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Optimal Placement of DGs in Distribution System Using an Improved Harris Hawks Optimizer Based on Single- and Multi-Objective Approaches

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ABSTRACT In this paper, improved single- and multi-objective Harris Hawks Optimization algorithms, called IHHO and MOIHHO, respectively are proposed and applied for determining the optimal placement of distribution generation (DG) in the radial distribution systems. Harris Hawks optimizer (HHO) is a new inspired meta-heuristic optimization technique that is mainly based on the intelligence behavior of the Harris hawks in chasing prey. The IHHO and MOIHHO are applied for determining the optimal size and location of DG at different operating power factors (p.f) with the aim of minimizing the total active power loss, reducing the voltage deviation (VD), and increasing the voltage stability index (VSI) considering the operational constraints of distribution system. In IHHO, the performance of the conventional HHO algorithm is improved using the rabbit location instead of the random location. In MOIHHO, grey relation analysis is applied for identifying the best compromise solution among the non-dominance Pareto solutions. To verify the effectiveness of the proposed algorithms, IEEE 33-bus and IEEE 69-bus radial distribution systems are used, and the obtained results are compared with those obtained by other optimization techniques. The results prove the efficiency of the proposed algorithms in terms of best solutions obtained so far for the single- and multi-objective scenarios.

INDEX TERMS Harris hawks optimizer, single- and multi-objective optimization, DG placement, distribution systems, power loss reduction, voltage deviation, voltage stability index.

I. INTRODUCTION

A. MOTIVATION AND INCITEMENT

Radial distribution systems have been changed from their passive structure into an active one with multi-directional power flows by the integration of Distribution generators (DGs). DGs are small generating units that can be connected to distribution systems to enhance the reliability of the power delivery, reduce the power loss, and improve the voltage level [1]. These DGs units can be grouped into conventional types such as diesel engines and renewable types such as photovoltaic and wind power. However, the future expansion of the large-scale penetration of renewable DGs type will bring both positive and negative consequences. The negative consequences include occurring of reverse power flows, undesirable voltage levels and power losses [2]. Hence, to overcome these negative consequences, the best sizes and locations of these DGs should be carefully determined.

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B. LITERATURE REVIEW

In the literature, numerous optimization techniques have been employed to find the optimal locations and sizes of the DGs [3], [4]. The problem of the DG allocation has been solved using single- and multi-objective optimization techniques. In the single-objective optimization problem, one objective function has been implemented to be optimized, hence minimizing the power losses has been considered the main objective function in this type. On the other hand, more than one objective function should be simultaneously optimized in the multi-objective optimization problem. Metaheuristic optimization techniques have been widely used in the DG allocation in both single- and multi-objective problems.

For the single-objective problem, a genetic algorithm (GA) has been employed to optimally allocate the DG into the distribution system for minimizing the total power loss [5]. Particle swarm optimization (PSO) has been introduced in [6], [7] to minimize the active power loss using DG allocation including different load models. Artificial intelligence-based optimization methods have been applied to determine the optimal placement for multiple DGs in [8], [9]. Fuzzy and clonal selection algorithm has been developed in [10] for DG allocation. Recently, many nature-inspired optimization technique have been used in the DG allocation problem such as backtracking search optimization algorithm (BSOA) [11], bacterial foraging optimization algorithm (BFOA) [12], stud krill herd algorithm (SKHA) [13], whale optimization algorithm (WOA) [14], and chaotic sine cosine (CSCA) [15].

On the other hand, the multi-objective optimization problem has been utilized to deal with the DGs allocation based on two methodologies. In the first one, a weighting sum for individual objective functions has been used. Many research works have been introduced based on this methodology to optimize three objective functions namely power loss, voltage deviation (VD), and voltage stability index (VSI) such as GA [16], PSO [16], GA/PSO [16], teaching-learning based optimization (TLBO), its quasi-oppositional version (QOTLBO) [17], swine influenza model-based optimization with quarantine SIMBO-Q, its quasi-oppositional QOSIMBO-Q [18], and imperialist competitive algorithm and genetic algorithm (ICA/GA) [19]. However, this methodology faces some challenges represented in the selection of the weighting factor. The second multi-objective methodology utilizes a trade-off among the objective functions based on the Pareto dominance concept. In Pareto dominance, the obtained solutions are classified into dominated and non-dominated solutions. then the best solution can be chosen from the non-dominated solutions by the decision-maker [4]. Numerous algorithms have been formulated based on this methodology such as; Pareto archived evolution strategy (PAES), nondominated sorting genetic algorithm (NSGA-II), strength Pareto evolutionary algorithm (SPEA), improved version SPEAII, and multi-objective particle swarm optimization (MOPSO) [20]. For the DG allocation problem, MOPSO has been applied with fuzzy decision making to minimize the power loss and improve the VD in [21]. Multi-objective whale optimization (MOWOA) has been proposed to enhance the VSI and reduce the VD and active power loss [22]. In [23], a multi-objective shuffled bat algorithm has been suggested to study the influence of DGs with different load models. Taguchi method (TM) and multi-objective Taguchi approach (MOTA) have been used to optimally integrate the DG unit in distribution systems [24].

C. CONTRIBUTION AND PAPER ORGANIZATION

In this paper, a new nature-inspired optimization algorithm known as improved Harris hawks optimization (IHHO) is proposed to find the optimal size and location of DG in radial distribution systems. Harris hawks optimization algorithm (HHO) has been proposed in [25] based on the hunting technique of the Harris hawks. The major advantages of the HHO are its simplicity and have a few exploratory and exploitative mechanisms. HHO has been employed in many optimization problems such as parameter identification for the fuel cell module [26] and photovoltaic cell module [27]. However, in this research work, IHHO is proposed for the allocation of DG through both single and multi-objective optimization problems. Hence the main contributions of this work are summarized as follows:

- Proposing an Improved Harris hawks optimization algorithm (IHHO) based on the rabbit location instead of the random location.
- Proposing Multi-objective Improved Harris hawks Algorithm (MOIHHO) with grey relation decision making.
- Appling the proposed IHHO and MOIHHO to determine the optimal allocation of DG units in the radial distribution system to minimize the total losses, voltage deviation, and maximize VSI, simultaneously.
- The effectiveness of the proposed methodology is compared to the conventional HHO and other well-known optimization methods using standard IEEE 33-bus and 69-bus distribution systems with different operating scenarios.

This paper is organized as follows: Section II presents the problem formulation including the main objective functions. Section III presents an overview of the HHO. Section IV describes the improved HHO. Section V presents the application of the IHHO in DG allocation. Section VI illustrates the multi-objective HHO with grey relation analysis and its application in DG allocation is presented in Section VII. In Section VIII, the numerical results based on the test systems are presented. Finally, the conclusions and future directions are presented in Section IX.

II. PROBLEM FORMULATION

This section introduces the main objective functions, which are used for optimal placement of the DG into distribution systems.

A. OBJECTIVE FUNCTIONS

The main purpose of allocating DG in the distribution system is to minimize power losses for the single-objective problem and minimize the VD, and maximize the VSI for the multi-objective problem. The mathematical formulation for the three objective functions is presented in the following subsections:

1) MINIMIZATION TOTAL ACTIVE POWER

Active power losses in the distribution system are high due to the radial structure of these systems hence, it is important to reduce the power loses, P_{loss}.

$$f_1 = min\,(P_{loss}) \tag{1}$$

The total power losses P_{loss} in the distribution system are computed using the branch current loss formula as [28]:

$$P_{loss} = \sum_{z=1}^{N_{br}} |I_z|^2 R_z \tag{2}$$

where, z is the branch number, N_{br} is the total number of branches, $|I_z|$ the absolute value of the current passing through the branch, and R_z is the branch resistance.

