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A Novel Multiobjective Hybrid Technique for Siting and Sizing of Distributed Generation and Capacitor Banks in Radial Distribution Systems

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Abstract: Distributed generation (DG) and capacitor bank (CB) allocation in distribution systems (DS) has the potential to enhance the overall system performance of radial distribution systems (RDS) using a multiobjective optimization technique. The benefits of CB and DG injection in the RDS greatly depend on selecting a suitable number of CBs/DGs and their volume along with the finest location. This work proposes applying a hybrid enhanced grey wolf optimizer and particle swarm optimization (EGWO-PSO) algorithm for optimal placement and sizing of DGs and CBs. EGWO is a metaheuristic optimization technique stimulated by grey wolves. On the other hand, PSO is a swarm-based metaheuristic optimization algorithm that finds the optimal solution to a problem through the movement of the particles. The advantages of both techniques are utilized to acquire mutual benefits, i.e., the exploration ability of the EGWO and the exploitation ability of the PSO. The proposed hybrid method has a high convergence speed and is not trapped in local optimal. Using this hybrid method, technical, economic, and environmental advantages are enhanced using multiobjective functions (MOF) such as minimizing active power losses, voltage deviation index (VDI), the total cost of electrical energy, and total emissions from generation sources and enhancing the voltage stability index (VSI). Six different operational cases are considered and carried out on two standard distribution systems, namely, IEEE 33- and 69-bus RDSs, to demonstrate the proposed scheme's effectiveness extensively. The simulated results are compared with existing optimization algorithms. From the obtained results, it is observed that the proposed EGWO-PSO gives distinguished enhancements in multiobjective optimization of different conflicting objective functions and high-level performance with global optimal values.

Keywords: capacitor bank (CB); distributed generation (DG); enhanced grey wolf optimizer and particle swarm optimization (EGWO-PSO); power loss; voltage deviation index (VDI); voltage stability index (VSI)

1. Introduction

1.1. Background

The growing consumption of electric energy mainly produced by burning fossil fuels leads to various environmental and financial issues [1]. The penetration of distributed generations (DGs) in distribution systems (DS) takes the upper hand for a few decades to overcome such issues through various feasible resources. However, DS has the largest

portion of the power loss about 70%, because of its low voltage level with high current carrying configuration [2,3]. Further, voltage profile deviation and high power losses are the major issues in distribution networks due to the high value of R/X ratio, load expansion, and inductive nature of loads [4,5]. Therefore, power loss reduction is one of the most interesting and important matters in power system studies [1]. In this regard, one of the most cost-effective and economical solutions to solve this problem is considered for this study, i.e., DG resource placement [1,2].

The installation and integration of DGs in distribution systems can offer numerous technical, economic, and environmental advantages [3,6]. It can be achieved by selecting the optimal site and size of DG units. However, an unsuitable installation of DG units leads to an increase in power losses due to reverse power flow, voltage rise beyond the secure limit, a complication of protective relay coordination, voltage stability, and power quality issues. Moreover, inadequate DG sizes could not fulfill their potentials and redundant allocation, resulting in huge investment costs. Hence, the optimal placement and size of DG units in the radial distribution power networks have been considered a global challenge for electric utilities [7–9].

Furthermore, optimal size and placement of capacitor banks (CBs) in the distribution system need static or switchable capacitors for reactive power compensation at strategically identified locations in the distribution system that resolves the power quality issues. Additionally, it provides numerous technical and economic advantages such as the reduction in power loss, improved load-bus voltage, improved power factor, and reduced reactive power demand from the supply side [4,5,10]. Therefore, efficient and optimal planning for reactive power compensation is mandatory to cope with the ever-growing energy demand and technical and economic issues of distribution networks [4,6,10].

1.2. Literature Survey

Several strategies are adapted for optimal allocation problems, such as classical, analytical, metaheuristic, and heuristic applications with single or multiple objective functions [11,12]. Among these methods, heuristic methods are highly applied for this application because it is based on engineering experience. The metaheuristic and heuristic methods outnumber the analytical and classical approaches due to their advanced computation procedures. The most commonly used metaheuristic techniques are as follows: genetic algorithm (GA), particle swarm optimization (PSO), harmony search (HS), artificial bee colony (ABC), Big Bang–Big Crunch (BBBC) algorithm, grey wolf optimizer (GWO), teaching learning-based optimization (TLBO) algorithm, backtracking search algorithm (BSA), and krill herd algorithm (KHA). They have been widely applied to optimize the CB and DG planning studies with satisfactory results and less computational efforts. However, these methods require long-running time due to their iterative solving process and they need a tuning procedure for a great number of parameters. Further, they show an unstable performance depending on the problem type and the designers' experience [5,9,11]. Considering all these, a holistic review of several state-of-the-art works of literature related to the site and size of DGs and CBs in the radial distribution systems (RDS) is briefly presented in Table 1 for ready reference to the readers [9,13,14].

