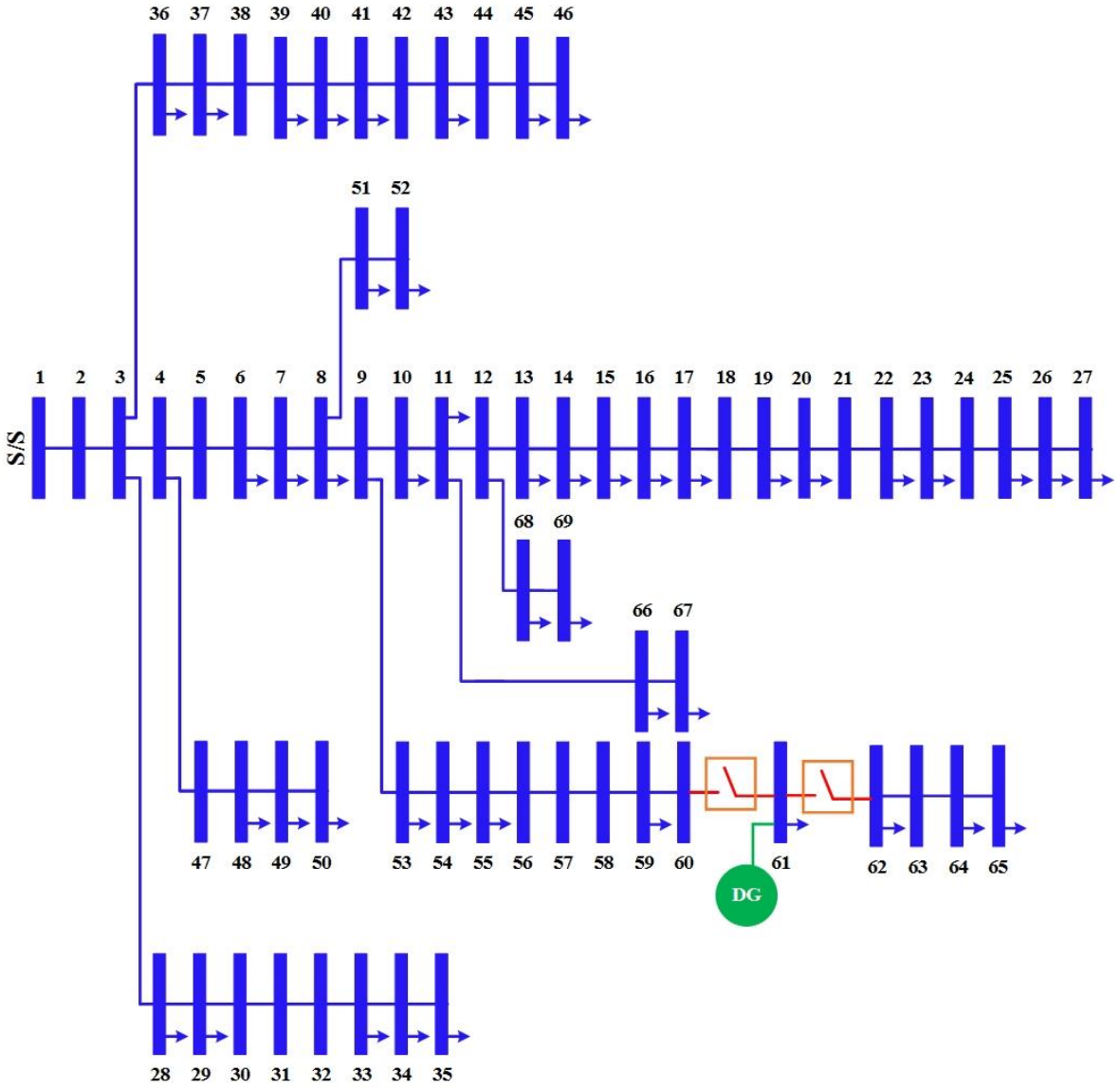


Figure 21. A modified IEEE 69 bus test

A five reliability indicators CAIDI, SAIFI, SAIDI, ASAI, and ENS are used here to assess the system reliability. Tables 4 and 5 explain the reliability indices for IEEE 33 & 69 bus systems in the base case after applying automatic recloser and applying a dual AR and DG. By comparisons: SAIFI is decreased, SAIDI is decreased, CAIDI is decreased, ASAI is increased and ENS is decreased, which means that the test systems reliability is improved as indicated in figures 22 & 23.