2) MINIMIZATION TOTAL VOLTAGE DEVIATION (VD)

The total voltage deviation VD indicated the level of the RDS voltage and how is far from the specified value V_{sep}, Hence, VD for the system can be calculated using the voltage magnitude V_i at bus i based on a specified voltage as:

$$VD = \sum_{i=1}^{n\_bus} \left(V_{sep} - V_i\right)^2 \tag{3}$$

where, V_{sep} is taken 1.00 p.u. Therefore, the second objective function is:

$$f_2 = min\,(VD) \tag{4}$$

3) MAXIMIZATION VOLTAGE STABILITY INDEX (VSI)

The VSI is defined as the ability of the system to keep the voltage within the satisfied range. Where the main target exists in maximizing the VSI which owns the lowest VSI in the system [29]:

$$VSI_j = V_i^4 - 4\left(P_jR_{ij} + Q_jX_{ij}\right)V_i^2 - 4(P_jX_{ij} - Q_jR_{ij}) \tag{5}$$

where, i, j are the sending and receiving bus; P_j, Q_j are active and reactive power at the receiving bus; and R_{ij}, X_{ij} are the resistance and reactance between buses i, j. The third objective function can be expressed as:

$$f_3 = max\left(min(VSI_j)\right) \tag{6}$$

B. PROBLEM CONSTRAINTS

The problem of DG allocation in the distribution system should be subjected to two main constraints as follows:

1) EQUALITY CONSTRAINTS

To avoid the reverse power a balance between the generation and the power demand plus the power loss should be considered hence this constraint can be expressed as:

$$\sum_{i=1}^{NG} P_{g_i} = P_{loss} + P_d \tag{7}$$

where, NG is the number of installed DG, P_{g_i} indicates the injected power of the installed DG, and P_d is the demand power by the loads.

2) INEQUALITY CONSTRAINTS

The operational limits of the distribution systems should be taken into account such as:

a) Generation active power limits

$$P_{g_i}^{min} \le P_{g_i} \le P_{g_i}^{max} \tag{8}$$

b) Generation reactive power limits

$$Q_{g_i}^{min} \le Q_{g_i} \le Q_{g_i}^{max} \tag{9}$$

c) Voltage limits

$$0.95 \le V_i \le 1.05 \tag{10}$$

III. OVERVIEW OF HARRIS HAWKS OPTIMIZER (HHO)

HHO is a population-based technique that has been implemented using exploration and exploitation phases. The mathematical formulation can be derived as presented in the following subsections:

A. EXPLORATION PHASE

The main objective of the Harris hawks is to hunt the prey which is usually a rabbit. Hence, firstly, the hawks explore for the rabbit. The exploration process can be expressed using two strategies. The first one supposes that the hawks' locations should be close to the family members and the prey. However, the second strategy assumes that the hawks located at random trees. The mathematical implementation of these strategies is modeled as:

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1\left|X_{rand}(t) - 2r_2X(t)\right|, & q \ge 0.5 \\ (X_{rab}(t) - X_m(t)) - r_3\left(LB + r_4\left(UB - LB\right)\right), & q < 0.5 \end{cases} \tag{11}$$

where, t represents the current iteration, $X(t+1)$ is the position of hawks at iteration $t+1$, $X(t)$ is the hawk's positions at the current iteration t. $X_{rab}(t)$ indicates the position of the rabbit (prey), and $X_{rand}(t)$ is randomly selected hawks' position. The parameters $r_1, r_2, r_3,$ *and* r_4 are used as random numbers within [0,1], LB *and* UB are used to denote the lower and upper limits of the search space. The two exploration strategies can be switched using a random variable q between [0,1].

$X_m(t)$ express the mean position of the hawks and can be obtained as follows:

$$X_m(t) = \frac{1}{n}\sum_{i=1}^{n} X_i(t) \tag{12}$$

where, $X_i(t)$ represents the hawk position i, and n is the total number of hawks.

B. CHANGE FROM EXPLORATION TO EXPLOITATION

The escaping energy of the rabbit E during the chasing has been used to change between the exploration and exploitation in the HHO and that can be expressed as follows:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \tag{13}$$

where, T is the maximum iteration numbers, E_0 indicates the random initial energy of the rabbit between [−1,1]. On one hand, in the case of $E \geq 1$, that denotes the ability of the rabbit to escape, hence the exploration process should be continued by the hawks. On the other hand, $E < 1$, that shows the weakness of the rabbit, so the hawks should start exploiting near to the rabbit place.

C. EXPLOITATION PHASE

In the HHO, the exploitation phase has been implemented subject to the chance of the rabbit to escape r and escaping energy E. Where, the rabbit can do a successful escaping when $r < 0.5$, and an unsuccessful onewhen $r \geq 0.5$. However, based on the escaping energy, the hawks can do a soft besiege when $|E| \geq 0.5$, and a hard besiege when $|E| < 0.5$.

Consequently, the exploitation process of the HHO can be mathematically modeled based on four chasings besieges in.

1) SOFT BESIEGE

The soft besiege is performed when $r \geq 0.5$ and $|E| \geq 0.5$, which represents the attempts of the rabbit in escaping with aid of random jumps notwithstanding the hawks surround it softly. The mathematical formulation of this besiege is expressed as:

$$X(t+1) = \Delta X(t) - E\left|JX_{rab}(t) - X(t)\right| \tag{14}$$

$$J = 2(1 - r_5) \tag{15}$$

$$\Delta X(t) = X_{rab}(t) - X(t) \tag{16}$$

where, $\Delta X(t)$ indicates the distance between the rabbit location and the hawks' position, J denotes the random jump of the rabbit for escaping, and r_5 is a random number between [0,1].

2) HARD BESIEGE

When $r \geq 0.5$ and $|E| < 0.5$, the hard besiege could happen. In this case, the rabbit is exhausted and the hawks have hardly surrounded the prey. This action can be presented as:

$$X(t+1) = X_{rab}(t) - E\left|\Delta X(t)\right| \tag{17}$$

3) SOFT BESIEGE WITH PROGRESSIVE RAPID DIVES

This besiege considered an intelligence strategy that distinguishes the HHO over the other swarm methods. In the case of $r < 0.5$ and $|E| \geq 0.5$, the rabbit has the ability to run away and the hawks softly surround it. A Levy flight (LF) concept has been employed to formulate this besiege as follows:

$$Y = X_{rab}(t) - E\left|JX_{rab}(t) - X(t)\right| \tag{18}$$

where Y denotes the soft besiege position. The hawks dive based on the LF as:

$$Z = Y + S \times LF(D) \tag{19}$$

where, D indicates the problem dimension, S is a vector of random values with size $1 \times D$. The LF is expressed as:

$$LF(x) = 0.01 \times \frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}} \tag{20}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \tag{21}$$

where, β is a constant value set to 1.5, μ, and v are random values between [0,1].

Hence, the hawk's position at the next iteration is obtained as:

$$X(t+1) = \begin{cases} Y, & F(Y) < F(X(t)) \\ Z, & F(Z) < F(X(t)) \end{cases} \tag{22}$$

4) HARD BESIEGE WITH PROGRESSIVE RAPID DIVES

In this case, $r < 0.5$ and $|E| < 0.5$, the rabbit is exhausted and it has been surrounded hardly by the hawks. Similarly, Levy flight (LF) concept is employed to state this besiege as in Eq (18) to (21), but Y are estimated by follows:

$$Y = X_{rab}(t) - E\left|JX_{rab}(t) - X_m(t)\right| \tag{23}$$

IV. IMPROVED HARRIS HAWK'S OPTIMIZER (IHHO)

In the HHO algorithm, if the hawks exceed the position limits, the following equation is used to return the hawks back:

$$X(t+1) = \begin{cases} X(t+1), & X_{min} \leq X(t+1) \leq X_{max} \\ X_{min}, & X(t+1) < X_{min} \\ X_{max}, & X(t+1) > X_{max} \end{cases} \tag{24}$$

where, X_{min} and X_{max} are the minimum and maximum of the optimization problem variables.

In order to improve the HHO, it is suggested that if the hawks exceed the limits, they should return back to the rabbit position X_{rab} which is considered the best solution as follow:

$$X(t+1) = \begin{cases} X(t+1), & X_{min} \leq X(t+1) \leq X_{max} \\ X_{rab}(t), & X(t+1) < X_{min} \\ X_{rab}(t), & X(t+1) > X_{max} \end{cases} \tag{25}$$

Fig. 1 shows the flowchart of the IHHO.

V. APPLICATION OF IHHO IN DG ALLOCATION

The application of the IHHO into DG allocation can be summarized in the following steps:

Step 1: Read the system data (line data and load data) and define the objective function.

Step 2: Randomly initialize a set of hawks' searches within the upper and lower limits of the DG sizes and locations, HHO parameters, and Max. number of iterations K_{max}.