Table 1. Summary of existing works related to the optimal allocation of distributed generations (DGs) and capacitor banks (CBs).

Ref. No.	Year	Objective Function	Optimization Method	Installation		Inferences	Research Gap (Technical Limitations/ Drawbacks)
				DG	CB		
[15]	2016	Minimizing network power losses, improving voltage regulation, and increasing the voltage stability	GA-IWD	✓		High-quality solution, a linear increase of computational time	Only active power injection considered, DG investment cost ignored
[16]	2016	Minimizing the total cost	FPA		✓	Net saving maximized	Load uncertainties ignored
[17]	2016	Minimizing power losses	Hybrid HSA-PABC	✓	✓	Enhanced solution accuracy and rate of convergence	Economic evaluations ignored
[18]	2016	Minimizing total real power loss	Analytical + PSO	✓		Improved voltage profile and power factor	No voltage stability assessment
[2]	2016	Minimizing total cost of losses	IMDE	✓	✓	Improved performance for loss reduction	Investment cost ignored
[11]	2017	Minimizing total real power losses	HGWO	✓		Best performance without tuning of the algorithm	No reliability and uncertainties of load considered
[19]	2017	Reducing power losses and improving voltage profile and VSI	ALO	✓		Robust algorithm and improved performance	Only PV and wind turbine DGs considered
[20]	2017	Minimizing the cost of total power losses	PSO		✓	Near-optimal solution with enhanced performance	Not robust in the larger system
[21]	2017	Minimization of power loss, and voltage deviation, and voltage stability improvement	MOPSO	✓	✓	Increased search capability and improved performance	Longer computation time and only one test system is considered
[6]	2018	Minimizing distribution power losses, power generation costs, and generation units' emissions, and improving voltage profile and voltage stability index	WCA	✓	✓	Good convergence characteristics, substantial technical, economic, and environmental benefits	Reactive power injection of DGs alone case not considered and the multiobjective for two cases only
[10]	2018	Minimizing generation cost, power loss, and voltage deviation	IGWO	✓	✓	Enhanced convergence rate and quality of the solution	Power factor constraints and voltage stability ignored

Table 1. Cont.

Ref. No.	Year	Objective Function	Optimization Method	Installation		Inferences	Research Gap (Technical Limitations/ Drawbacks)
				DG	CB		
[22]	2018	Minimizing power loss and operating cost, and improving voltage profile	WOA	✓		More effective in the multiobjective placement of DGs	Power factor constraints ignored
[23]	2018	Minimizing total net present cost	PSO	✓		Improved power system performance	Only one test system considered
[12]	2018	Minimizing power losses	Hybrid GWO-PSO	✓		Fast, small number of iterations and optimal solution	Power factor constraints ignored, no voltage stability assessment
[1]	2019	Minimizing power losses and improving reliability	MOHTLBOGWO	✓		Better convergence speed and not trapped at all in local optimal	Only PV and wind sources considered
[5]	2019	Minimizing power loss and improve voltage profile	New heuristic	✓	✓	Robust, fast, and easy to implement	Loosened network constraints
[24]	2019	Minimization of active power, reactive power, and real power loss. Improvement of branch current capacity, voltage profile, and voltage stability	Fuzzy GA	✓	✓	Improved power system performance	Economic considerations are ignored
[4]	2020	Minimizing annual operating cost	PBOA		✓	Improved performance and fast convergence	Power factor constraints ignored
[8]	2020	Minimizing total real power losses	ALO	✓		Lesser number of iterations and CPU time	No voltage stability assessment, only PV and wind sources studied
[13]	2020	Minimizing active and reactive power losses, and total voltage deviation, and improving voltage stability index	Cf-PSO	✓	✓	Stable and steady convergence	Reactive power injection of DGs not considered

Table 1. Cont.