Table 8. Reliability indices for IEEE - 33 bus system

Scenario	SAIFI	SAIDI	CAIDI	ASAI	ENS
BASE	19.576	9.6957	0.49529	0.99889	36019.650 9
AR	12.7202	6.3171	0.49662	0.99928	23490.465 3

AR+DG	**8.2069**	**3.9625**	**0.48283**	**0.99955**	**14724.823 6**

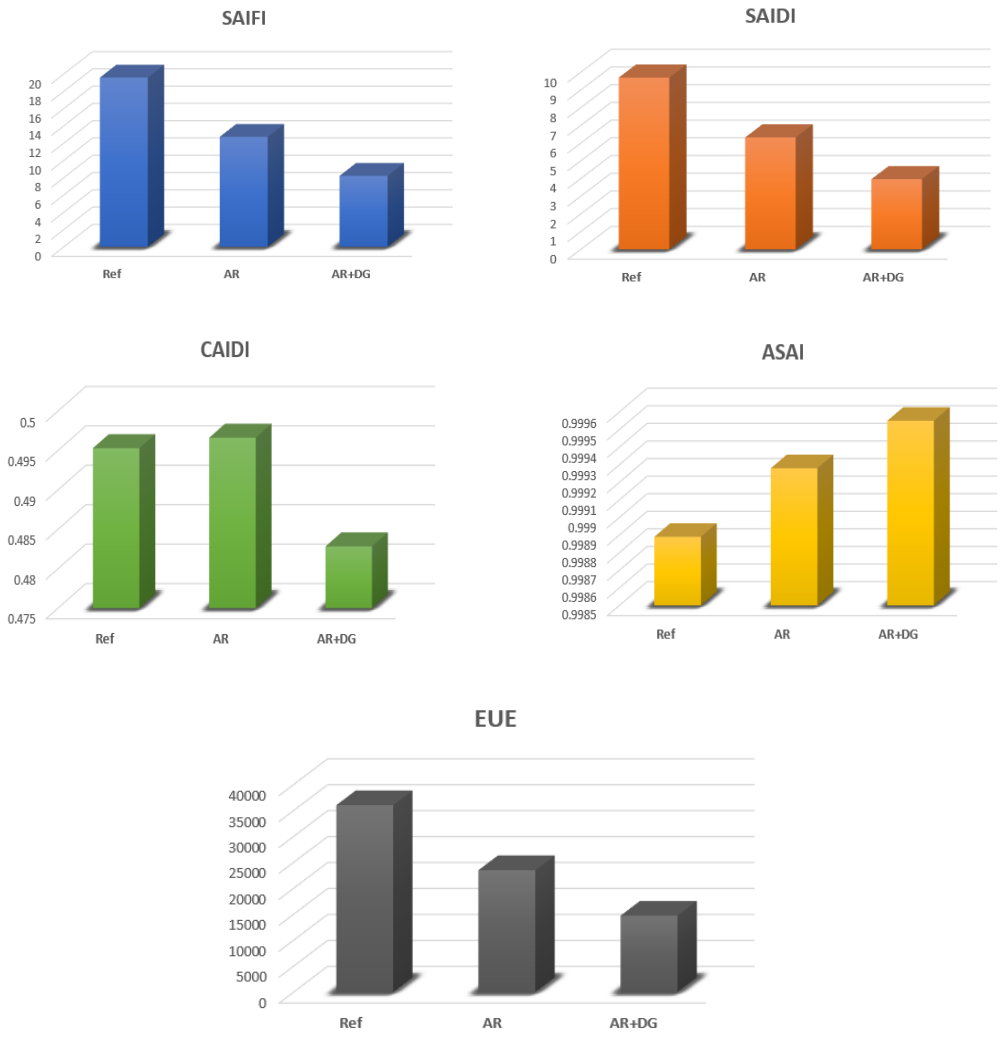


Figure 22. Comparative results of IEEE-33 system reliability

Table 9. Reliability indices for IEEE - 69 bus system

Scenario	SAIFI	SAIDI	CAIDI	ASAI	ENS
BASE	19.609	57.7215	2.9436	0.99341	215927.91 7
AR	18.1781	52.7577	2.9083	0.99398	197296.90 5
AR+DG	**10.4966**	**30.5274**	**2.9023**	**0.99652**	**116230.16 5**

