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A Novel Hybrid Optimization-Based Algorithm for the Single and Multi-Objective Achievement With Optimal DG Allocations in Distribution Networks

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ABSTRACT Distribution networks are facing new challenges with the emergence of smart grids, such as capacity limitations, voltage instability, and many others. These challenges can potentially lead to brownouts and blackouts. This paper presents an innovative technique for optimal siting and sizing of distributed generators (DGs) in radial distribution networks (RDNs). The proposed technique uses a novel algorithm that combines improved grey wolf optimization with particle swarm optimization (I-GWOPSO) by incorporating dimension learning-based hunting (DLH). The proposed I-GWOPSO employs a novel aspect of DLH to reduce the gap between local and global searches to maintain a balance. The main optimization objectives aim to optimally site and size the DG with minimization of active power loss, voltage deviation, and improvement of voltage stability in RDNs. Case studies are simulated with IEEE 33-bus and IEEE 69-bus test systems, for the optimal allocation of DG units by considering various power factors. The results validate the efficacy of the proposed algorithm with a significant reduction in real power loss (up to 98.1%), improvement in voltage profile, and optimal reduced cost of DG operation with optimal sizing across all considered cases. A comparative analysis of the proposed approach with existing literature validates the improved performance of the proposed algorithm.

INDEX TERMS Distributed generation, dimension learning-based hunting, grey wolf optimization, particle swarm optimization, radial distribution network, voltage deviation, voltage stability index.

I. INTRODUCTION AND MOTIVATION

Nowadays, rising demands make distribution networks (DNs) more prone to voltage drops and line losses [1]. Electricity service providers are continuously planning to expand their existing networks to meet increasing load demands. The traditional planning solution is to construct a new substation or expand the existing one [2]. However, this is not economically viable as it results in high operative costs. Also, this method has a negative environmental impact i.e., dominated use of fossil fuels for power generation. A better alternative solution to meet the rising demand is the use of distributed generation units (DG) in DNs. DGs are more economical than the traditional means of production as they have small-scale generation capabilities to correlate with changing loads. Similarly, DGs are environmental friendly as they involve renewable energy resources (RER) of production i.e., wind, solar, hydro, and geothermal energy. The use of DGs along with renewable sources makes power production technically viable, environmental friendly, and economically feasible [3]. The overall voltage of the network can be increased, and losses can be reduced by connecting DGs with DNs via proper allocation. Also, DGs help out to reduce the congestion on DNs and relieves the capacity of transmission lines [4]. If DG units

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are allocated improperly, it may result in high power losses (PL), voltage rise, and low network stability. In distribution network planning, optimal DG allocation (ODGA) should be cautiously determined to enhance the technical, environmental, and economical benefits.

The energy management with DGs is an important research dimension in the last decade that aims at optimal sitting and sizing of DGs. In recently published research works, numerous optimization methods have been employed to solve ODGA problems in radial configured DN (RDN). The aimed objectives include the minimization of PL [1], [5]–[9], reduce voltage deviation (VD) [4], [10]–[16], maximizing voltage stability index (VSI) [5], [13], [16]–[18], improved transient stability [19], enhanced reliability [20]–[24]and drop in greenhouse gas emission [25].

II. LITERATURE REVIEW

The capitalization of DG integration is considered a multi-dimensional problem from an objective perspective. Several analytical methods based on the exact formula have been used to solve the optimum DG integration problems [26], mixed-integer non-linear programming (MINLP) [27], loss sensitivity [28], etc., are presented in the reported research. A two stage-framework used in [29], shows that in the first stage, bus locations were determined based on voltage stability (VS) and loss sensitivity factor (LSF). In the second stage, an analytical technique was utilized to determine the appropriate DG size. Analytical techniques are simple to use, and their computational time is less in ODGA. However, these abovementioned techniques are subjected to various issues i.e., DG types, multiple numbers of DG units, and multi-objective functions. The ODGA problems are addressed with the classification of single and multi-objective optimization methods. The accommodation of single objective function in single-objective optimization problems (SOOPs) mostly aims at minimizing the PL. In contrast, multi-objective optimization problems (MOOPs) simultaneously address more objectives.

In ODGA based problems, metaheuristic optimization methods have broadly been implemented in DG sizing and sitting in both SOOPs and MOOPs, respectively. For the SOOPs, particle swarm optimization (PSO) is employed for minimizing the real power loss (RPL) to optimize DG allocation (sitting and sizing) [30]. An improved variant in [9] uses multileader particle swarm optimization (MLPSO) to resolve ODGA problems aiming at reducing the system PL. Moreover, in [7] the novel heuristic technique is proposed to optimally allocate the active and reactive power in RDNs. The techniques include artificial bee colony (ABC) [1], ant line optimization (ALO) [6], efficient analytical method (EA) [31], stud krill herd algorithm (SKHA) [32]. These techniques are used for DG allocation problems for PL minimization and enhance the overall performance of RDN.

Artificial intelligence (AI) methods besides the aforementioned techniques are also used for ODGA. The authors in [33] have proposed a genetic algorithm (GA) for ODGA problems i.e., RER uncertainties, load demand calculation, cost at energy losses, upgradation, and interpretation cost of a network. To deal with multi-objective issues i.e., improved voltage profile, PL, voltage stability, the cloud theory GA (CAGA) was incorporated. In [34], the author has formulated the PSO method to address the ODGA problem with various load models. In this research multi-objective function was used to optimize PL, VD, and short-circuit intensity of a DN. Generally, GA takes a lot of time for convergence and falls in local optima, and hence the quality of solution decreases with higher-dimensional problems. PSO in comparison is more efficient than GA in global research, though it doesn't guarantee an efficient solution for complex problems. However, both GA and PSO have certain parameters which can be fine-tuned to obtain efficient solutions [35].

The study in [36], proposes the invasive weed optimization (IWO) method to find the optimum size of multiple DGs, whereas the optimum DG location is found with the LFS method. The basic aim of this research is PL reduction, VS improvement, and minimizing the operational cost in 33-bus and 69-bus RDNs. The author in [15] recommended the Taguchi method (TM) which uses the TOPSIS method to optimize MOOPs. The multi-objective opposition-based chaotic differential evolution (MOCDE) technique is suggested in [16] to address MOOP with the objectives of minimizing the PL and VD and maximizing economic benefits. In [37], the authors introduced the flower pollination algorithm (FPA) to solve the MOOP to increase loading ability without changing VS of the DN and PL reduction. In comparison, AI techniques acquire a strong capability to find optimum solutions. However, these techniques are hard to code, need rich data, may deteriorate from local optima, and need more computation time to address multi-dimensional issues.

The hybrid techniques have been established to deal with the limitations left in individual techniques, for solving ODGA problems. These hybrid techniques have an edge from a single algorithm i.e., enhance proficiency and convergence accuracy. In [38], hybrid GA/PSO was developed for determining the ODGA in RDNs, in which PSO was utilized to optimize the DG sizes while GA determined the optimal location DG units. The aim was to simultaneously optimize RPL, VD, and improve the VSI in networks. Hybrid GA and intelligent water drops (IWD) in [39] address a similar issue as in [38]. Authors in [31], proposed the efficient analytical (EA) technique and optimal power flow (EA-OPF) technique for optimizing DG sitting and sizing with the objective of reduction in RPL. Initially, the optimum size is determined with EA based approach. Then, the size of DG units is calculated by the OPF for the predefined sites. Although hybrid techniques generally offer superior solution quality than individual techniques, they may endure complexity in execution and larger computation time due to complicated configurations subjected to numerous control constraints.

Recently, the authors in [2] proposed Quasi-oppositional swine influenza model-based optimization with quarantine

(QOSIMBO-Q), quasi-oppositional chaotic symbiotic organisms search (QOCSOS) [4], Chaotic Sine Cosine Algorithm (CSCA) [10], improved and multi-objective elephant herding optimization (IMOEHO) [11], the improved decomposition-based evolutionary algorithm (I-DBEA) [12], improved single- and multi-objective Harris Hawks Optimization (IHHO and MOIHHO) [14], stochastic fractal search algorithm (SFSA) [17], and Quasi-Oppositional Teaching Learning Based Optimization (QOTLBO) [18] to solve the ODGA problem using single and multi-objectives. Authors in [2], do not examine the DG operation with the optimal PF and the allocation problem associated with the large system. It is observed that most above mentioned literature didn't address properly the effect of various PF of DG units on RDNs. DG units operate at any PF according to the IEEE standard 1547 [40]. Thus, this work considered various PF of DGs i.e., unity PF, 0.95 PF, and Optimal PF for DG allocation problem.

An improved grey wolf optimizer (I-GWO) is proposed in [41] for the solution of ODGA based optimization problems. The I-GWO has the advantage of simplicity in design, mitigates the difference between exploration and exploitation, proper convergence of GWO, and reduces population diversity issues. A new approach in [41] named dimension learning-based hunting (DLH) is beneficial for the I-GWO algorithm that is driven by the behavior of individual hunting of wolves in nature. DLH utilizes a distinct technique to build up a network for each wolf in its surroundings to share the information among neighboring wolves. This feature of DLH reduces the gap between local and global search to keep the balance.

In this paper, the bridging of limitations in previous works serve as the very novelty and a new improved GWO-PSO hybrid (I-GWOPSO) algorithm is proposed for ODGA for both SOOPs and MOOPs. The proposed hybrid algorithm reduces the solution's chances to fall into a local minimum. Contributions of paper are as follows:

- Proposed a hybrid improved I-GWOPSO based on DLH (to reduce search space).
- The I-GWOPSO method addresses ODGA problems for SOOP, aiming at PL reduction.
- The I-GWOPSO method addresses ODGA problems for MOOP, aiming at optimizing the three objectives simultaneously i.e., PL reduction, VD, and VSI.
- The effectiveness proposed algorithm is evaluated across two test systems i.e., 33-bus and 69-bus RDNs.
- The achieved numerical are compared with reported optimization methods and outperforms based on techno-economic indices. Hence validates the approach.
- The ODGA optimization has conducted across various power factor (PF) values.
- Optimal results have achieved at optimal PF (lagging) in both test DNs.

The paper is organized as follows: Section III represents the mathematical design of the major objective functions. Section IV mentions the summary of I-GWO and I-GWOPSO. The results and discussions are presented in section V. In Section VI the numerical values resulted from the conclusion.

III. PROBLEM FORMULATION

This section includes the ODGA in RDN.

A. OBJECTIVE FUNCTIONS

The major objective of the research is to allocate the DG in RDN in an efficient way to reduce the real PLs with SOOP. DG allocation problem particularly focuses on three objectives i.e., reduction of real power loss, minimization of VD, and maximization of VSI. The main objectives with their mathematical calculations are presented below subsections:

1) REAL POWER LOSS REDUCTION

RPL in RDN is calculated through the following equation [42]:

$$RPL = \sum_{k=1}^{M_{br}} |I_k|^2 R_k \tag{1}$$

where branch number is denoted by K, $M_{\mathbf{br}}$ is the total number of branches, the absolute current $|I_k|$ which is passing through the branch, and R_k is the resistance of the branch.