Ref. No.	Year	Objective Function	Optimization Method	Installation		Inferences	Research Gap (Technical Limitations/ Drawbacks)
				DG	CB		
[25]	2020	Minimizing power loss and improving voltage stability	BPSO-SLFA	✓		Enhanced reliability of results	Economic and environmental concerns ignored
[26]	2020	Minimizing power losses, energy cost, and pollutant emissions, and enhancing voltage profile and VSI	MODE	✓		Excellent convergence characteristics and enhanced distribution system performance	Only two cases of DGs studied
[27]	2020	Minimizing power losses and enhancing voltage profile	Hybrid CWOA+LSF	✓	✓	Better performance	Fixed DG number, only one test system considered
[7]	Early Access	Minimizing real power losses and voltage deviation, and maximizing voltage stability index	I-DBEA	✓		Solving effectively nonlinear and mixed-integer variable problems, and is independent of local trappings and penalty factor	Power factor constraint ignored; economic evaluations ignored
[28]	2020	Minimization of power losses, power generation costs, and generation units' emissions. Enhancement of voltage profile.	SSA	✓	✓	Improved system parameters and reduction in energy losses with condensed cost and emission	Voltage stability is not considered and only one test system is demonstrated.
[29]	2021	Minimizing the cost of energy losses, peak power losses, and the capacitor	SHO	✓	✓	High convergence speed and more annual net savings	Only one test system is considered

1.3. Research Gap

In total, the following limitations can be found in the existing methods:

- Some approaches consider only the active power injection, i.e., DG with unity power factor.
- Few methodologies are appropriate for the allocation of a single DG unit.
- Locations of DGs and/or CBs are fixed in some cases.
- Environmental concerns are not considered.
- Few network constraints are unnoticed.
- Economic considerations are ignored in some articles.
- The computational time of some methods is so high.
- The results found by some presented methods are not optimal.

Given these limitations, there is a need to increase the distribution system parameters using DGs further. Therefore, a new multiobjective hybrid optimization is proposed using enhanced grey wolf optimizer (EGWO) and particle swarm optimization (PSO), i.e., EGWO-PSO, by utilizing the benefits of both methods. It is expected that this hybridization eliminates the disadvantages and emphasizes the advantages of both techniques simultaneously and may prove its suitability for the large distribution system to reach the optimal solution. The observed results will be compared with existing outcomes extensively to validate the effectiveness of the proposed technique [12].

1.4. Paper Contributions

This work proposes hybrid EGWO-PSO, a hybrid metaheuristic technique to attain the optimal DGs/CBs placement and sizing in RDSs. It targets to realize the following benefits:

- Demonstrating the penetration of DGs and CBs to improve the technical, environmental, and economic concerns of RDS by satisfying three technical objectives, that is, power loss reduction, voltage profile improvement, and stability index enhancement
- Considering two economic issues, namely, minimizing the costs of generated power and CBs, and reducing the emission as an environmental value for realizing the clean operation
- Considering six operational cases of DGs/CBs with multiobjective optimization to discover the technical, economic, and environmental impacts through the proposed EGWO-PSO method and comparison with other techniques
- Applying the proposed method to standard radial distribution systems

1.5. Paper Organization

This work is structured as follows: Section 2 describes the problem formulation for the proposed system. Section 3 demonstrates the proposed hybrid optimization algorithm for the optimal sizing and siting of CB and DGs. Section 4 discusses different test systems and cases to analyze the effectiveness of the proposed technique. Section 5 discusses the results for various test cases and systems in detail and Section 6 presents the conclusion of this article based on the observed results.

2. Problem Formulation

The problem formulation involves finding the optimum sizing and location of DGs and CBs using multiobjective functions (MOF) while guaranteeing the operational constraints such as equality and inequality constraints as follows.

2.1. Objective Functions

The proposed scheme aims to accomplish three key objective functions: technical, economic, and environmental.

2.1.1. Technical Objective Functions

- In the distribution network, the power losses are related to the line current. The line currents can be reduced with the proper placement of CBs and DGs. Minimization of the distribution power losses (of_1) can be expressed [6] using Equation (1).

$$of_1 = \min(\sum_{i=1}^{nL} |I_i|^2 * R_i), \quad (1)$$

- To ensure quality supply voltage, one of the effective ways is to minimize the voltage deviation index (VDI). It is a measure of the deviation of the voltage at all the load buses in the system. Minimization of VDI (of_2) can be described as follows [7]:

$$of_2 = \min(VDI) = \min(\sum_{i=1}^{NPQ} (V_i - 1)^2), \quad (2)$$

- An Optimal allocation of DGs and CBs in the distribution network enhances the voltage stability index (VSI) in the network. An improved VSI of the distribution means that the voltage profile of the bus is maintained within an acceptable limit over the variable loading scenarios. Maximization of voltage stability index (of_3) can be expressed as follows [6,7]:

$$of_3 = \max(VSI), \quad (3)$$

$$VSI(t) = \{ |V_i|^4 - 4(P_j X_{ij} - Q_j R_{ij})^2 - 4(P_j R_{ij} + Q_j X_{ij}) |V_i|^2 \}. \quad (4)$$

For stable distribution system operation with “n” number of buses, $VSI(t) \geq 0$, for $t = 2, 3, \dots, n$.