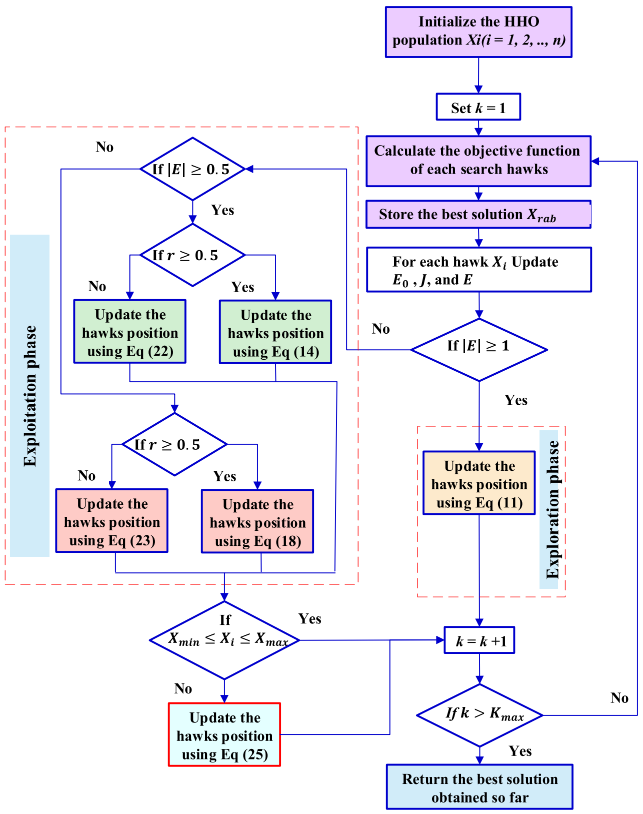

FIGURE 1. Flowchart of IHHO.

Step 3: Run the power flow and calculate the objective function (power loss) for each search hawk.
Step 4: Store the best solution X_{rab}.
Step 5: Update the parameters of HHO (E, E_0, and J).
Step 6: Update the sizes and locations of the best solutions based on the exploration and exploitation phases' strategies.
Step 7: Check the sizes and locations' limits and update the position using (25)
Step 8: Check if ($k < K_{max}$) **Step 3**
Step 9: Return the final best solution stored (DG locations and sizes).
Step 10: Run the power flow and obtain the voltage profile.

VI. MULTI-OBJECTIVE HARRIS HAWK'S OPTIMIZER (MOIHHO)

To implement the MOIHHO, two structures called archive, and leader selection are used. The archive is responsible to arrange the non-dominate solutions obtained so far and the leader selection used to guide the hawks to update their position directly to the rabbit position. In addition, a suitable decision making is required to find the best compromise solution among the non-dominated solutions [30]. In this research work, a grey relation analysis is developed.

A. GREY RELATIONAL ANALYSIS

Grey relational analysis is employed to attain the best solution among non-dominated solutions using the following steps [31].

1) GREY RELATIONAL GENERATION

A normalization for all nondominated solutions within the maximum and minimum values must be calculated to accomplish the grey relational as follows:

$$u_i^j = \frac{F_i^{max} - F_i^j}{F_i^{max} - F_i^{min}} \quad for\ i = 1, 2, .m\ and\ j = 1, 2.n \tag{26}$$

where, u_i^j indicates the normalized value of the nondominated solution j of the objective function i, n is number of the non-dominated solutions, m represents the number of the objective functions, F_i^{max}, F_i^{min} are the maximum and minimum of the objective function values, respectively.

2) REFERENCE SEQUENCE DEFINITION

After obtaining the normalized values for all objective functions within [0,1], the reference sequence u_i^{max} value for all objective functions should be 1.

3) GREY RELATIONAL COEFFICIENT

The closeness of the solution u_i^j to the reference u_i^{max} can be determined using a grey relation coefficient ζ_i^j which is expressed as:

$$\zeta_i^j = \frac{\Delta^{min} + \zeta\,\Delta^{max}}{\Delta_i^j + \zeta\,\Delta^{max}} \tag{27}$$

where,

$$\Delta_i^j = \left|u_i^{max} - u_i^j\right| \tag{28}$$

Δ^{min} and Δ^{max} are the minimum and maximum values of the Δ_i^j, respectively, and ζ is the distinguishing coefficient $\in [0, 1]$.

4) GREY RELATIONAL GRADE

Finally, the grey relation grad γ^j for all nondominated solutions is calculated as:

$$\gamma^j = \frac{1}{n}\sum_{i=1}^{n} \zeta_i^j \tag{29}$$

According to the above steps, the best compromise solution is the one has a highest-grade value subject to all nondominated solutions. The overall MOIHHO process is presented in Fig.2

B. SPACING METRIC (SP-METRIC)

To check the robustness of the multi-objective optimization techniques spacing metric has been frequently used [32]. Spacing metric computes the variance scale of the neighboring trajectories in the Pareto front as:

$$SP = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2} \tag{30}$$

$$d_i = \min\left(\sum_{k=1}^{m}\left|f_k^i - f_k^j\right|\right) \tag{31}$$

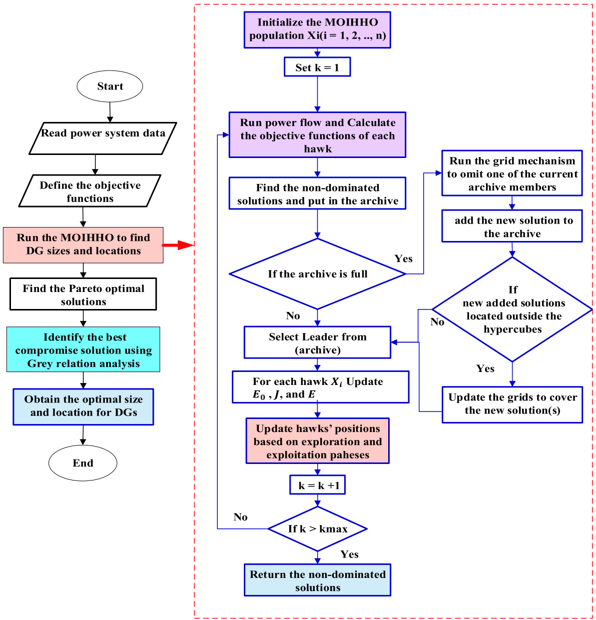

FIGURE 2. MOIHHO for optimal allocation of DG in a distribution network.

where n is the number of nondominated solutions, m represents the number of objective functions and $\bar{d}$ indicates the mean of all d_i.

VII. APPLICATION OF MOIHHO IN DG ALLOCATION

Implementation of the MOIHHO for optimal DG allocation into distribution systems is presented in the following steps:

Step 1: Read the system data (line data and load data) and define the objective functions (P_{loss}, VD, and VSI).
Step 2: Randomly initialize a set of search hawks, HHO parameters, and Max. number of iterations K_{max}.
Step 3: Run power flow and calculate the objective functions for each search hawk,
Step 4: Arrange the non-dominate solutions in the archive and select the leader.
Step 5: Update the parameters of HHO (E, E_0, and J).
Step 6: Check the archive, if it is full, apply grid mechanism.
Step 7: Run the leader selection.
Step 8: If $k < K_{max}$, repeat Step 2.
Step 9: Return the stored final non-dominated solutions in the archive.
Step 10: Run the grey relation decision making to find the best compromise solution
Step 11: Run the power flow and obtain the voltage profile.

VIII. RESULT AND DISCUSSION

In this section, the improved techniques (IHHO and MOIHHO) are applied for two standard IEEE 33-node and 69-node distribution systems. The optimal sizing and sitting of multiple DGs units are determined to minimize the total power loss as a single-objective optimization problem.

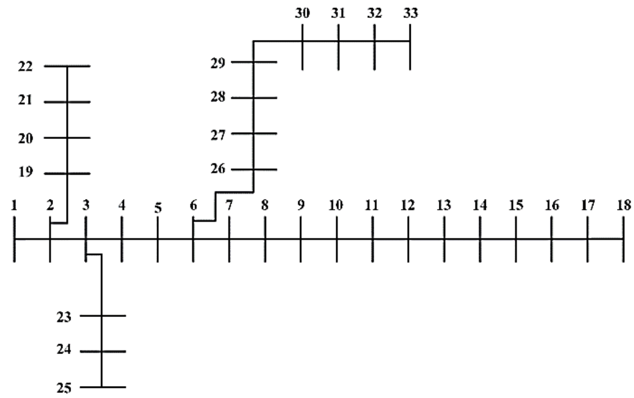

FIGURE 3. Single line diagram of the IEEE 33-node test system.