It is important to reduce RPL because it is high due to the radial structure of DN. The first objective function (OF) is shown as:

$$OF_1 = \min(RPL) \tag{2}$$

2) TOTAL VOLTAGE DEVIATION

Bus VD is minimized as an OF to improve voltage for that consumer that is using voltage-sensitive equipment. The OF is determined as in [18], [38].

$$TVD = \sum_{i=1}^{m\_bus} (V_{ref} - V_i) \tag{3}$$

where reference voltage (V_{ref}) is always taken as 1.00 p.u., Hence, the second OF (OF_2) is given as follows:

$$OF_2 = \min(TVD) \tag{4}$$

3) MAXIMIZATION OF VSI

For the security level of DN, besides VD, VSI is also an important factor to incorporate. When a bus in DN violates permissible voltage limits due to various reasons, it may result in voltage instability of the whole system, designated with VSI. For stable operation, VSI must be retained at a stable limit across all the buses of a DN. The expression of VSI for RDN is given as follows [43]:

$$VSI_i = \left|v_j\right|^4 - 4\left(P_i \varkappa_{ij} - Q_i r_{ij}\right)^2 - 4\left|v_j\right|^2\left(P_i r_{ij} - Q_i \varkappa_{ij}\right) \tag{5}$$

where, P_i, and Q_i are the real power and reactive power of the load and $\varkappa_{ij}$, and r_{ij} are the inductive reactance and resistance of the line. This equation serves as a criterion for determining the RDN's voltage stability. For RDNs to operate stably, VSI_i must be greater than zero. The voltage collapse occurs when the VSI on the bus is at its lowest value [44]. VSI_i must be maximized to improve VS. The third OF (OF_3) is given as:

$$OF_3 = \max(\min(VSI_i)) \tag{6}$$

4) MULTI-OBJECTIVE FUNCTIONS

Every single objective has its distinct nature. For the integrated mathematical representation of all the distinct objectives, each Single OF (SOF) is divided according to its base value and integrated with its weights. The weighted sum of the real power loss reduction, total voltage deviation, and voltage stability index is used to express the multi-objective function. Weighted sum methods are simple to apply, effective, and practical for generating a strongly non-dominated solution that can be utilized as a starting point for further methods [45]. The weighting coefficients method assists in the transformation of three SOFs into one combined OF and the entire fitness function is represented as:

$$\begin{aligned} fit &= \min\left(w_1 \times f_1 + w_2 \times f_2 + w_3 \times f_3\right) \\ &= min\left(w_1 \times \frac{RPL}{RPL_{base}} + w_2 \times \frac{TVD}{TVD_{base}} \right. \\ &\quad \left. + w_3 \times \frac{VSI^{-1}}{VSI^{-1}_{base}}\right) \end{aligned} \tag{7}$$

where RPL_{base}, TVD_{base}, and VSI^{-1}_{base} are the total real power loss, the total voltage deviation, and the voltage stability index improvement of the network in the base case (the network without DG). Therefore, ($w_1+w_2+w_3 = 1$) are three weights. The equal weight is given to each function because each function is treated as equally important in these MOOPs. In this study, weights are set to be equal i.e., 1/3 (or 0.3334).

5) ECONOMICAL INDEX

Another objective of this paper is to reduce the operational cost of DG operation subjected to its optimal size. The mathematical formulation [46] of the cost of active power DG (CPDG) is represented in Equation (8).

$$CPDG(\$/MWh) = a \times P_{DG}^2 + b \times P_{DG} + c \tag{8}$$

where, a = 0, b = 20, and c = 0.25.

B. PROBLEM CONSTRAINTS

In the distribution network the problem of DG allocation should be subjected to major constraints which are given below:

1) EQUALITY CONSTRAINTS

It is important to keep the generation balance which is equal to the sum of the Power demand (PD) and PLs to avoid reverse power which may harm the system. Thus, these constraints can be stated as:

$$\sum_{j=1}^{M\_DG} P_{Gen,j} = P_{demand} + RPL; \quad j = 1 \ldots\ldots M\_DG \tag{9}$$

$$\sum_{j=1}^{M\_DG} Q_{Gen,j} = Q_{demand} + QPL; \quad j = 1 \ldots\ldots M\_DG \tag{10}$$

where, M_DG is the number of DG integrated, P_{Gen} is the generation power that comes from the installed DG, QPL denotes the reactive power loss and P_{demand} is power demand by the load.

2) INEQUALITY CONSTRAINTS

Two inequality constraint sets have to be fulfilled. The boundary limitations are forced on the network which comprises the voltage limits, and DG technical constraints which incorporate of DG size limit and its power factor (PF).

a: VOLTAGE LIMITS

The magnitude of voltage should be retained within maximum and minimum Voltage limits as shown below [15], [47]:

$$0.95p.u \le V_j \le 1.05\, p.u \tag{11}$$

b: THERMAL LIMIT [15], [47]

$$I_{j,i} \le I_{j,i}^{max} \tag{12}$$

where $I_{j,i}^{max}$ is the maximum current flowing through the branch linked between the *jth* and the *ith* bus.

c: DG SIZE LIMIT

The maximum and minimum output power of DG units are given below [15][48]:

$$Real\ Power\ limit: P_{Gen}^{min} \le P_{Gen} \le P_{Gen}^{max} \tag{13}$$

$$Reactive\ Power\ limit: Q_{Gen}^{min} \le Q_{Gen} \le Q_{Gen}^{max} \tag{14}$$

d: DG POWER FACTOR LIMIT

DG units can function in a range of power factors as follows:

$$p.f_{DG,j}^{min} \le p.f_{DG,j} \le p.f_{DG,j}^{max}; \quad j = 1, \ldots\ldots\ldots \mathrm{M\_DG} \tag{15}$$

The DG unit's operating power factor must be within the stated parameters [0.7, 1] [49]–[51].

Where PF is shown by the following relationship.

$$p.f_{DG,j} = P_{DG,j}^2 \Big/ \sqrt{P_{DG,j}^2 + Q_{DG,j}^2} \tag{16}$$

IV. HYBRID PROPOSED OPTIMIZATION ALGORITHM

In this research, the proposed hybrid algorithm I-GWOPSO makes use of I-GWO and PSO metaheuristic methods. A hybrid method has been proposed by using these two algorithms to generate adequate results. The details are mentioned below.

A. GREY WOLF OPTIMIZER TECHNIQUE

In 2014, Lewis and Mirjalili [52] presents a metaheuristic optimization technique named a grey wolf optimizer. Its idea comes from the behavior and hunting methods of the grey wolf in nature. The GWO technique consists of three leader wolves named α, β, and δ as the best solutions for leading the rest of the wolves named wolves to find the global solution [53]. Three fundamental steps complete wolf hunting.

1) ENCIRCLING

The hunting strategy of grey wolves in [54] the encircling network can be formed as given in Equation (17) and (18):

$$D = \left|C \times V_{pr}(t) - V(t)\right| \tag{17}$$

$$V(t+1) = V_{pr}(t) - A \times D \tag{18}$$

In the above equations, V_{pr} represents the location of prey, V locates the position vector of the grey wolf, the current iteration is given by t. In [52], coefficient vectors are C and A given in Equations (19) and (20).

$$A = 2 \times A \times r_1 - a(t) \tag{19}$$

$$C = 2 \times r_2 \tag{20}$$

When iterations are done, the vector element goes down from 2 to 0 representing the random vectors, r_1 and r_2 by Equation (21).

$$a(t) = 2 - (2 \times t)/Max_{iter} \tag{21}$$

2) HUNTING

It is about the mathematical analysis of wolves hunting attitude, presumed as α, β, and δ can find the prey from its location by good knowledge. Hence, keeping in view, the three best solutions provided by the locations of α, β, and δ, other wolves will follow them. Their hunting skills are mentioned in Equations (22)-(24).

$$\begin{aligned} D_\alpha &= \left|C_1 \times V_\alpha - V(t)\right| \\ D_\beta &= \left|C_1 \times V_\beta - V(t)\right| \\ D_\delta &= \left|C_1 \times V_\delta - V(t)\right| \end{aligned} \tag{22}$$

where C_1, C_2, and C_3, are determined by Equations (19) and (20).

$$\begin{aligned} V_{j1}(t) &= V_\alpha(t) - A_{j1}(t)\,D_\alpha(t) \\ V_{j2}(t) &= V_\beta(t) - A_{j2}(t)\,D_\beta(t) \\ V_{j3}(t) &= V_\delta(t) - A_{j3}(t)D_\delta(t) \end{aligned} \tag{23}$$

$$V(t+1) = \frac{V_{j1}(t) + V_{j2}(t) + V_{j3}(t)}{3} \tag{24}$$

3) ATTACKING

The hunting method ends when the prey stops moving and sticks in a place. Then the wolves start the attacking process. This expression mathematically can be derived by the reduction of the value of a within a specific interval. In this model, the value of a is changed on a range between 2 to 0 as presented in Equation (21).

The fluctuating value of a in the interval (2, 0) shows that the Subsequent location of the searcher can be at any point among the present position of a hunter and the position where prey is located. In each iteration, the first three wolves α, β, and δ are considered best in fitness. Each wolf changes its location according to the above-mentioned steps of encircling, hunting, and attacking. By the continuous iterations, the exact spot of prey which is α's can be traced out.

GWO is efficient and is valid for many applications. However, there is a certain drawback of GWO. It has no population diversity capabilities. Further, it suffers from the imbalance between exploration and exploitation and untimely convergence. Moreover, the position regulator equation is suitable for exploitation, but it doesn't come up with an efficient solution.

B. IMPROVED GREY WOLF OPTIMIZER (I-GWO)

To solve the shortcomings of GWO, this research has proposed an improved grey wolf (I-GWO). I-GWO is comprised of a new search approach in which selection and updating of different values take place for the exact point location. The improved-GWO is comprised of three phases which are, initializing phase, movement phase, selection, and updating phase as follows.

1) INITIALIZING PHASE

In the initializing phase, N wolves are randomly placed within a specified range of search area $[lj, ui]$ by Equation (25).

$$\mathrm{V_{ji}} = \mathrm{l_i} + \mathrm{rand_i}[0, 1] \times (\mathrm{u_i} - \mathrm{l_i}), \quad \mathrm{j} \in [1, \mathrm{N}],\ \mathrm{i} \in [1, \mathrm{D}] \tag{25}$$

The position of the j-th wolf in the t-th iteration is denoted as a real value of the vector $V_j(t) = \left\{V_{j1}, V_{j2}, \ldots\ldots., V_{jD}\right\}$, where D is the problem's dimension number. The population of wolves is stored in a matrix Pop, which has N rows and D columns. The fitness function (fit ($\mathrm{V_j}$(t)) determines the optimal value of $\mathrm{V_j}$(t).