2.1.2. Economic Objective Function

It aims to minimize the power generation costs that can be expressed using the following Equations [6]:

$$of_4 = \min(\sum_{i=1}^{nDG} (C_{DG_i}) + C_{Grid} + C_{CB}), \quad (5)$$

where generation cost for each DG unit (C_{DG_i}) can be calculated as

$$C_{DG_i} = a + b, \quad (6)$$

Then the fixed generation cost coefficient (a) and variable generation cost coefficient (b) can be calculated as follows:

$$a = \frac{DG \text{ Capital cost } (\$/kW) * DG \text{ capacity } (kW) * G_r}{\text{life time (year)} * 8760 * LF}, \quad (7)$$

$$b = (DG \text{ Fuel cost } (\$/kWh) + DG \text{ O \& M cost } (\$/kWh)) * P_{DG_i}, \quad (8)$$

Further, the generated cost of the substation (C_{Grid}) can be calculated as follows:

$$C_{Grid} = P_{gGrid} * P_{rGrid}, \quad (9)$$

Further, the Investment cost (C_{CB}) of the capacitor bank can be calculated using Equation (10). The various components of C_{CB} are installation cost (e_i), purchase cost (C_{Ci}), and the actual lifetime of the CB.

$$C_{CB} = \frac{\sum_{i=1}^{NC} (e_i + C_{Ci} |Q_{Ci}|)}{\text{life time (year)} * 8760}. \quad (10)$$

2.1.3. Environmental Objective Function

It aims to minimize the generation unit emissions (of_5) because power generation produces the most severe pollutants such as carbon dioxide (CO_2), sulfur dioxide (SO_2),

and nitrogen oxides (NO_x). The mathematical formulation of this function can be expressed as follows [6]:

$$\text{of}_5 = \min \left(\sum_{i=1}^{N_{PV}} (E_{PV_i}) + \sum_{i=1}^{N_{WT}} (E_{WT_i}) + \sum_{i=1}^{N_{GT}} (E_{GT_i}) + E_{\text{Grid}} \right), \quad (11)$$

$$E_{PV_i} = (\text{CO}_2^{\text{PV}} + \text{NO}_x^{\text{PV}} + \text{SO}_2^{\text{PV}}) * P_{PV_i}, \quad (12)$$

$$E_{WT_i} = (\text{CO}_2^{\text{WT}} + \text{NO}_x^{\text{WT}} + \text{SO}_2^{\text{WT}}) * P_{WT_i}, \quad (13)$$

$$E_{GT_i} = (\text{CO}_2^{\text{GT}} + \text{NO}_x^{\text{GT}} + \text{SO}_2^{\text{GT}}) * P_{GT_i}, \quad (14)$$

$$E_{\text{Grid}} = (\text{CO}_2^{\text{Grid}} + \text{NO}_x^{\text{Grid}} + \text{SO}_2^{\text{Grid}}) * P_{\text{gGrid}}. \quad (15)$$

2.2. Constraints

The proposed objective functions formulated in Section 2.1 are subjected to the following constraints.

2.2.1. Equality Constraints:

The constraints for power balance requirements are as follows [8,15]:

$$P_s + \sum_{i=1}^{N_{DG}} P_{DG_i} = \sum_{j=1}^{nL} P_{\text{Loss}_j} + \sum_{i=1}^n P_{di}, \quad (16)$$

$$Q_s + \sum_{i=1}^{N_{DG}} Q_{DG_i} + \sum_{i=1}^{N_C} Q_{Ci} = \sum_{j=1}^{nL} Q_{\text{Loss}_j} + \sum_{i=1}^n Q_{di}. \quad (17)$$

2.2.2. Inequality Constraints

- Generation operating constraints [6]:

$$P_{DG_i}^{\min} \leq P_{DG_i} \leq P_{DG_i}^{\max}, \quad (18)$$

$$Q_{DG_i}^{\min} \leq Q_{DG_i} \leq Q_{DG_i}^{\max}. \quad (19)$$

- DGs capacity constraint [30]:

$$\sum_{i=1}^{N_{DG}} P_{DG_i} \leq P_D. \quad (20)$$

- Reactive power resources constraints:

The injection of reactive power by CB and DG is controlled by minimum and maximum limits [10] as given in Equation (21):

$$Q_{Ri}^{\min} \leq Q_{Ri} \leq Q_{di}, i = 1 \dots N_R. \quad (21)$$

- Bus voltage constraints:

The voltage constraints [31] are represented as follows:

$$V_{Li}^{\min} \leq V_{Li} \leq V_{Li}^{\max}, i = 1 \dots N_{PQ}, \quad (22)$$

Furthermore, the IEEE 1547 standard represents the voltage regulation limits between the nodes within $\pm 5\%$. Hence, $V_{Li}^{\min}$ and $V_{Li}^{\max}$ are assumed to be 0.95 p.u. and 1.05 p.u., respectively [32].