In addition, minimizing the total VD and maximizing VSI are considered for the multi-objective problem. To prove the feasibility and efficiency of the improved techniques, a comprehensive comparison with other well-known optimization techniques is carried out.

In addition, the IHHO compared with the conventional HHO through ten runs to evaluate the best, worst, and average costs for the single objective function and calculate the SP-metric for the multi-objective. The following four cases are considered in the two studied systems:

Base case (without DG);
Integrating 3 DGs with unity power factor (p.f).
Integrating 3 DGs with 0.95 p.f.
Integrating 3 DGs with optimal p.f.

A. IEEE 33-NODE SYSTEM

The proposed method is tested using the IEEE 33-node test system. The full description of this test system including the line and load data is given in [33]. The single line diagram is presented in Fig.3. The base kV = 12.66 and MVA = 100.

1) SINGLE-OBJECTIVE ANALYSIS

The power flow results for the base case indicate that the active and reactive power losses are 210.98 kW and 143.14 kVAR, respectively. To minimize the total power losses, three DG units with different p.f are optimally allocated using the IHHO.

a: DG ALLOCATION

The optimal sizes and locations of the DG at unity p.f are given in Table1. It can be observed from this table that using the IHHO the optimal locations of three DGs are 14, 24, and 30 with active power capacities equal 775.54 kW, 1080.83 kW, and 1066.69 kW respectively and that leads to reduce the power losses from 210.98 kW to 72.79 kW where the loss reduction (LR) reaches 65.50 %. In addition, compared to the other optimization techniques and the conventional HHO, the developed IHHO gives the lowest power loss.

TABLE 1. Optimal DG allocation for IEEE 33-node system based on single-objective using different optimization techniques at unity p.f.

Method	Optimal DG Bus	Optimal DG Size (kW)	Power loss (kW)	LR %
LSF [9]	18	720	85.07	59.72
	33	810		
	25	900		
Fuzzy -IAS[10]	32	2071	117.36	42.45
	30	1113.8		
	31	150.3		
BSOA[11]	13	632	89.05	57.76
	28	486		
	31	550		
BFOA **[12]**	14	779	73.53	65.14
	25	880		
	30	1083		
TLBO [17]	10	824.6	75.54	64.20
	24	1031.1		
	31	886.2		
QOTLBO [17]	12	880.8	74.10	64.88
	24	1059.2		
	29	1071.4		
SIMBO-Q [18]	14	763.8	73.4	65.21
	24	1041.5		
	29	1135.2		
QOSIMBO-Q [18]	14	770.8	72.8	65.49
	24	1096.5		
	30	1065.5		
HHO	14	745.69	72.98	65.40
	24	1022.69		
	30	1135.78		
IHHO	14	775.54	**72.79**	**65.50**
	24	1080.83		
	30	1066.69		

Moreover, Table 2 presents the results of the optimal allocation for multi DG with fixed p.f equals 0.95. The results show that the developed IHHO finds the optimal locations and sizes which have the minimum power loss (28.5 kW). The power loss obtained by the IHHO is lower than the power loss from SIMBO-Q [18] which is 29 kW and the conventional HHO which is 29.7 kW and approximately equals to the power of QOSIMBO-Q [18].

To observe the impact of the power factor of the DG on the power loss minimization, optimal DG allocation with optimal power factor is carried out using the developed approach. Table 3 summarizes the results of the optimal p.f obtained by the IHHO compared to BSOA [11], BFOA [12], and HHO. As obvious in the table, a significant LR in the power loss reaches 94.39 % is given by the IHHO.

Clearly, the results in the three DG allocation scenarios show that the IHHO has a lower power loss compared to the other optimization methods.

b: VOLTAGE PROFILE

The influence of the DG installation on the voltage profile of the distribution system with different p.f is presented in Fig 4. This figure shows that a significant improvement has been achieved when integrating multiple DGs with optimal p.f.

TABLE 2. Optimal DG allocation for IEEE 33-node system based on single-objective using different optimization techniques at 0.95 p.f.

Method	Optimal DG Bus	Size (kW)	Size kVAR	p.f	Power loss (kW)	LR %
SIMBO-Q [18]	13	887.5	291.7	0.95	29	86.26
	24	1085.3	356.7	0.95		
	30	1309.2	430.3	0.95		
QOSIMBO-Q [18]	13	830.3	272.9	0.95	28.5	86.49
	24	1123.9	369.4	0.95		
	30	1239.8	407.5	0.95		
HHO	13	871.34	286.40	0.95	29.71	85.92
	24	1326.76	436.08	0.95		
	30	1076.05	353.68	0.95		
IHHO	14	793.81	260.91	0.95	**28.5**	**86.49**
	24	1132.44	372.21	0.95		
	30	1257.76	413.41	0.95		

TABLE 3. Optimal DG allocation for IEEE 33-node system based on single-objective using different optimization techniques at optimal p.f.

Method	Optimal DG Bus	Size (kW)	Size kVAR	p.f	Power loss (kW)	LR %
BSOA[11]	13	698	414	0.86	29.65	85.97
	29	402	399	0.71		
	31	658	671	0.7		
BFOA [12]	14	600	307	0.89	27.5	86.97
	25	598	402	0.83		
	30	934	504	0.88		
HHO	12	913.05	557.01	0.85	14.94	92.92
	24	882.86	616.60	0.82		
	30	1079.05	734.19	0.83		
IHHO	14	761.82	373.50	0.90	**11.83**	**94.39**
	24	1141.92	536.07	0.91		
	30	1013.83	1003.21	0.71		

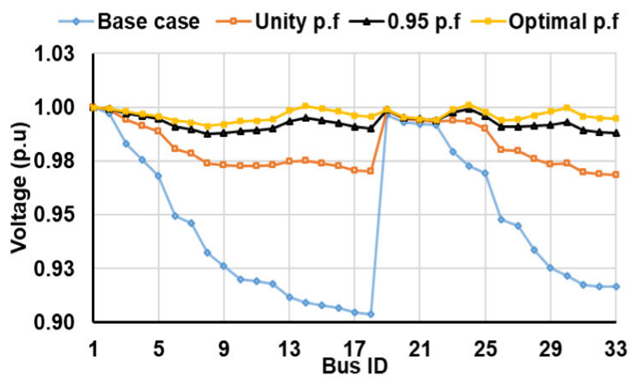

FIGURE 4. Voltage profile of the IEEE 33-node test system at different case studies for the single-objective optimization problem.

c: PERFORMANCE AND STATISTICAL ANALYSIS FOR THE DEVELOPED TECHNIQUE

A statistical analysis based on the best, average, and worst costs is carried out through ten runs for the conventional HHO and IHHO to prove the efficiency of the developed method. Table 4 gives a summary of this analysis and it is clear that the IHHO has the lowest values through all the study cases. Additionally, the convergence characteristics for the HHO

TABLE 4. Statistical analysis for the HHO and IHHO for Sigle -objective (IEEE 33-node test system).

Method		Best Cost	Average Cost	Worst Cost
Unity p.f	HHO	72.98	79.73	85.16
	IHHO	72.79	76.63	79.83
0.95 p.f	HHO	29.71	37.38	45.89
	IHHO	28.55	36.81	46.00
Optimal p.f	HHO	14.94	21.70	27.32
	IHHO	11.83	15.83	24.98

TABLE 5. Optimal DG allocation for the IEEE 33-node system based on multi-objective using different optimization techniques at unity p.f.