2) MOVEMENT PHASE

The social behavior of grey wolves hunting strategy is the base of I-GWO. Like the grey wolves hunting behavior, I-GWO is comprised of dimension learning-based hunting (DLH) method. In dimensional learning, each wolf is informed by its surrounding wolves to occupy the updated position $V_j(t)$.

a: DIMENSION LEARNING-BASED HUNTING (DLH) SEARCH APPROACH

For each wolf in the original GWO, three leader wolves are responsible for generating a new position. This mode causes GWO displays slow convergence, losses of population diversity too prompt, and wolves are trapped in the local optimal. To mitigate these defects, in the proposed DLH search approach, the hunting of each wolve is considered that is learned by its neighbors.

In the DLH searching method, the dimension of V_j wolf is a new position determined by Equation (29), shown later in the expression. Each wolf learns about the new position from his surrounding members as well as randomly provided information by a wolf. Based on this strategy, another candidate for the wolf $V_j(t)$ position, called $V_{j-DLH}(t+1)$, is generated, in addition to one generated from Equation (24), namely $V_{j-GWO}(t+1)$.

To formulate a new wolf $V_j(t)$ position, radius $R_j(t)$ must be calculated by finding the Euclidean distance separating the candidate position $V_{j-GWO}(t+1)$ from the present position $V_j(t)$, as in Equation (24) and a new position is shown in Equation (26).

$$R_j(t) = \left\| V_j(t) - V_{j-GWO}(t+1) \right\| \tag{26}$$

Further, the surrounding wolves of $V_j(t)$, as shown by $N_j(t)$, are determined in Equation (27) concerning radius $R_j(t)$, with D_j indicating Euclidean distance between $V_j(t)$ and $V_i(t)$.

$$N_j(t) = \left\{ \left(V_i(t) \mid D_j\left(V_j(t), V_i(t) \right) \right) \leq R_j(t),\ V_i(t) \in Pop \right\} \tag{27}$$

Following the structure of $V_j(t)$ neighborhood, the multi-neighbor learning stage continues, as shown in Equation (28).

$$V_{j-DLH,m}(t+1) = V_{j,m}(t) + rand \times \left(V_{n,m}(t) - V_{r,m}(t) \right) \tag{28}$$

where the m-th dimension of $V_{j-DLH,m}(t+1)$ is determined by utilizing the m-th dimension of an arbitrary neighbor $V_{n,m}(t)$ choose from $N_j(t)$, and an arbitrary wolf $V_{r,m}(t)$ from Pop.

3) SELECTING AND UPDATING PHASE

This stage has around three stages. In the initial step, an examination of the fitness value for the two candidates $V_{j-GWO}(t+1)$ and $V_{j-DLH}(t+1)$ is done to decide the better candidate, as communicated in Equation (29).

$$V_j(t+1) = \begin{cases} V_{j-GWO}(t+1), & \text{if } f\left(V_{j-GWO}\right) < f(V_{j-DLH}) \\ V_{j-DLH}(t+1), & \text{otherwise} \end{cases} \tag{29}$$

In the second step, the position of new $V_j(t+1)$ needs to be upgraded. So, check the fitness value of the selected candidate if it's less than $V_j(t)$, the selected candidate is upgraded to $V_j(t)$. Otherwise, the value stays the same in Pop. Finally, after doing this cycle for each individual, the counter of cycles is expanded by one, and the search can be iterated till the predefined number of cycles ($Max\__{\text{iter}}$) is attained. The pseudo implementation of Suggested I-GWO is displayed in Figure 1.

Algorithm 1: *Pseudo Code for I-GWO*

```
Input: Search Agent (SA), Dimension, Max_iter, α, β,
                                          and δ Pos.
Output: Global Optima
Start
Initialize( In each space to find rand [0,1]
            distributed N wolves and their fitness)
For iteration = 2 to Max_iter
  | Determine V_α, V_β, and V_δ
  | For j = 1 to N
  |   | Calculating objective fitness function for
  |   |                          each Search Agent
  |   | Evaluating V_j1, V_j2, and V_j3 by using Eq.(23)
  |   | Evaluating V_j-GWO(t + 1) by using Eq.(24)
  |   | Determining R_j(t) by Eq.(26)
  |   | Determining Neighborhood V_i(t) using Eq.(27)
  |   | For  m = 1 to D
  |   |   | V_j-DLH,m(t + 1) = V_j,m(t) + rand(0,1) ×
  |   |   |                        (V_n,m(t) − V_r,m(t))
  |   | End
  |   | Choosing Superior (V_j-GWO(t + 1),
  |   |                          V_j-DLH(t + 1))
  |   | Upgrading Pop.
  | End
End
Return to Global optima
End
```

FIGURE 1. I-GWO pseudocode.

C. PARTICLE SWARM OPTIMIZATION (PSO)

In 1995, James Kennedy and Russell Eberhart [55] presented a metaheuristic technique named particle swarm optimizer (PSO). The basic thought of PSO is that a gathering of particles is moving in the pursuit of space searching for the food or best arrangement numerically and has two attributes: its velocity and position. Distance and direction are defined by the velocity to optimize the position at the next iteration, whereas position signifies the present values in the solution. Their positions are changed concerning the time which is based on their present value, experience, and experience of their neighbors. The upgrading procedure of particle position is given in [55] as:

$$\begin{aligned} X^{(t+1)} = {} & W^t X_j^t + C_1 r_1 \left(V_{j1}(t) - V(t) \right) \\ & + C_2 r_2 \left(V_{j2}(t) - V(t) \right) + C_3 r_3 \left(V_{j3}(t) - V(t) \right) \end{aligned} \tag{30}$$

$$V_j^{t+1} = V_j^t + X_j^{(t+1)} \tag{31}$$

where t represents the iteration number, r_1 and r_2 are random numbers in between [0,1], W^t indicates the weighting coefficient, C_1 and C_2 represent the weighting factors, X_j^t the velocity of a particle at t iteration, $X_j^{(t+1)}$ represents the upgraded particle j velocity, V_j^t is the j position of a particle at t iteration, $V_{j1}(t)$ is the personal best particle (P_{best}) and $V_{j2}(t)$ is the global best particle (G_{best}).

In the proposed approach, the improved edition of the I-GWO technique is employed to help the PSO algorithm to lessen the chance of falling into a local minimum. The key concept to adapt hybridizing is to improve the ability of

TABLE 1. Control parameters of proposed I-GWOPSO.

Weight of inertia (w)	0.5	Max_iter	150
Social acceleration weight c1	1.5	Size of Pop.	50
Cognitive acceleration weight c2	2.0	Min. p.f	0.7
Constant a	Linearly decreased from 2 to 0	Max. p.f	1.0
Coefficient r1 and r2	Random number between [0,1]	Max. MVA	2000

exploitation in PSO with the provision of improved exploration in I-GWO to enhance stability and quality for the solution more. The preliminary population is revised by I-GWO, and the revised solutions are once more updated by PSO. The G_{best} is returned to the improved edition of I-GWO, and the algorithm remains to the run-up until the optimum solution is attained.

Nevertheless, the running time is lengthened while the PSO technique is also utilized in addition to the I-GWO algorithm. However, when the accomplishment of the outcomes and the amount of extra time required are carried into deliberation, the lengthened time can be considered as acceptable dependent on the optimization problem solved. The execution of the recommended I-GWOPSO algorithm for ascertaining the ODGA is reviewed in the subsequent steps of the I-GWOPSO pseudo-code presented in Figure 2 and illustrated through the flowchart presented in Figure 3.

V. RESULT AND DISCUSSION

In this section, the advanced algorithms (I-GWO and I-GWOPSO) are employed for two benchmark IEEE 33-bus and 69-bus distribution networks. The size of the population or the wolves' number is considered as 50. For PSO, the weight of inertia, social and cognitive acceleration weights are 0.5, 1.5, and 2.0, respectively [16]. The selection of stopping criteria is determined by the maximum number of iterations [4], [16], [17], i.e., fixed as 150. The setting of control parameters of the proposed algorithm is presented in Table 1. The optimum sitting and sizing of multiple DGs units are concluded to lessen the total PL as a SOOP. In addition, reducing the TVD and increasing VSI are judged for the MOOP. To verify the viability and effectiveness of the advanced methods, a complete contrast with other well-recognized optimization methods is carried out. The operational cost of DGs by the other approaches utilized in previous research is calculated for the given size of DGs. The proposed algorithm is coded in Matlab2020 and runs on a system with Intel(R) Core (TM) i7-7500U CPU (2.7 GHz) and 8 GB of RAM.

In addition, the I-GWOPSO associated with the traditional I-GWO over ten runs to calculate the minimum RPL, maximum RPL, and average RPL for the SOF. The following four cases are studied in the two examined networks:

- Without DG (Normal Case)
- Integrating three DGs at unity PF (UPF)
- Integrating three DGs at 0.95 lagging PF (LPF)
- Integrating three DGs at Optimal LPF (OPF).

A. IEEE 33-BUS NETWORK

The IEEE 33-bus network is used to analyze the proposed technique. The complete description of the 33-bus network. containing the load and line data in [56]. The single line diagram of 33-bus DN is presented in Figure 4. The base values of the 33-bus network are taken as kV = 12.66 and MVA = 100.

1) SINGLE-OBJECTIVE ASSESSMENT FOR 33-BUS DN

Real and reactive PLs are calculated based on power flow results which are 210.05 kW and 142.42 kVAR respectively. Optimum allocation is done by using I-GWOPSO of three DG units with different power factors to reduce the total PL.

a: DG SITTING AND SIZING FOR 33-BUS DN

For UPF ODGA is presented in Table 2. From the table, it is clear that by use of I-GWOPSO, the optimum three DGs locations are 14, 24, and 30. The capacities of these three DGs are 0.786MW, 1.032MW, and 1.094MW respectively. It is observed RPL of the network is reduced from 210.05KW to 70.64KW. The reduction of RPL is very much improved than other methods mentioned in the table. The cost of active power DG (CPDG) obtained from the given size of DGs are less than the SFSA [17], QOSIMBO_Q [2], QOTLBO [18], CSCA [10], QOCSOS [4], IHHO [14], and I-GWO which is 58.49 $\$/MWh$. Moreover, I-GWOPSO is comparatively economical than others analyzed methods.

Furthermore, Table 3 represents the conclusions of the optimum sitting and sizing for multi-DG with 0.95 LPF. The conclusions indicate that the proposed I-GWOPSO achieves the optimum allocation which has the minimum PL (27.683 kW). The PL achieved by the I-GWOPSO is smaller than the PL from conventional I-GWO which is 27.77 kW. This result was lower than that from SFSA [17], SIMBO_Q[2], QOCSOS [4], IHHO [14] and QOSIMBO_Q[2]. The CPDG obtained by I-GWOPSO is less than the SFSA [17], SIMBO_Q [2], and QOCSOS [4] and equal to I-GWO, IHHO [14], and QOSIMBO_Q [2] which is 63.59 $\$/MWh$. From table it can be observed that the proposed technique provides best technical and economical results.