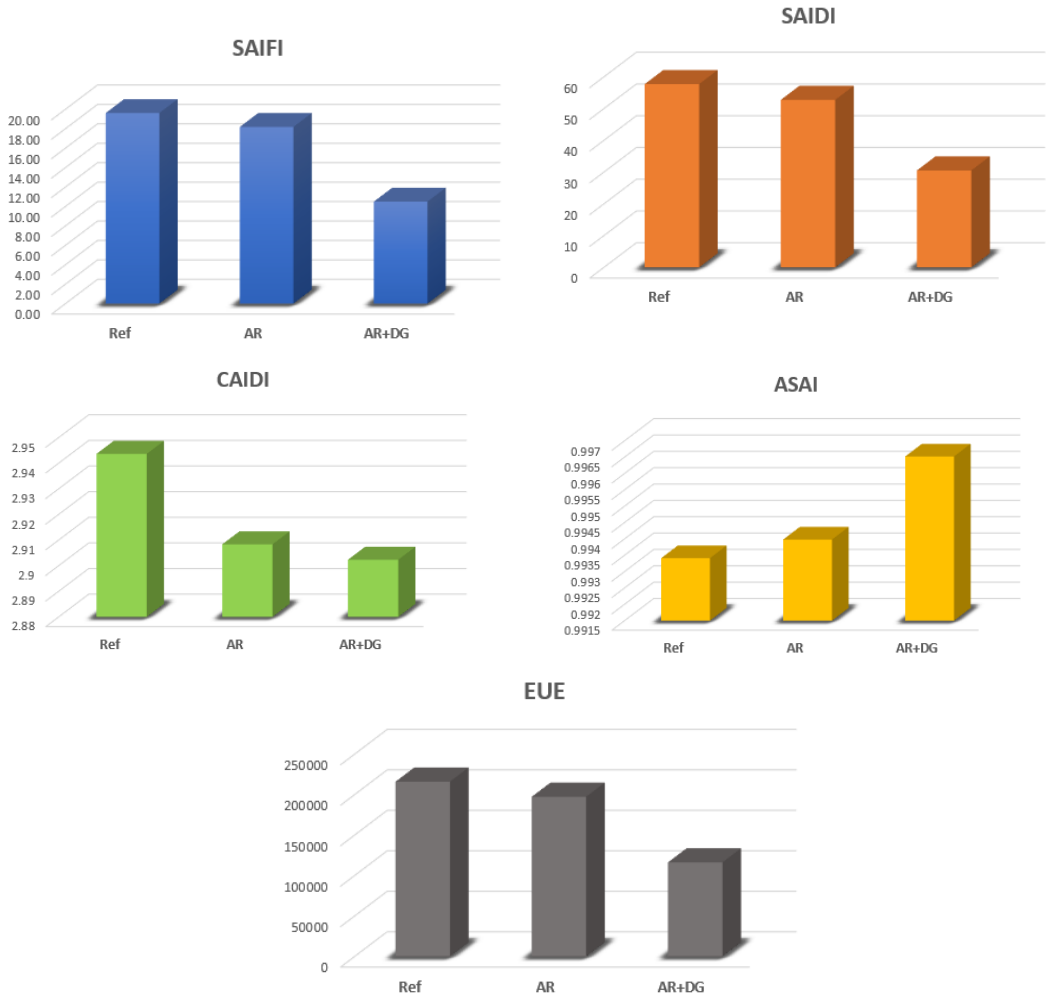


Figure 23. Comparative results of IEEE-69 system reliability

6. Conclusions

An effective optimizer called IWHO has been developed here to mend the performance of the original WHO, which was recently published and applied for the optimal site and size of DGs to slash the operational losses, boost the voltage profile, and raise the system reliability. The IWHO is created to defeat the weaknesses of the traditional WHO by meliorative the poise between the reconnoitring and utilization and hurry the algorithm convergence. The performance of the developed IWHO algorithm has been verified using various standards of the IEEE 33-bus and IEEE 69-bus test systems and compared with some meta-heuristic methods to discover its notability. From the findings, it can be seen that the IWHO algorithm lessened the objective function better than other comparative metaheuristic techniques. The simulated results confirm that the IWHO outperforms other compared techniques for solving ODGs problems with optimal power factors in terms of robustness and effectiveness. Lastly, the reliability evaluation is a vital component of distribution system design and planning, and the developed procedure is mainly designed to replicate the random nature of the system and power failure. The acquired findings demonstrate that the technique can guess the probability density

function (PDF) of several reliability indices with the necessary precision for systems in the presence and absence of DGs. Because the DG units may actively participate in system recuperation, incorporation of them raises the system reliability. The reliability improvement can be maximized if DG units are allocated properly.

Conflicts of Interest: The authors declare no conflict of interest.

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