Method	Optimal DG		P_{loss}	VD (p.u)	VSI (p.u)
	Bus	Size (kW)	(kW)		
GA [16]	11	1500	106.3	0.0407	0.949
	29	422.8			
	30	1071.4			
PSO [16]	8	1176.8	105.3	0.0335	0.9255
	13	981.6			
	32	829.7			
GA/PSO [16]	11	925.0	103.4	0.0124	0.9508
	16	863.0			
	32	1200.0			
TLBO [17]	12	1182.6	124.7	0.0011	0.9503
	28	1191.3			
	30	1186.3			
QOTLBO [17]	13	1083.4	103.4	0.0011	0.9530
	26	1187.6			
	30	1199.2			
TM [24]	15	719.9	102.30	0.0040	0.9371
	26	719.9			
	33	1439.7			
MOTA [24]	7	980.0	96.30	0.0014	0.9551
	14	960.0			
	30	1340.0			
SIMBO-Q [18]	13	140.0	104.3	0.0011	0.9615
	24	919.8			
	31	1400.0			
QOSIMBO-Q [18]	12	1436.8	101.9	0.0009	0.9669
	25	826.2			
	31	1443.3			
MOHHO	13	1207.0	92.95	0.0020	0.9654
	25	763.0			
	31	1400.0			
MOIHHO	14	1223.0	92.25	0.0019	0.9580
	24	1144.0			
	31	1290.0			

and IHHO are shown in Fig 5.a, Fig 5.b, and Fig 5.c for unity p.f, 0.95 p.f, and optimal p.f respectively. These figures prove the efficiency of the IHHO over the conventional HHO.

2) MULTI- OBJECTIVE ANALYSIS

In this case, a multi-objective optimization problem is solved to find the optimal allocation of the DG unit to minimize the power loss, VD, and maximize the VSI in the IEEE 33-node system. The base case power flow results show that the power loss is 210.98 kW, the VD equals 0.1338 p.u, and the VSI is 0.6681 p.u.

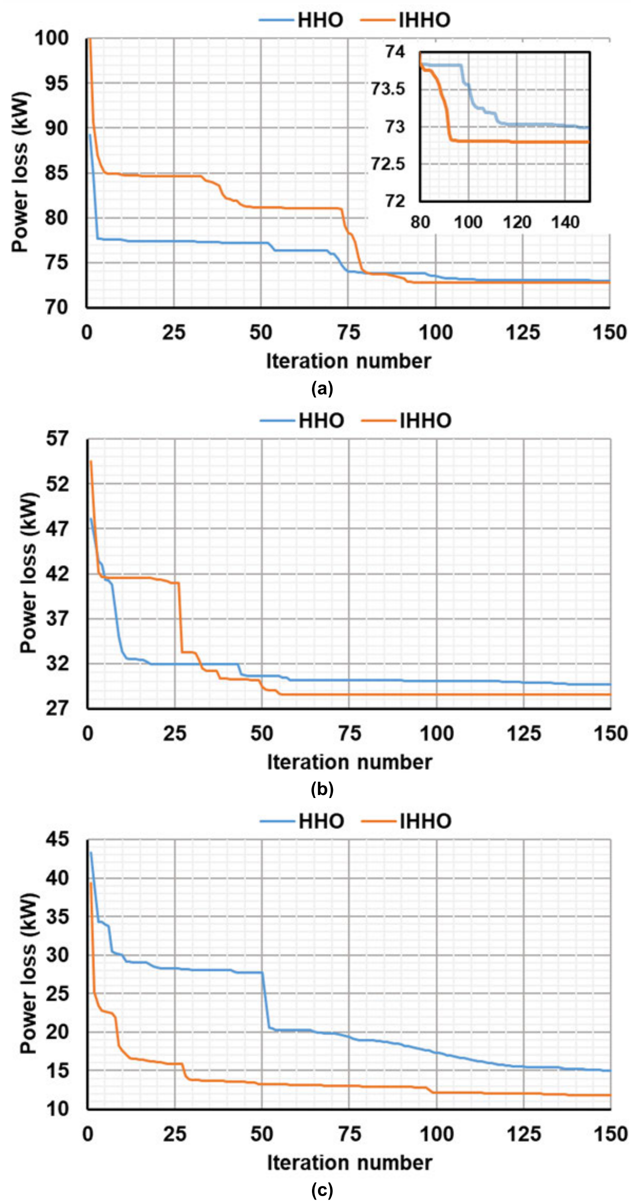

FIGURE 5. Convergence characteristics of the HHO and IHHO at different operating p.f for IEEE 33-node test system. (a) unity p.f, (b) 0.95 p.f, and (c) optimal p.f.

a: DG ALLOCATION

The developed MOIHHO is employed to find the optimal size and location of the DG at unity p.f and compared to those methods which have been used for the same problem as presented in Table 5. The table shows that the minimum power loss is obtained by the developed MOIHHO which is 92.25 kW. However, the VD obtained by the MOIHHO is 0.0019 p.u which is lower than 0.0020 p.u form MOHHO, 0.004 p.u from TM [24], 0.0124 p.u from GA/PSO [16], 0.0335 p.u achieved by PSO [16], and 0.0407 p.u obtained by GA [16]. Besides, MOIHHO gives a high VSI which equal 0.9580 p.u and that is better these values obtained by 0.9551 MOTA [24], TM [24], TLBO [17], QOTLBO [17], GA/PSO [16], PSO [16], and GA [16].

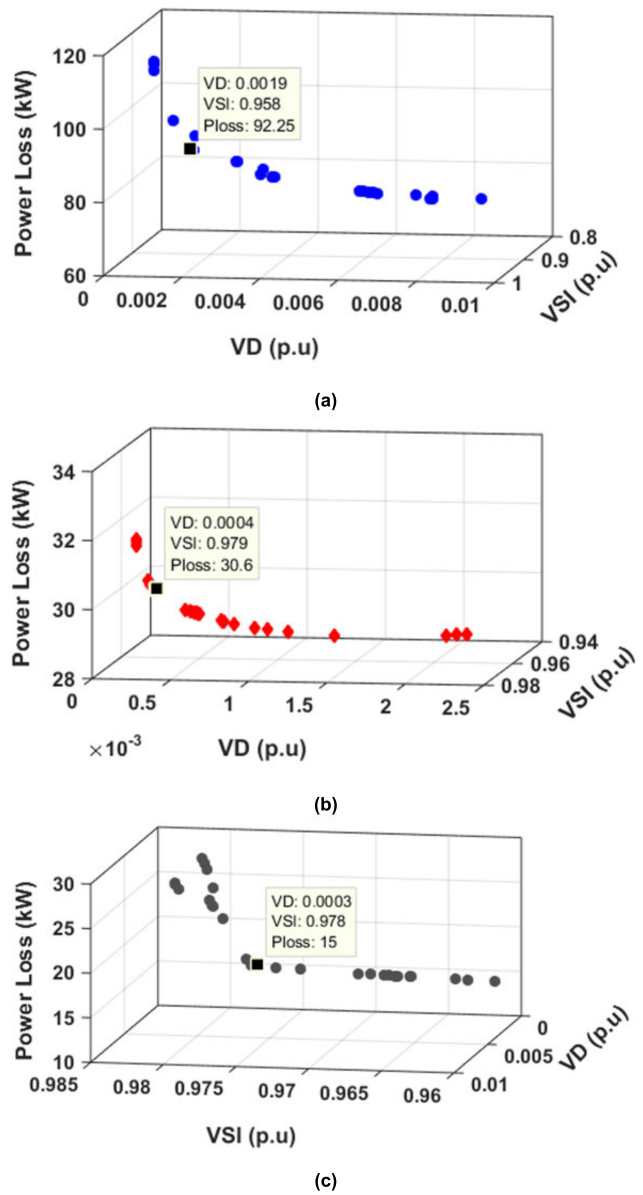

FIGURE 6. Nondominated Pareto optimal solutions obtained by MOIHHO for IEEE 33-bus considering DG operating at: (a) unity p.f, (b) 0.95 p.f, and (c) Optimal p.f.

Additionally, the allocation of DG with fixed p.f equals 0.95 is performed and the obtained results are presented in Table 6. In this case, two of the objective functions namely power loss and VSI achieved by the developed MOIHHO which equal 30.6 kW and 0.979 p.u respectively are better than those obtained by SIMBO-Q [18] and QOSIMBO-Q [18]. However, compared to MOHHO, the MOIHHO gives better results for all the three objective functions. Moreover, the results show a considerable reduction in the active power loss compared to the unity p.f due to the injected reactive power.