To examine the effect of the PF of the DG on the PLR, optimum DG sitting and sizes with OPF are carried out utilizing the established method. Table 4 reviews the conclusions of the OPF obtained by the I-GWOPSO compared to SOS [4], QOCSOS [4], IHHO [14], EA-OPF[31], and I-GWO. It can be observed from the table, a considerable loss reduction in the PL achieves 94.4 % is given by the I-GWOPSO and PL achieved by I-GWO is 94.46%. The CPDG of I-GWOPSO is slightly less than the I-GWO equals

Algorithm 2: *Pseudo Code for I-GWOPSO*

Input: *Search Agent (SA), Dimension,* Max_{iter}, $\alpha, \beta,$ *and* δ *Pos*

Output: *Global Optima*

Start

Step 0: *Initialization*

Choose the Pop. size N, Max_{iter}, *total no. of DG locations* $N_{DG,loc}$, *capacity of DG unit S in kVA, p.f, set as*

$$p.f = \begin{cases} 1 & for\ p\ type \\ [0.7, 1] & for\ PQ^{+} - type \end{cases}$$

Generate the initial Pop. of N feasible solution vectors, that satisfy all the constraints listed in Section 2.2.

Initial Pop. of organisms is denoted by an $\boldsymbol{V_j}$ *matrix*

$$V_j = \begin{bmatrix} V_j^1 \\ V_j^2 \\ \vdots \\ \vdots \\ V_j^N \end{bmatrix} = \begin{bmatrix} S_1^1 \cdots & S_{N_{DG,loc}}^1 & l_1^1 \cdots & l_{N_{DG,loc}}^1 & pf_1^1 \cdots & pf_{N_{DG,loc}}^1 \\ S_1^2 \cdots & S_{N_{DG,loc}}^2 & l_1^2 \cdots & l_{N_{DG,loc}}^2 & pf_1^2 \cdots & pf_{N_{DG,loc}}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ S_1^N \cdots & S_{N_{DG,loc}}^N & l_1^N \cdots & l_{N_{DG,loc}}^N & pf_1^N \cdots & pf_{N_{DG,loc}}^N \end{bmatrix}$$

where $j = 1, 2, \ldots, N_{DG,loc}$ *is the bus number*

Each organism represents a solution vector consisting of sizes of DG units and variables of locations.

For each scenario, the operation of DG units was considered with different cases

Case 1: *DG units operate with unity p.f*
Case 2: *DG units operate with fixed p.f*
Case 3: *DG units operate with optimal p.f*

Each wolf represents a solution vector consisting of sizes of DG units and variables of locations

A vector solution for the ODGA problem is expressed for Case 1 and Case 2 as in Eqn. (A), and for Case 3 as in Eq. (B) as follows:

$$\boldsymbol{V_j} = [\ P_{DG,1}, \ldots, P_{DG,NDG},\ lo_{DG,1}, \ldots, lo_{DG,NDG}] \quad \text{(A)}$$
$$\boldsymbol{V_j} = [\ P_{DG,1}, \ldots, P_{DG,NDG},\ Q_{DG,1}, \ldots, Q_{DG,NDG}\ \ lo_{DG,1}, \ldots, lo_{DG,NDG}] \quad \text{(B)}$$

The organisms of I − GWOPSO are randomly initialized within the boundaries. Thus, the solution variables for the number of buses (loDG, j), and sizes of DG units (PDG, j, QDG, j) are generated as follows:

$$\boldsymbol{lo_{DG,j} = round\,[\,lo_{DG\,min,j} + rand(0,1) \times (\,lo_{DG\,max,j} - lo_{DG\,min,j}\,)]} \quad \text{(i)}$$
$$\boldsymbol{P_{DG,j} = round\,[\,P_{DG\,min,j} + rand(0,1) \times (\,P_{DG\,max,j} - P_{DG\,min,j}\,)]} \quad \text{(ii)}$$
$$\boldsymbol{Q_{DG,j} = round\,[\,Q_{DG\,min,j} + rand(0,1) \times (\,Q_{DG\,max,j} - Q_{DG\,min,j}\,)]} \quad \text{(iii)}$$

Where $\boldsymbol{i = 1, 2, \ldots\ldots N_{DG}}$

Step 1: *Run the load flow for each grey wolf and find the power loss in the distribution system. Evaluate the fitness using the objective function (7).*

Personal best fitness and position obtained by each wolf

Step 2: ***For*** *iteration* $= 2$ *to* Max_{iter}
For $j = 1$ *to N*

Apply the encircling operator (17) and Evaluating V_{j1}, V_{j2}, *and* V_{j3} *by using Eqn. (23)*

Step 3: ***Move to PSO***

Initial Pop. of PSO is the final Pop. of GWO

The DG size for each particle is allocated to the same buses considered for I − GWO and the fitness function of all the particles is evaluated

Step 4: *compute fitness func. of each particle, Pbest & Gbest*

Step 5: *Evaluating swarm particle's Pos. and Velocity by Using Eqn. (30) & (31)*

Step 6: *The fitness value of each particle is computed for the updated sizing of DGs placed at the best nodes obtained in step 4.*

Step 7: *Max. iter reahed? if yes move to next step, otherwise move to step 5*

Step 8: *Determining* $R_j(t)$ *to find the Euclideandistance separating the candidate position* $V_{j-GWO}(t+1)$ *from the present position* $V_{-j}(t)$ *by Eqn. (26)*

Step 9:

Determining Neighborhood $V_i(t)$ *using Eq. (27)*

Step 11:
For $m = 1$ *to D*

$$V_{j-DLH,m}(t+1) = V_{j,m}(t) + rand(0,1) \times \left(V_{n,m}(t) - V_{r,m}(t)\right)$$

End

Choosing Superior $(V_{j-GWO}(t+1), V_{j-DLH}(t+1))$

Upgrading Pop.

End

End

Return *to Global optima*

End

FIGURE 2. **I-GWOPSO pseudocode.**

57.75 $\$/MWh$. However, in comparison of I-GWOPSO with I_GWO and other optimization techniques it is concluded that I-GWO is more economical.

b: VOLTAGE PROFILE FOR 33-BUS DN

The voltage profile (VP) of DN is affected by DG installation at the various PF is represented in Figure 5. It is observed that a considerable increase in voltage has been attained when adding multiple DGs with OPF.

c: STATISTICAL ANALYSIS AND PERFORMANCE FOR PROPOSED METHOD

Statistical analysis is performed on minimum, average, and maximum RPL. It's conducted by ten runs for the traditional

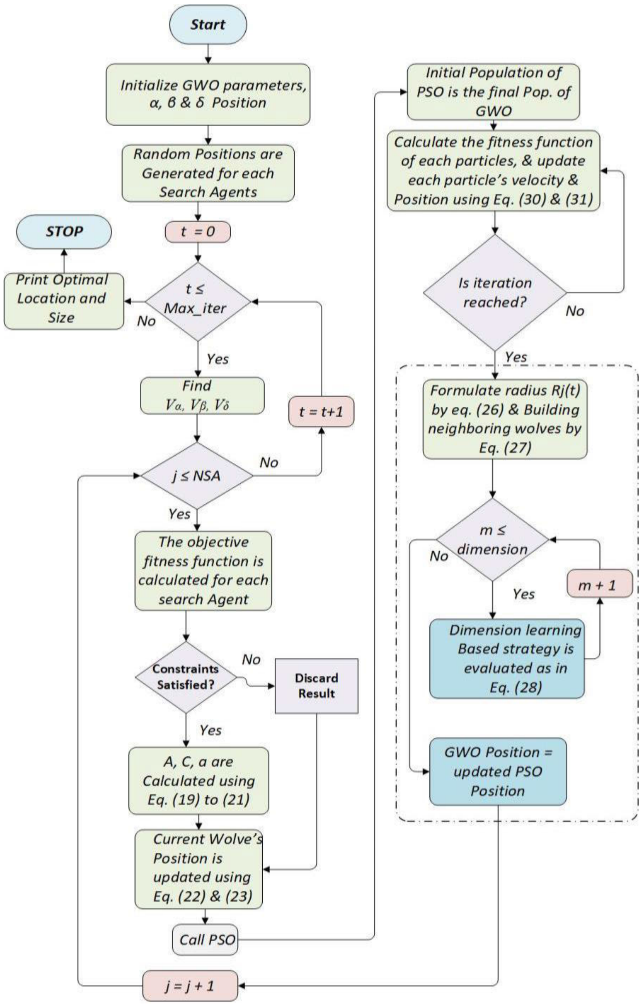

FIGURE 3. Flow chart of I-GWOPSO based approach.

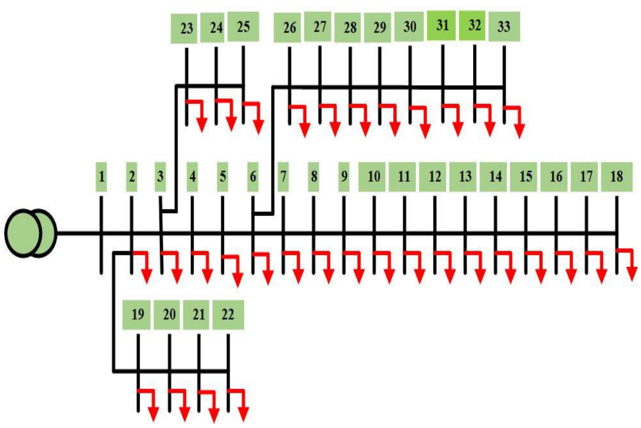

FIGURE 4. Single-line diagram of 33-bus test RDN.

I-GWO and proposed I-GWOPSO for the verification of proposed techniques.

The summary of this analysis is given in Table 5. The convergence characteristics of hybrid I-GWOPSO and conventional I-GWO are shown in Figures 6(a), 6(b), and 6(c) for different power factors (unity, 0.95 and optimal). It can be seen that the efficiency of hybrid I-GWOPSO is better than traditional I-GWO.

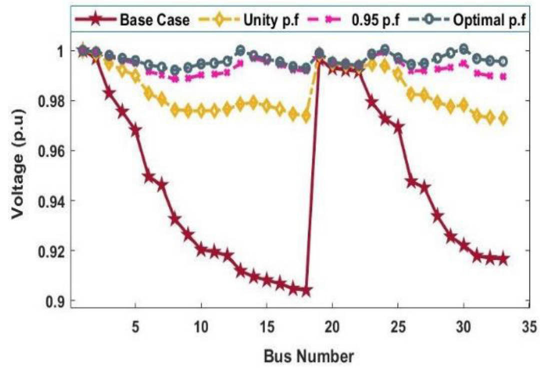

FIGURE 5. IEEE 33-bus DN voltage profile at various Cases for SOOP.

2) MULTI-OBJECTIVE ASSESSMENT FOR 33-BUS DN

In this scenario, a MOOP is solved to find the optimum sitting and sizing of the DG unit to reduce the PL, VD, and increase the VSI in the 33-bus network. The base case of the power flow result indicates that the PL is 210.05 kW, the voltage deviation equals 0.1328 p.u., and the VSI is 0.6697 p.u.

a: DG SITTING AND SIZING FOR 33-BUS DN

The proposed multi-objective I-GWOPSO is utilized to determine the ODGA at UPF and associated with those techniques which have been utilized for the similar dilemma as depicted in Table 6. It can be seen from the table the minimum PL is obtained from the multi-objective I-GWOPSO which is 76.6538 p.u., which is nearly equal to the I-GWO. Though, the VD attained by the hybrid I-GWOPSO is 0.0034526 p.u., which is smaller than 0.006514 p.u., from QOCSOS [4], and nearly equal to the 0.0033378 p.u., from I-GWO. Besides, I-GWOPSO obtains higher VSI which equals 0.9354 p.u., and that is superior to these values acquired by 0.9168 p.u., QOCSOS [4]. The operational cost of I-GWOPSO is much less than the others technique in this table.

Additionally, the sitting and sizing of DG with 0.95 LPF is executed, and the achieved findings are shown in Table 7. In this scenario, three of the OF such as PL, VD, and VSI attained by the advanced multi-objective I-GWOPSO which equal 30.0185 kW, 0.0002537 p.u., and 0.97045 p.u. correspondingly are improved than those achieved by I-GWO, QOSIMBO_Q [2], and MOIHHO [14].

However, compared to multi-objective I-GWO, the Multi-objective I-GWOPSO provides superior outcomes for the two objective functions. Furthermore, the results indicate a substantial decrease in the RPL compared to the UPF due to the inserted reactive power. Also, the operational cost of I-GWOPSO is less than the QOSIMBO_Q [2], MOIHHO [14], and I-GWO which is equal to 70.67 $\$/MWh$.

TABLE 2. ODGA for 33-bus network based on single-objective utilizing various optimization methods at UPF.

Method	Location	DG SIZE (MW)	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	210.05	0.1328	0.6697	1.4932	-
SFSA [17]	13, 24, 30	0.8020, 1.0920, 1.0537	72.785 (65.50%)	0.015099	0.8805	1.1357	59.204
QOSIMBO_Q [2]	24, 30, 13	1.0906, 1.0542, 0.8016	72.8 (65.34%)	0.0151	0.8805	1.1357	59.178
QOTLBO [18]	12, 24, 30	0.8808, 1.0592, 1.0592	74.101 (64.88%)	0.0160	0.8656	1.1552	60.234
CSCA[10]	13, 24, 30	0.8710, 1.0915, 0.9541	71.94 (64.5%)	-	-	-	58.582
QOCSOS [4]	13, 24, 30	0.8017, 1.0913, 1.0537	72.7869 (65.50%)	0.0150998	0.8805	1.1357	59.184
IHHO [14]	14, 24, 30	0.7755, 1.0808, 1.0667	72.79 (65.50%)	-	-	-	58.71
I-GWO [P]	14, 24, 30	0.758, 1.073, 1.099	**70.64 (66.369%)**	**0.0101**	0.8955	1.1167	58.85
I_GWOPSO [P]	14, 24, 30	0.786, 1.032, 1.094	**70.64 (66.369%)**	**0.0101**	**0.8956**	**1.1165**	**58.49**

TABLE 3. ODGA for IEEE 33-bus network based on single-objective utilizing various optimization methods at 0.95 LPF.

Method	Location	DG SIZE		PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
		MW	MVAR					
Base Case	-	-	-	210.05	0.1328	0.6697	1.4932	-
SFSA [17]	13, 24, 30	0.8306, 1.1256, 1.2396	0.2730, 0.3699, 0.4074	28.533 (86.48%)	0.002073	0.95298	1.0493	64.166
SIMBO_Q [2]	13, 24, 30	0.8875,1.0853, 1.3092	0.2917, 0.3567, 0.4303	29 (86.26%)	-	-	-	65.89
QOCSOS [4]	24, 13, 30	1.1246, 0.8301, 1.2396	0.3696, 0.2728, 0.4074	28.534 (86.48%)	0.002078	0.9530	1.0494	64.136
IHHO [14]	14, 24, 30	0.7938, 1.1324, 1.2578	0.2609, 0.3732, 0.4134	28.5 (86.49%)	-	-	-	**63.93**
QOSIMBO_Q [2]	13, 24, 30	0.8033,1.1239, 1.2398	0.2729, 0.3694, 0.4075	28.5 (86.49%)	0.0021	0.9530	1.0493	**63.59**
I-GWO [P]	24, 13, 30	1.083, 0.835, 1.252	0.354, 0.274, 0.410	27.77 (86.78%)	0.0017	**0.9578**	**1.0440**	**63.59**
I_GWOPSO [P]	14, 24, 30	0.8033, 1.1239, 1.2398	0.2729, 0.3694, 0.4075	**27.683 (86.82%)**	**0.0016**	0.9575	1.0443	**63.59**

TABLE 4. ODGA for IEEE 33-bus network based on single-objective utilizing various optimization methods at OPF.

Method	Location	DG SIZE			PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
		MW	MVAR	PF					
Base Case	-	-	-	-	210.05	0.1328	0.6697	1.4932	-
SOS [4]	13, 24, 30	0.7939,1.0695, 1.029	0.3732, 0.5180 1.0120	0.905, 0.90, 0.713	11.741 (94.44%)	0.00063	0.9688	1.0322	58.098
EA-OPF[31]	13, 24, 30	0.7942, 1.0699, 1.0302	0.3846, 0.5182, 1.0218	0.90, 0.90, 0.71	11.74 (94.44%)	-	-	-	58.136
QOCSOS [4]	13, 24, 30	0.7939, 1.0695, 1.029	0.3732, 0.5180, 1.0120	0.905, 0.90, 0.713	11.741 (94.44%)	0.00063	0.9688	1.0322	58.098
IHHO [14]	14, 24, 30	0.7618, 1.1419, 1.0138	0.3735, 0.5360, 1.0032	0.90, 0.91, 0.71	11.83 (94.39%)	-	-	-	58.6
I-GWO [P]	14, 24, 30	0.751, 1.070, 1.054	0.340, 0.526, 1.018	0.91, 0.85, 0.715	**11.635 (94.46%)**	0.0007537	**0.9810**	**1.0193**	**57.75**
I_GWOPSO [P]	13, 24, 30	0.793, 1.066, 1.038	0.374, 0.519, 1.000	0.87, 0.90, 0.72	11.744 (94.40%)	**0.0006281**	0.9807	1.0196	58.19

It can be observed from Table 8, the findings confirm the efficacy of the advanced multi-objective I-GWOPSO compared to the MOIHHO [14], MOHHO [14], and the I-GWO concerning the PL, VD, and CPDG which are 12.9135 kW, 0.0003271 p.u., and 62.57 $\$/MWh$. Pareto optimal solution is obtained at various operational PF by using multi-objective

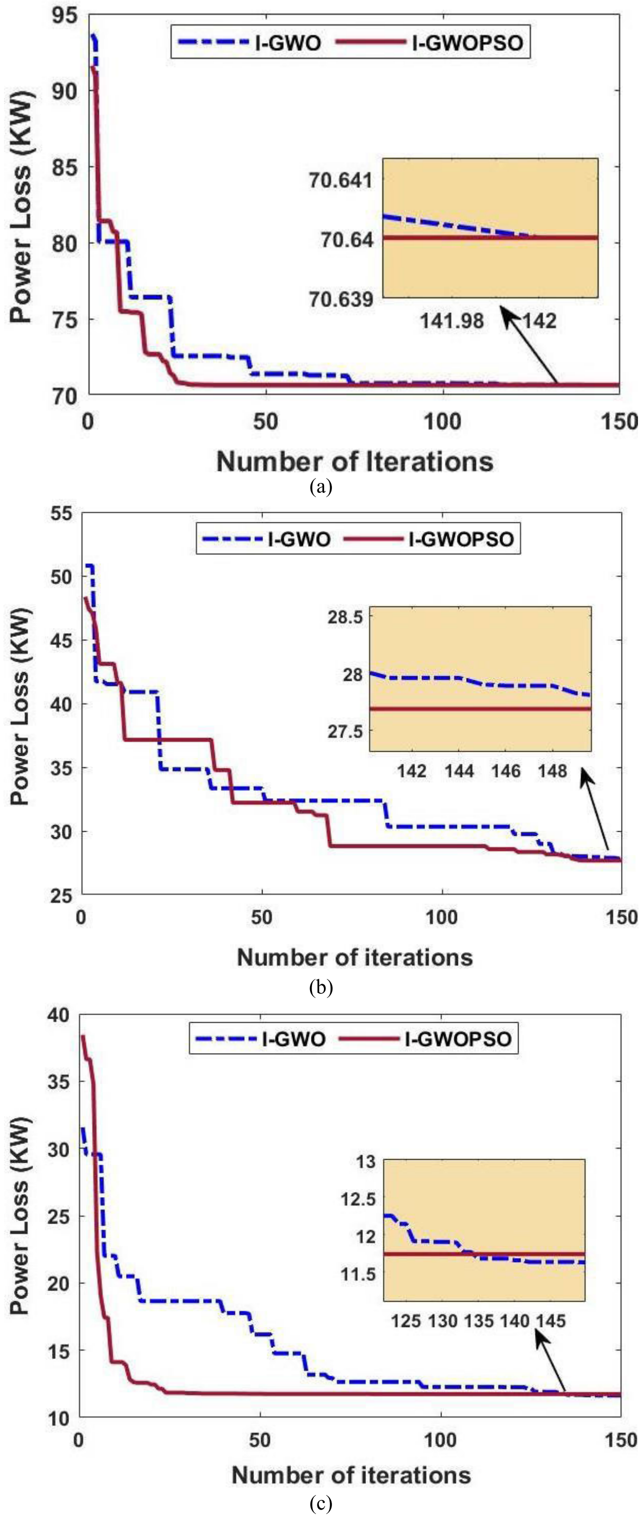

FIGURE 6. Convergence characteristics for IEEE 33-bus network of the I-GWO and I-GWOPSO at different operating power factors (a) UPF (b) 0.95 LPF and (c) OPF.