For optimal p.f (see Table 7), the results prove the effectiveness of the developed MOIHHO compared to the ICA/GA [19] and the MOHHO respect to the VD and VSI

TABLE 6. Optimal DG allocation for the IEEE 33-node system based on multi-objective using different optimization techniques at 0.95 p.f.

Method	Optimal DG				P_{loss}	VD	VSI
	Bus	Size					
		kW	kVAR	p.f	kW	p.u	p.u
SIMBO-Q [18]	30	1443	474	0.95	32.4	0.0003	0.977
	13	943	309	0.95			
	24	1327	436	0.95			
QOSIMBO-Q [18]	30	1419	467	0.95	31.7	0.0003	0.977
	24	1392	458	0.95			
	13	898	295	0.95			
MOHHO	13	1008	331	0.95	31.4	0.0005	0.976
	25	910	299	0.95			
	30	1334	439	0.95			
MOIHHO	13	924	304	0.95	**30.6**	**0.0004**	**0.979**
	24	1312	431	0.95			
	30	1356	446	0.95			

TABLE 7. Optimal DG allocation for the IEEE 33-node system based on multi-objective using different optimization techniques at optimal p.f.

Method	Optimal DG				P_{loss} (kW)	VD (p.u)	VSI (p.u)
	Bus	Size					
		kW	kVAR	p.f			
ICA/GA [19]	13	795	376	0.90	11.9	0.0006	0.969
	24	1069	518	0.90			
	30	1029	1021	0.71			
MOHHO	12	951	516	0.88	18.8	0.0005	0.978
	25	786	436	0.87			
	30	1381	809	0.86			
MOIHHO	12	916	576	0.85	**15.0**	**0.0003**	**0.978**
	24	1088	386	0.94			
	30	1171	830	0.82			

which are 0.0003 p.u and 0.978 p.u, however, the ICA/GA gives a better reduction in the active power loss that equals 11.9 kW.

Fig 6 illustrates optimal Pareto solutions obtained by the MOIHHO at different operating p.f. Besides the figures shows the best compromise solution obtained by the grey relation analysis among all nondominated solutions.

b: VOLTAGE PROFILE

The voltage profile of the IEEE 33-bus system has been significantly improved when considering the VD and VSI as objective functions for the multi-objective DG allocation problem. Fig 7 shows the impact of the DG at different operating p.f for the multi-objective problem and it is clear that the voltage profile is better than this obtained by the single-objective problem at the same operating p.f (see Fig 4).

c: PERFORMANCE AND STATISTICAL ANALYSIS FOR THE DEVELOPED TECHNIQUE

To study the performance of the multi-objective technique, the SP metric has been calculated for the developed MOIHHO and MOHHO for ten runs. Box plot presented in Fig 8 shows the comparison of the SP metric at different

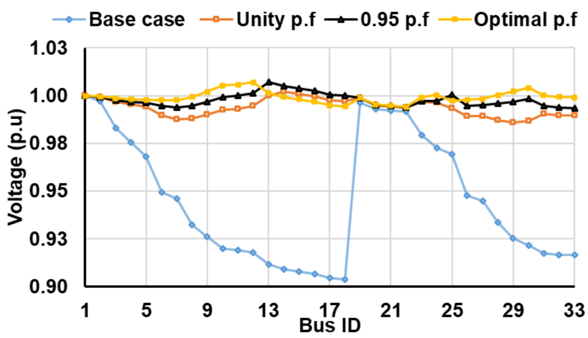

FIGURE 7. Voltage profile of the IEEE 33-node test system at different case studies for the multi-objective optimization problem.

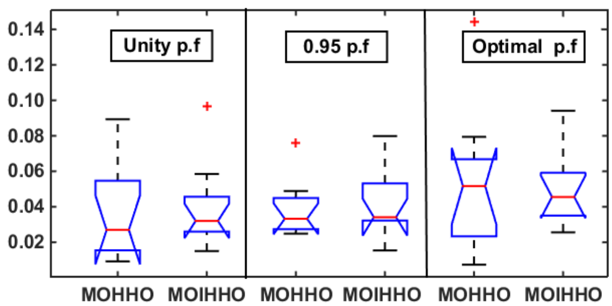

FIGURE 8. Box plot for SP metric of the MOHHO and MOIHHO at different operating p.f in case of the IEEE 33-node system.

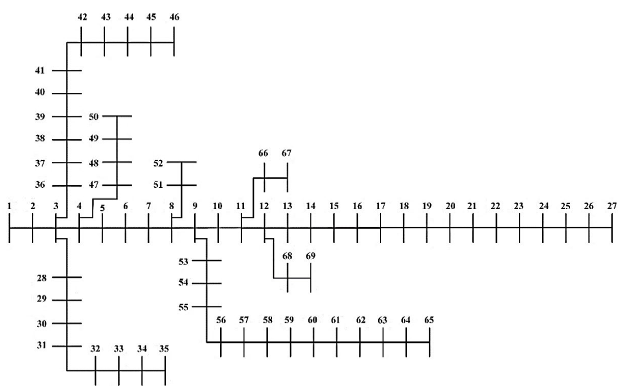

FIGURE 9. Single line diagram of the IEEE 69-node test system.

operating p.f. It is noticeable that MOIHHO has a better SP metric than the MOHHO at the unity p.f and optimal p.f which means that the nondominated solutions are distributed uniformly close to each other.

B. IEEE 69- NODES SYSTEM

In this subsection, the results of the IEEE 69-node test system obtained by the proposed method and other optimization techniques are discussed. The overall data of this system are given in [34]. Its single line diagram is shown in Fig 9.

1) SINGLE OBJECTIVE ANALYSIS

The base case power flow results for the IEEE 69-node system reported that the active power loss is 224.95 kW and the reactive power loss is 102.15 kVAR besides the minimum

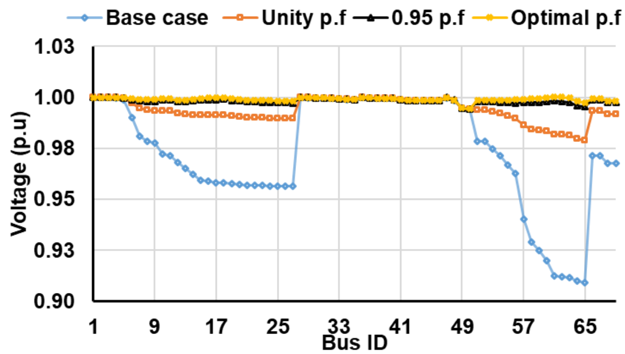

FIGURE 10. Voltage profile of the IEEE 69-node test system at different case studies for the single-objective optimization problem.

TABLE 8. Optimal DG allocation for IEEE 69-node system based on single-objective using different optimization techniques at unity p.f.

Method	Optimal DG		Power loss (kW)	LR %
	Bus	Size (kW)		
GAPSO **[13]**	63	884.9	81.1	63.96
	61	1196		
	21	910.5		
BFOA **[12]**	27	295.4	75.23	66.56
	65	446		
	61	1345.1		
SKHA**[13]**	61	1719.1	68.15	69.10
	17	371		
	11	527.1		
TLBO [17]	15	591.9	72.41	67.82
	61	818.8		
	63	900.3		
QOTLBO [17]	18	533.4	71.63	68.17
	61	1198.6		
	63	567.2		
SIMBO-Q [18]	9	618.9	71.3	68.31
	17	529.7		
	61	1500		
QOSIMBO-Q [18]	9	833.6	71.0	68.44
	18	451.1		
	61	1500		
HHO	11	378.3	69.73	69.00
	17	480		
	61	1706.1		
IHHO	11	527.2	**69.41**	**69.15**
	17	382.5		
	61	1719.4		

voltage is 0.9092 p.u on bus 65. Hence, on the way to decrease the power loss and enhance the performance of the distribution system, three DG units operating with different p.f are optimally allocated.

a: DG ALLOCATION

Table 8 demonstrates the effectiveness of the developed IHHO in the optimal allocation of the DG at unity p.f compared to the other optimization methods. Where, the highest LR is obtained by the IHHO which equals 69.15 % when placing three DG units at 11, 17, and 61 with injected active powers equal 527.2 kW, 382.5 kW, and 1719.4 kW respectively. Additionally, at 0.95 p.f, the developed method still

TABLE 9. Optimal DG allocation for IEEE 69-node system based on single-objective using different optimization techniques at 0.95 p.f.