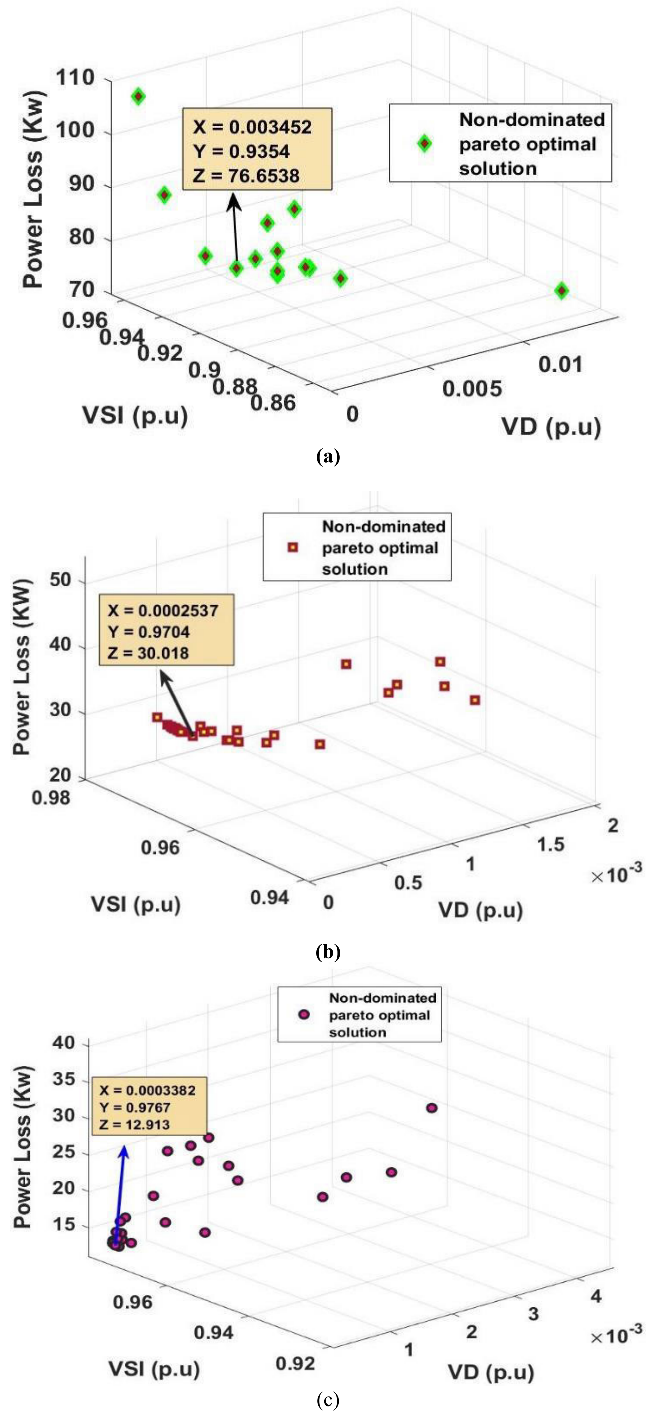

FIGURE 7. Non-dominated pareto optimal solutions obtained by multi-objective I-GWOPSO for IEEE 33-bus network including operation of DG at (a) UPF (b) 0.95 LPF (c) OPF.

I-GWOPSO which illustrates in figure 7. Moreover, the figures indicate the finest compromise solution achieved by the weighted-sum method including all nondominated solutions.

b: VOLTAGE PROFILE FOR 33-BUS DN

When the VD and VS are included as the objective functions for the multi-objective DG sizing and allocation, it is observed that the voltage profile of 33-bus has been improved. Figure 8 shows the effect of the DG at different PF for the MOP. It is observed that the voltage profile is

TABLE 5. Statistical analysis of IEEE 33-bus network for the I-GWO and I-GWOPSO for single-objective.

Method	Case	Min. RPL	Avg. RPL	Max. RPL
I-GWO	UPF	70.64	71.8038	72.91
I-GWOPSO		70.64	71.2043	72.682
I-GWO	0.95 LPF	27.77	28.1521	28.855
I-GWOPSO		27.683	29.0777	30.773
I-GWO	OPF	11.635	12.2389	14.859
I-GWOPSO		11.744	12.3062	14.047

significantly better than gained by the SOP operating at the same PF (see Figure 5).

B. IEEE 69-BUS NETWORK

In this subsection, IEEE 69-bus network is utilized to analyze the results of recommended technique and other optimization methods are reviewed. The single line diagram of 69-bus DN is shown in Figure 9. The whole data of this network are presented in [57].

1) SINGLE-OBJECTIVE ASSESSMENT FOR 69-BUS DN

The results of the power flow of the 69-bus network stated that the real PL is 224.59 kW, the reactive PL is 101.99 KVAR and the smallest voltage on 65 bus is 0.9102 p.u. Therefore, to reduce the PL and improve the performance of the DN, optimally allocate three DG units operating at various PF.

a: DG SITTING AND SIZING

In Table 9, a comparison is shown. This comparison is between the effectiveness of the proposed I-GWOPSO at UPF

TABLE 6. ODGA for 33-bus network based on multi-objective utilizing various optimization methods at UPF.

Method	Location	DG SIZE (MW)	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	210.05	0.1328	0.6697	1.4932	-
QOSIMBO_Q [2]	12, 24, 30	1.3465, 1.3043, 1.5000	97.1 (53.98%)	0.00088	0.9631	1.0383	83.266
IMOEHO [11]	12, 24, 30	1.0570, 1.0540, 1.7410	95.00 (53.13)	0.0008	**0.9673**	**1.0338**	77.29
QOCSOS [4]	24, 13, 30	1.1309, 0.9564, 1.2935	77.0414 (63.32%)	0.006514	0.9168	1.0908	67.866
I-DBEA [12]	13, 24, 30	1.0980, 1.0970, 1.7150	94.8514 (53.21%)	**0.0007**	0.9650	1.0363	78.54
MOIHHO [14]	14, 24, 31	1.223, 1.144, 1.290	92.25 (56.08%)	0.0019	0.9580	1.0438	73.39
I-GWO [P]	24, 30, 13	1.101, 1.330, 0.987	**75.6119 (64%)**	0.0033378	0.93716	1.0670	68.61
I_GWOPSO [P]	13, 24, 30	0.930, 0.929, 1.450	76.6538 (63.5%)	0.0034526	0.9354	1.0690	**66.43**

TABLE 7. ODGA for 33-bus network based on multi-objective utilizing various optimization methods at 0.95 LPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	210.05	0.1328	0.6697	1.4932	-
QOSIMBO_Q [2]	30, 24, 13	1.419, 1.392, 0.898	0.467, 0.458, 0.295	31.7 (84.9%)	0.0003	0.977	1.0235	74.43
MOIHHO [14]	13, 24, 30	0.924, 1.312, 1.356	0.304, 0.431, 0.446	30.6 (85.43%)	0.0004	**0.979**	**1.0214**	72.09
I-GWO [P]	24, 30, 13	1.197, 1.411, 0.948	0.391, 0.463, 0.311	30.4473 (85.5%)	0.0002642	0.972	1.0288	71.37
I_GWOPSO [P]	24, 30, 13	1.179, 1.412, 0.930	0.387, 0.464, 0.306	**30.0185 (85.7%)**	**0.0002537**	0.97045	1.0304	**70.67**

TABLE 8. ODGA for 33-bus network based on multi-objective utilizing various optimization methods at OPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	DG SIZE PF	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	-	210.05	0.1328	0.6697	1.4932	-
MOHHO [14]	12, 25, 30	0.951, 0.786, 1.381	0.516, 0.436, 0.809	0.88, 0.87, 0.86	18.8 (91.05%)	0.0005	**0.978**	**1.0224**	62.61
MOIHHO [14]	12, 24, 30	0.916, 1.088, 1.171	0.576, 0.386, 0.830	0.85, 0.94, 0.82	15.0 (92.85%)	**0.0003**	**0.978**	**1.0224**	63.75
I-GWO [P]	13, 24, 30	0.867, 1.124, 1.130	0.408, 0.539, 1.085	0.904, 0.83, 0.71	12.9174 (93.85%)	**0.0003238**	0.9766	1.0238	62.67
I_GWOPSO [P]	13, 24, 30	0.863, 1.116, 1.137	0.432, 0.517, 1.057	0.902, 0.83, 0.718	**12.9135 (93.85%)**	**0.0003271**	0.9767	1.0238	**62.57**

TABLE 9. ODGA for 69-bus network based on single-objective utilizing various optimization methods at UPF.

Method	Location	DG SIZE (MW)	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	224.59	0.0977	0.6897	1.4499	-
SFSA [17]	11, 18, 61	0.5273, 0.3805, 1.7198	69.428 (69.14%)	0.005185	0.9186	1.0886	52.802
QOSIMBO_Q [2]	9, 18, 61	0.8336, 0.4511, 1.5000	71 .0 (68.44%)	0.0071	0.8984	1.1131	55.944
CSCA-64 [10]	67, 61, 17	0.6525, 1.6758, 0.3659	70.07 (68.86%)	-	-	-	54.134
IHHO [14]	11, 17, 61	0.5272, 0.3825, 1.7194	69.41 (69.15%)	-	-	-	52.832
QOCSOS [4]	11, 18, 61	0.5269, 0.3803, 1.7190	69.4284 (69.14%)	0.005195	0.9186	1.0887	52.774
I-GWO [P]	21, 61, 11	0.298, 1.735, 0.511	**68.59 (69.4606%)**	**0.0044**	**0.9384**	**1.0656**	**51.13**
I_GWOPSO [P]	21, 61, 11	0.301, 1.738, 0.508	**68.59 (69.4606%)**	**0.0044**	**0.9384**	**1.0656**	**51.19**

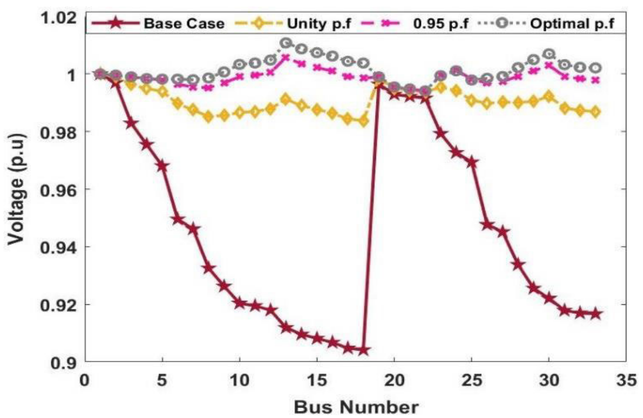

FIGURE 8. IEEE 33-bus network voltage profile at various Cases for MOOP.