Method	Optimal DG				Power loss (kW)	LR %
	Bus	Size (kW)	kVAR	p.f		
SIMBO-Q [18]	19	565.6	185.9	0.95	23.1	89.73
	61	1500.0	493.0	0.95		
	64	422.0	138.7	0.95		
QOSIMBO-Q [18]	17	582.8	191.6	0.95	22.8	89.87
	61	1500.0	493.0	0.95		
	64	427.2	140.4	0.95		
HHO	16	702.8	231.0	0.95	22.85	89.8
	50	286.6	94.2	0.95		
	61	1890.9	621.5	0.95		
IHHO	11	552.9	181.7	0.95	**20.71**	**90.8**
	18	419.5	137.9	0.95		
	61	1879.2	617.7	0.95		

TABLE 10. Optimal DG allocation for IEEE 69-node system based on single-objective using different optimization techniques at optimal p.f.

Method	Optimal DG				Power loss (kW)	LR %
	Bus	Size (kW)	kVAR	p.f		
PSO [7]	11	498.0	334.7	0.83	4.61	97.7
	18	372.6	269.8	0.81		
	61	1668.6	1208.1	0.81		
HHO	17	270.8	385.5	0.57	6.58	97.1
	61	1541.4	1300.8	0.76		
	66	696.8	177.7	0.97		
IHHO	11	456.2	284.4	0.85	**4.44**	**98.0**
	18	389.2	275.6	0.82		
	61	1714.8	1154.3	0.83		

has the best results (see Table 9) in which the power loss reaches 20.71 kW with LR equals 90.8 % and that is better than SIMBO-Q, QOSIMBO-Q, and the conventional HHO where the power loss in these methods are 23.1 kW, 22.8 kW, and 22.85 kW respectively.

With the change in the operating p.f to be optimal, the efficiency of the IHHO does not change where it gives the lowest power loss which equals 4.44 kW as presented in Table 10. Also, the optimal p.f plays an important role to decrease the power loss by 98% from the base case which is considered a significant LR.

b: VOLTAGE PROFILE

Due to the minimization of the active power loss, the voltage profile of the IEEE 69-node system has been improved as exhibited in Fig 10. The considerable enhancing in the voltage profile is reported at the optimal p.f because of the injected active and reactive power and it is approximately equalling to the one provided by the 0.95 p.f for the same reason.

c: PERFORMANCE AND STATISTICAL ANALYSIS FOR THE DEVELOPED TECHNIQUE

Ten runs are executed by the HHO and IHHO and the best, average, and worst costs are recorded in Table 11 to present the robustness of the developed IHHO method.

TABLE 11. Statistical analysis for the HHO and IHHO for Sigle -objective (IEEE 69-node test system).

Method		Best Cost	Average Cost	Worst Cost
Unity p.f	HHO	69.73	73.03	80.11
	IHHO	69.41	69.94	71.14
0.95 p.f	HHO	22.85	25.89	31.63
	IHHO	20.71	21.02	21.87
Optimal p.f	HHO	6.58	13.83	24.72
	IHHO	4.44	5.69	7.23

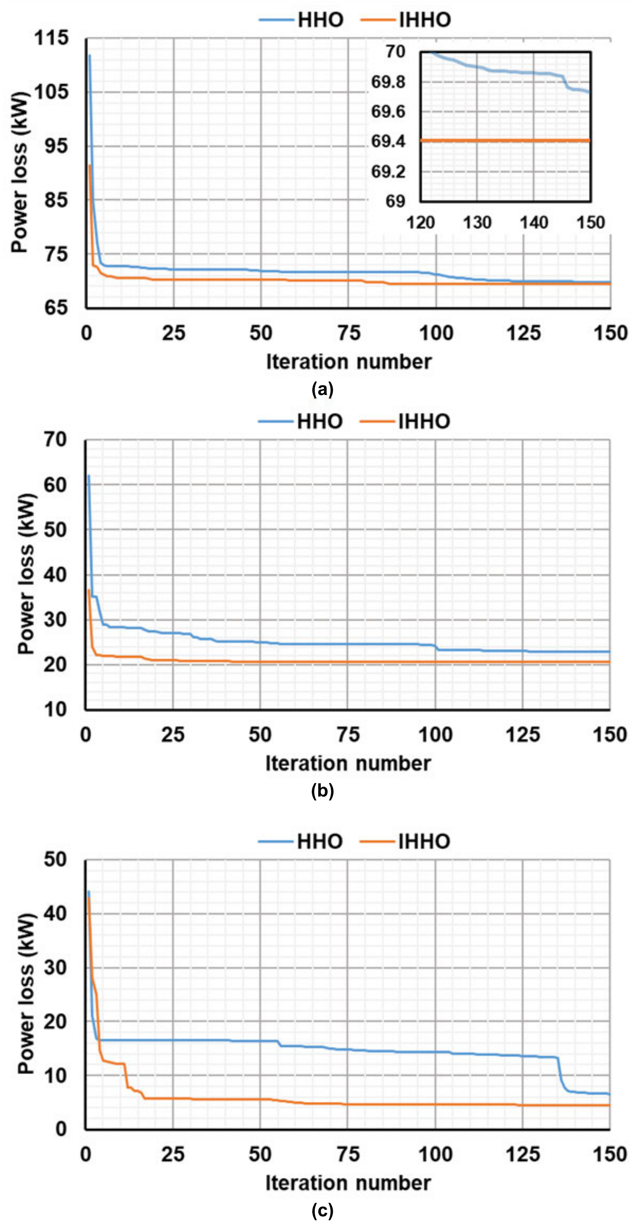

FIGURE 11. Convergence characteristics of the HHO and IHHO at different operating p.f for IEEE 69-node test system. (a) unity p.f, (b) 0.95 p.f, and (c) optimal p.f.

The achieved results declare the ability of the IHHO in obtaining the optimal solution more than the HHO and this can be noticeable from the convergence characteristics shown in Fig 11.

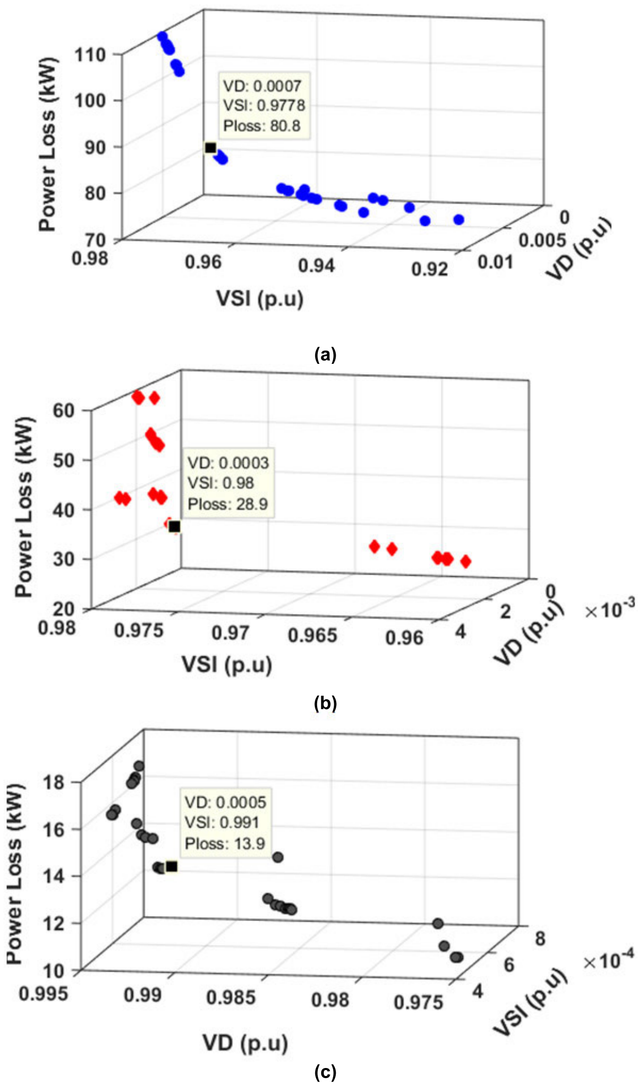

FIGURE 12. Nondominated Pareto optimal solutions obtained by MOIHHO for IEEE 69-bus considering DG operating at: (a) unity p.f, (b) 0.95 p.f, and (c) Optimal p.f.

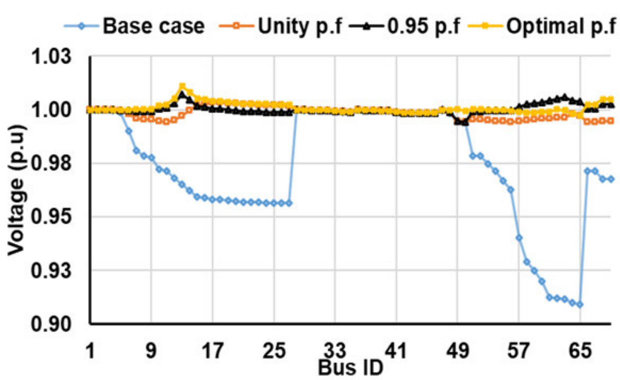

FIGURE 13. Voltage profile of the IEEE 69-node test system at different case studies for the multi-objective optimization problem.

2) MULTI- OBJECTIVE ANALYSIS

Similarly, the multi-objective problem is implemented for the allocation of the DG into the IEEE 69-node system to optimize the power loss, VD, and VSI where the base case values of these objective functions are 224.95 kW, 0.0993 p.u, and 0.6842 p.u.

TABLE 12. Optimal DG allocation for the IEEE 69-node system based on multi-objective using different optimization techniques at unity p.f.

Method	Bus	Size (kW)	P_{loss} (kW)	VD (p.u)	VSI (p.u)
GA [16]	21	929.7	89.0	0.0012	0.9705
	62	1075.2			
	64	984.8			
PSO [16]	17	992.5	83.2	0.0049	0.9676
	61	1199.8			
	63	795.6			
GA/PSO [16]	21	910.5	81.1	0.0031	0.9768
	61	1192.6			
	63	884.9			
TLBO [17]	13	1013.4	82.2	0.0008	0.9745
	61	990.1			
	62	1160.1			
QOTLBO [17]	15	811.4	80.6	0.0007	0.9769
	61	1147.0			
	63	1002.2			
SIMBO-Q [18]	61	1397.5	80.5	0.0007	0.9770
	15	780.3			
	62	790.7			
QOSIMBO-Q [18]	61	1498.6	79.8	0.0007	0.9770
	15	785.1			
	63	662.3			
MOHHO	20	643.6	81.0	0.0008	0.9720
	60	971.4			
	61	1328.2			
MOIHHO	18	796.2	**80.8**	**0.0007**	**0.9778**
	61	1447.1			
	64	707.5			

a: DG ALLOCATION

The optimal sizes and locations of the DG at unity p.f using different optimization methods are arranged in Table 12. In this case, the MOIHHO achieves the highest VSI which is 0.9778 p.u in comparison to all methods. However, the developed method gives VD which is 0.0007 p.u and that equals the value obtained by QOTLBO [17], SIMBO-Q [18], and QOSIMBO-Q [18] and better than 0.0008 p.u from TLBO [17], 0.0031p.u by GA/PSO [16], 0.0049 p.u has given in PSO [16], and 0.0012 p.u using GA [16]. In addition, the power loss in MOIHHO is 80.8 kW and that better than those obtained by GA, PSO, GA/PSO, TLBO, and MOHHO however it is higher than 80.6 kW obtained in QOTLBO, 80.5 kW in SIMBO-Q, and 79.8 kW achieved by QOSIMBO-Q.

In Table 13, the result of the DG operating at 0.95 p.f is given and declared that the MOIHHO gives the best results in two of the objective functions (power loss and VSI) compared to the other method which proves the ability of the MOIHHO.

Finally, Table 14 gives the DG allocation at the optimal p.f where the outcome of the MOIHHO is compared with MOHHO. It can be noticed that a considerable improvement

TABLE 13. Optimal DG allocation for the IEEE 69-node system based on multi-objective using different optimization techniques at 0.95 p.f.

Method	Optimal DG				P_{loss} kW	VD (p.u)	VSI (p.u)
	Bus	Size					
		kW	kVAR	p.f			
SIMBO-Q [18]	13	953	313	0.95	29.7	0.0003	0.977
	59	1002	329	0.95			
	62	1121	369	0.95			
QOSIMBO-Q [18]	17	487	160	0.95	31.4	0.0002	0.977
	56	1260	414	0.95			
	63	1500	493	0.95			
MOHHO	23	519	171	0.95	30.2	0.0010	0.980
	60	1176	387	0.95			
	62	1179	387	0.95			
MOIHHO	13	1038	341	0.95	**28.9**	**0.0003**	**0.980**
	61	799	263	0.95			
	63	1229	404	0.95			

TABLE 14. Optimal DG allocation for the IEEE 69-node system based on multi-objective using different optimization techniques at optimal p.f.

Method	Optimal DG				P_{loss} kW	VD (p.u)	VSI (p.u)
	Bus	Size					
		kW	kVAR	p.f			
MOHHO	15	332	846	0.37	21.8	0.0008	0.980
	60	314	838	0.35			
	61	1784	335	0.98			
MOIHHO	13	1064	779	0.81	**13.9**	**0.0005**	**0.991**
	49	1235	403	0.95			
	62	1610	1181	0.81			

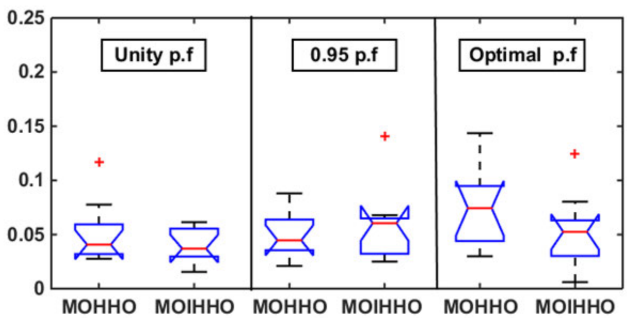

FIGURE 14. Box plot for SP metric of the MOHHO and MOIHHO at different operating p.f in case of the IEEE 69-node system.

in the VSI is achieved with the MOIHHO and that equals 0.991 p.u which means that the distribution system becomes more stable can withstand at the abnormal conditions. The Pareto optimal front is revealed in Fig 12 at the different operating p.f besides the best compromise solution obtained by the grey relation analysis.

b: VOLTAGE PROFILE

Fig 13 displays the voltage profile of the IEEE 69-node system in case of solving the multi-objective DG allocation problem at various operating p.f. Significant improvement is clear in the figure in the three scenarios of the p.f as a result of considering the VD and VSI.

c: PERFORMANCE AND STATISTICAL ANALYSIS FOR THE DEVELOPED TECHNIQUE

Box plot shown in Fig 14 illustrates the SP metric of the MOHHO and MOIHHO for various operating p.f. It is clear that the MOIHHO has a better distribution of the nondominated solution than the MOHHO at unity and optimal p.f.

IX. CONCLUSIONS AND FUTURE DIRECTIONS

In this paper, the optimal allocation of DG in the radial distribution system has been achieved using single- and multi-objective approaches based on the proposed IHHO and MOIHHO. In the single-objective problem, minimizing the active power loss has been considered the main target of the DG allocation, however, three objective functions (power loss, VD, and VSI) have been optimized using the multi-objective problem. Grey relation decision making has been utilized to achieve the best compromise solution from the Pareto optimal set for the multi-objective problem. The improved algorithm has been validated using standard IEEE 33-node and 69-node at different operating p.f. The IHHO and MOIHHO have been compared with conventional HHO and MOHHO based on statistical analysis as well as other well-known optimization techniques. The results proved the superiority of the improved algorithms for accomplishing the optimal allocation of DG in the radial distribution system to minimize the total power and voltage deviation and enhance the overall voltage profile. Moreover, the results achieved by the developed algorithms showed that the highest LR in IEEE 33-node and 69-node were 94.39 % and 98 % respectively, and the maximum VSI was 0.979 p.u and 0.991 p.u respectively, however, the minimum VD was 0.0003 p.u for the two test systems.

In future work, the optimal allocation of DG considering different levels of DG penetration at different load demands could be studied. In addition, the influence of the intermittent nature of renewable DG could be addressed based on uncertainty modeling.

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