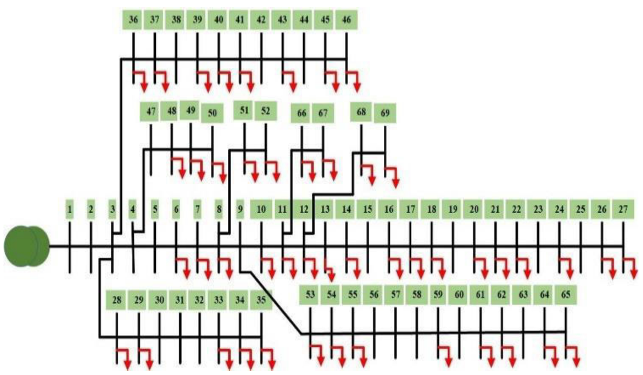

FIGURE 9. Single line diagram of 69-bus test RDN.

and other optimization techniques. The maximum PLR is achieved by the I-GWOPSO and I-GWO which is 68.4609%. The maximum PLR is achieved when three DG units are operating at 21, 61, and 11 with the real powers equal to 0.301MW, 1.738MW, and 0.508MW; respectively. The operational cost of DG for the proposed algorithm is less than the SFSA [17], QOSIMBO_Q [2], CSCA-64 [10], IHHO [14], QOCSOS [4], and nearly equals to I-GWO, i.e., 51.19 $\$/MWh$.

The proposed technique I-GWOPSO and other techniques result at 0.95 LPF as shown in Table 10. In the achieved results the PL is 20.73kW, PLR equals 90.77% which is nearly equal to IHHO [14]. The operational cost of DG is far better than QOCCSOS [4], IHHO [14] and the traditional I-GWO equals 55.91 $\$/MWh$. The effectiveness of I-GWOPSO doesn't change with the Change in PF in order to achieve an optimal value of PF. At the optimal value of PF, it provides the least PL and CPDG which is approximately equal to 4.26 kW and 51.15 $\$/MWh$ and slightly less than the I-GWO as depicted in Table 11. Moreover, the optimal value of PF is crucial in reducing the PL by 98.1% from the base case.

b: VOLTAGE PROFILE FOR 69-BUS DN

Figure 10 shows that with the reduction of active PL of 69 bus its voltage profile has been significantly improved. It is noted the voltage profile has been improved at the optimal value of PF. Reactive and active power has been injected in a balance at 0.95 PF for the identical goals.

c: STATISTICAL ANALYSIS AND PERFORMANCE FOR PROPOSED METHODS

Ten iterations are performed by the I-GWO and I-GWOPSO and the minimum, average, and maximum RPL are attained in Table 12 to represent the robustness of the proposed I-GWOPSO technique. The attained findings affirm the capability of the I-GWOPSO in achieving the optimum result more than the I-GWO and this can be perceptible from the convergence characteristics exhibited in Figure 11.

2) MULTI-OBJECTIVE ASSESSMENT FOR 69-BUS DN

Similarly, the MOP is employed for the allotment of the DG into the IEEE 69-bus network to optimize the PL, VD, and VSI where the base case values of these OF are 224.59 kW, 0.0977 p.u., and 0.6897 p.u.

TABLE 10. ODGA for 69-bus network based on single-objective utilizing various optimization methods at 0.95 LPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	224.59	0.0977	0.6897	1.4499	-
QOCSOS [4]	11, 61, 18	0.5597, 1.878, 0.417	0.1839, 0.6172, 0.137	20.7144 (90.79%)	**0.0002721**	0.9772	1.0234	57.344
IHHO [14]	11, 18, 61	0.552, 0.419, 1.879	0.1817, 0.1379, 0.6177	**20.71 (90.8)**	-	-	-	57.25
I-GWO [P]	21, 11, 61	0.322, 0.618, 1.877	0.106, 0.203, 0.617	20.94 (90.67%)	0.000399	0.9815	1.018	56.59
I_GWOPSO [P]	11, 61, 21	0. 562, 1.880, 0. 341	0.185, 0.618, 0.112	20.73 (90.77%)	0.0004147	**0.9815**	**1.018**	**55.91**

TABLE 11. ODGA for 69-bus network based on single-objective utilizing various optimization methods at OPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	DG SIZE PF	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	-	224.59	0.0977	0.6897	1.4499	-
SFSA [17]	11, 21, 61	0.5669, 0.3360, 1.6752	0.3970, 0.2227, 1.1788	0.819, 0.833, 0.818	4.298 (98.09%)	**0.000116**	0.9773	1.0233	51.812
QOCSOS [4]	11, 61, 18	0.4944, 1.6746, 0.3789	0.3541, 1.1950, 0.2517	0.813, 0.814, 0.836	4.2674 (98.10%)	0.0001286	0.9773	1.0233	51.208
PSO [38]	11, 18, 61	0.498, 0.3726, 1.6686	0.3347, 0.2698, 1.2081	0.83, 0.81, 0.81	4.61 (97.7%)	-	-	-	51.034
IHHO [14]	11, 18, 61	0.4562, 0.3892, 1.7148	0.2844, 0.2756, 1.1543	0.85, 0.82, 0.83	4.44 (98.0%)	-	-	-	51.454
I-GWO [P]	21, 61, 11	0. 302, 1.622, 0. 531	0.215, 1.169, 0.391	0.85, 0.82, 0.81	4.29 (98.08%)	0.0007568	0.9815	1.0188	**49.35**
I_GWOPSO [P]	11, 61, 21	0.541, 1.696, 0.308	0.334, 1.184, 0.222	0.85, 0.82, 0.81	**4.26 (98.1%)**	0.000203	**0.9815**	**1.0188**	51.15

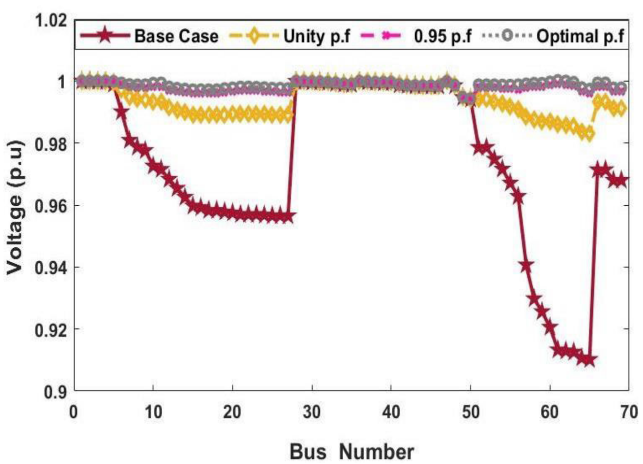

FIGURE 10. IEEE 69-bus DN voltage profile at various cases for SOOP.

a: DG SITTING AND SIZING FOR 69-BUS DN

The ODGA at UPF using various optimization approaches is organized in Table 13. In this scenario, multi-objective I-GWOPSO attains minimum PL which is 71.5889 kW (PLR 68.12%), and minimum VD 0.00061898 p.u., which is less than MOSCA [10], SFSA [17], GA/PSO [38] and I-GWO and highest VSI achieved by the MOCSCA [10] which is 0.9798. The operational cost obtained by I-GWOPSO is 59.97 $\$/MWh$ which is less than the other techniques provide in table.

TABLE 12. Statistical analysis of IEEE 69-bus network for the I-GWO and I-GWOPSO for sigle -objective.

Method	Case	Min. RPL	Avg. RPL	Max. RPL
I-GWO	UPF	68.59	68.819	69.35
I-GWOPSO		68.59	68.7675	69.2
I-GWO	0.95 LPF	20.94	21.6516	23.21
I-GWOPSO		20.73	21.4191	22.44
I-GWO	OPF	4.29	4.9333	5.85
I-GWOPSO		4.26	4.7591	5.74

In Table 14, the outcome of the DG operating at 0.95 LPF is presented and confirmed that the multi-objective I-GWOPSO provides the finest results in two of the OF (PL, and VD) compared to the other technique which confirms the ability of the multi-objective I-GWOPSO. Moreover, MOIHHO [14] gives maximum VSI which is 0.980 p.u. The real power loss obtained by I-GWOPSO is 20.7046 kW and VD is

TABLE 13. ODGA for 69-bus network based on multi-objective utilizing various optimization methods at UPF.

Method	Location	DG SIZE (MW)	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	224.59	0.0977	0.6897	1.4499	-
GA/PSO[38]	21, 61, 63	0.9100, 1.193, 0.8850	81.1 (63.89%)	0.0031	0.9768	1.0238	60.01
SFSA [17]	11, 19, 61	0.5703, 0.4661, 1.9674	72.445 (67.743%)	0.001434	0.9537	1.0485	60.326
QOCSOS [4]	11, 20, 61	0.6271, 0.4352, 1.9469	72.1284 (67.94%)	0.001548	0.9516	1.0508	60.434
MOCSCA[10]	21, 61, 67	0.4531, 2.1907, 0.6763	79.69 (64.57%)	**0.0002**	**0.9798**	**1.0206**	66.652
I-GWO [P]	11, 61, 21	0.630, 2.000, 0.318	71.6402 (68.10%)	0.00075723	0.96971	1.031	**59.21**
I_GWOPSO [P]	11, 61, 21	0.676, 1.970, 0.340	**71.5889 (68.12%)**	0.00061898	0.96706	1.034	59.97

TABLE 14. ODGA for 69-bus network based on multi-objective utilizing various optimization methods at 0.95 LPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	224.59	0.0977	0.6897	1.4499	-
SIMBO_Q [2]	11, 59, 62	0.953, 1.002, 1.1210	0.313, 0.329, 0.369	29.7 (86.78%)	0.0003	0.977	1.0235	61.77
QOSIMBO_Q [2]	14, 60, 61	0.828, 0.5339, 1.5000	0.2720, 0.1755, 0.4930	25.7 (88.56%)	0.0002	0.9771	0.9771	57.488
MOIHHO [14]	13, 61, 63	1.038, 0.799, 1.229	0.341, 0.263, 0.404	28.9 (87.13%)	0.0003	0.980	1.0204	61.57
QOCSOS [4]	18, 11, 61	0.4236, 0.579, 1.900	0.1392, 0.1905, 0.62449	20.7689 (90.75%)	**0.0001602**	0.9772	1.0234	58.3
I-GWO [P]	21, 11, 61	0.335, 0.638, 1.872	0.110, 0.210, 0.615	20.97 (90.66%)	0.0002	**0.9887**	**1.0114**	57.15
I_GWOPSO [P]	61, 11, 21	1.891, 0.586, 0.337	0.622, 0.192, 0.111	**20.7046 (90.78%)**	**0.0001626**	0.97725	1.0232	**56.53**

TABLE 15. ODGA for 69-bus network based on multi-objective utilizing various optimization methods at OPF.

Method	Location	DG SIZE MW	DG SIZE MVAR	DG SIZE PF	PL (KW) (PLR%)	VD (p.u)	Min. VSI (p.u)	Max. VSI^{-1} (p.u)	CPDG ($/MWh)
Base Case	-	-	-	-	224.59	0.0977	0.6897	1.4499	-
MOIHHO [14]	13, 49, 62	1.064, 1.235, 1.610	0.779, 0.403, 1.181	0.81, 0.95, 0.81	13.9 (93.81%)	0.0005	**0.991**	**1.009**	78.43
I-GWO [P]	19, 61, 11	0.325, 1.700, 0.655	0.218, 1.052, 0.414	0.83, 0.85, 0.84	5.3273 (97.628%)	0.0001311	0.9773	1.0232	53.85
I_GWOPSO [P]	61, 11, 21	1.671, 0.688, 0.298	1.099, 0.516, 0.216	0.82, 0.80, 0.81	**4.8687 (97.83%)**	**0.000117**	0.9774	1.0231	**53.39**

0.0001626 p.u., which is less than the MOIHHO [14], QOSIMBO_Q [2], and I-GWO. Hence, the proposed technique provides the minimum operational cost which is 56.53 $\$/MWh$.

Lastly, Table 15 provides ODGA at the OPF where the conclusion of the multi-objective I-GWOPSO is compared with multi-objective I-GWO. It can be observed that a significant improvement in the PL, VD, and CPDG

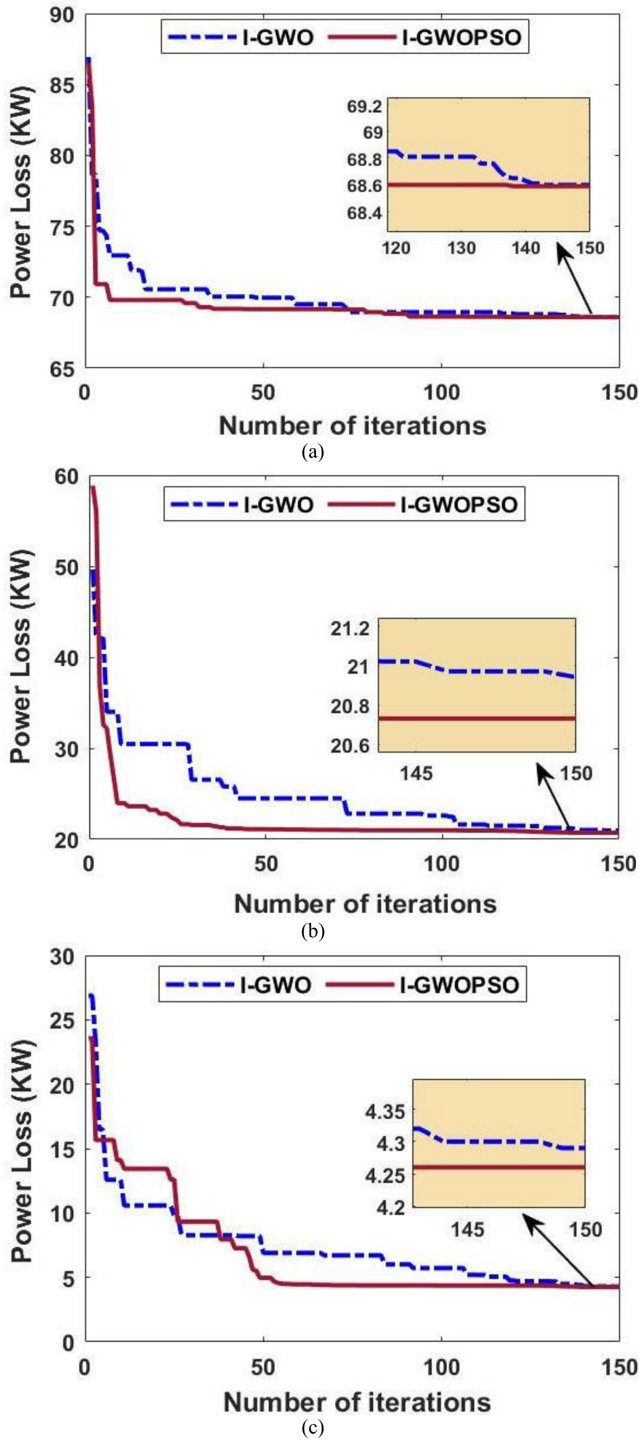

FIGURE 11. Convergence characteristics of the I-GWO and I-GWOPSO for IEEE 69-bus network at different operating power factors (a) UPF (b) 0.95 LPF and (c) OPF.

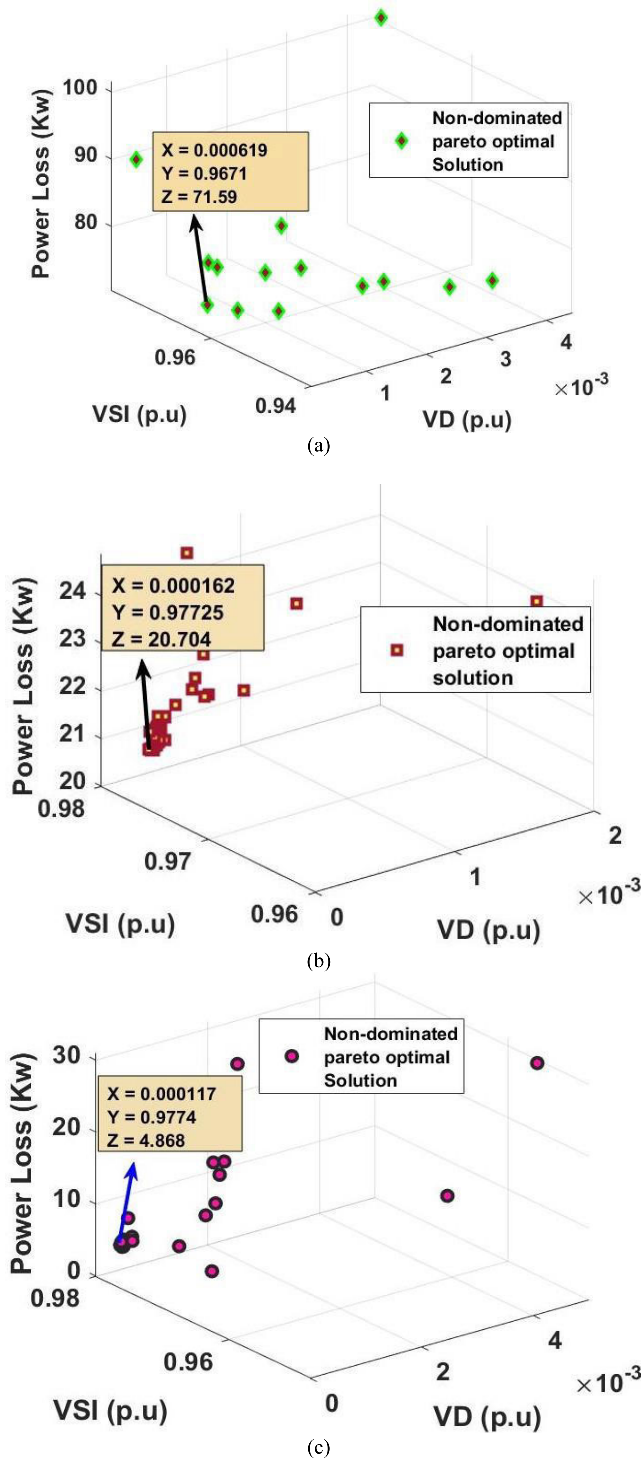

FIGURE 12. Non-dominated pareto optimal solutions obtained by multi-objective I-GWOPSO for IEEE 69-bus network including operation of DG at (a) UPF (b) 0.95 LPF (c) OPF.

attained by I-GWOPSO and that approximates 4.8687 kW, 0.000117 p.u., and 53.39 $/*MWh* which indicates that the DN develops more balanced can tolerate the unusual circumstances. While MOIHHO [14] provides maximum VSI which is 0.991 p.u. Figure 12 shows that the Pareto optimal solution at various operating PF anyway the finest compromise result achieved by the weighted-sum method.

b: VOLTAGE PROFILE FOR 69-BUS DN

Figure 13. demonstrates the voltage profile of the IEEE 69-bus network in case of resolving the multi-objective DG sitting and sizing problem at different operating p.f. Considerable progress is obvious in the figure in the

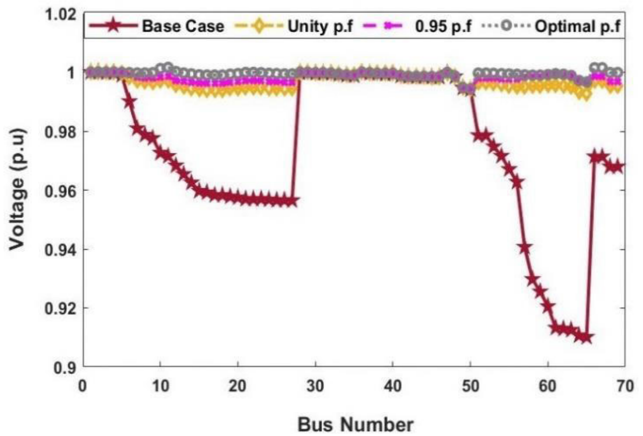

FIGURE 13. IEEE 69-bus DN voltage profile at various cases for MOOP.

three scenarios of the p.f as an outcome of including the VD and VSI.

VI. CONCLUSION

In this paper, the problems associated with optimum DG allocation are framed with the single and multiple objective functions. The single objective function includes the minimization of real power loss. To formulate the multi-objective problems, power loss, voltage deviation, and voltage stability index are integrated into a single objective utilizing weights. The proposed I-GWOPSO in this study provides an effective solution for optimized DG allocation in RDN. The effectiveness of the proposed I-GWOPSO hybrid algorithm is evaluated across 33-bus and 69-bus test radial distribution networks. The operation of distributed generators is also performed by regulating various values of power factors. The obtained results at different PF (unity, fixed, and optimal pf) showed a clear reduction in real power loss, the least deviation in voltage stability, and an improved voltage stability index. As a SOF, the DG operating at OPF on 33 and 69-bus RDN has observed a significant reduction in PL by 94.40% and 98.1% respectively. For MOOP in 33-bus test DN, the DG operating at OPF has resulted from more reduction in PL by 93.85%. Also, VD is reduced to 99.75% of the initial value and VSI is significantly improved i.e., close to unity. Furthermore, in MOOP in 69-bus test DN, PL is reduced by 97.93%, VD reduced to 99.88% of its initial value and VSI is significantly improved, respectively. The comparative study of results obtained from I-GWOPSO with reported works shows that the proposed approach outperforms in several aspects. Also, the cost of active power generation from respective DGs is the least as compared to reported findings. Hence validating its use as a planning tool for future studies. Further I-GWOPSO is more efficient than I-GWO in the accuracy and speed of convergence. Conclusively, I-GWOPSO can be a more efficient, economical, and optimal solution for the DG allocation in RDNs.

In future work, the proposed work will be extended to new concepts like microgrid planning and microgrid scheduling with renewable resources and variable loads across multiple planning horizons.

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