- DG Power factor constraint [6,11]:

$$0.7 \leq \text{PF}_{DG} \leq 1. \quad (23)$$

The operating power factor of DGs can be set as:

PF = 1 for Type-I DGs and PF = [0.7, 1] for Type-III DGs.

2.3. Optimal Location of CB and DGs Based on LSF

Loss Sensitivity Factor (LSF) is adopted in this work to locate the candidate nodes for CBs and DGs in the distribution system and it can be computed using Equation (24) at each node of the system in the base case load-flow solution. Further, it is sorted in descending order to form the priority list [16].

$$LSF = \frac{\partial P_{ij \text{ loss}}}{\partial Q_j} = \frac{2Q_j R_{ij}}{|V_j|^2} \quad (24)$$

Furthermore, the normalized voltages are calculated for all the nodes by assuming the minimum acceptable bus voltage as 0.95 using Equation (25) [15,33].

$$\text{Normalized } V_i = V_i/0.95. \quad (25)$$

The optimal locations of CB and DG placement are calculated based on the normalized voltage magnitudes and the LSF. The candidate nodes for CB and DGs placements are selected when the normalized values are less than 1.01. The maximum value of the normalized voltage is considered as 1.01 at the buses where compensation is desired.

Moreover, DGs can be demonstrated as negative active and reactive loads PQ [34,35]. The new real and reactive power consumed (P_{ndi} and Q_{ndi}) at the i th node after the positioning of DGs is computed using Equations (26) and (27):

$$P_{ndi} = P_d - P_{DG}, \quad (26)$$

$$Q_{ndi} = Q_d - Q_{DG}. \quad (27)$$

3. Proposed Hybrid Optimization Algorithm

The proposed hybrid enhanced GWO-PSO algorithm utilizes the enhanced GWO and PSO metaheuristic methods. A hybrid approach has been formulated using these two algorithms to yield successful results, which are described in the following sections.

3.1. Enhanced GWO

The GWO is a swarm intelligence algorithm proposed based on how grey wolves can hunt their prey [36]. It is inspired by the leadership hierarchy of grey wolves, which are at the top of the food chain. There are four groups of grey wolves within the leadership hierarchy, such as alpha (α), beta (β), delta (δ), and omega (ω). In the GWO algorithm, the social hierarchy modeling of wolves considers the fittest solution as the alpha (α), whereas the second and third best solutions are taken as β and δ , respectively, in the population. Furthermore, the rest of the candidate solutions in the population are considered to be ω . In this algorithm, the hunting is performed by α , β , and δ wolves, while ω wolves follow these wolves for the global minimum [37,38]. It includes the following three main parts: (1) tracking, chasing, and approaching the prey; (2) pursuing, encircling, and harassing the prey till it stops moving; (3) attacking the prey. After the prey is traced by a wolf pack, it is surrounded by the wolf pack. The encircling behavior can be mathematically formulated as follows [10]:

$$D = |C \cdot X_p(t) - X(t)|, \quad (28)$$

$$X(t+1) = X_p(t) - A \cdot D. \quad (29)$$

Coefficients A and C are calculated using the following equations [36]:

$$A = a_0 (2r_1 - 1), \quad (30)$$

$$C = 2r_2, \quad (31)$$

where r_1 and r_2 are uniformly selected random numbers [0,1].

In the conventional GWO algorithm, the components of “ a_0 ” are linearly decreased from 2 to 0 throughout iterations. However, it is an exploratory effect that has a bad effect on the convergence of the conventional GWO algorithm, decreasing the convergence rate of the algorithm. Therefore, the proposed modification in [10] is employed in this work to enhance the exploration–exploitation balance and convergence rate of the conventional GWO using the following:

$$a_0 = \zeta \exp(-\theta \cdot t), \quad (32)$$

where ζ and θ are two control parameters that rule the convergence characteristic’s behavior of the GWO algorithm over iterations t for each point. Moreover, by converting vector “ a_0 ” to a random nonlinear vector, the exploratory feature can be maintained, and the convergence of the algorithm is accelerated.

In the mathematical modeling of the hunting process, α , β , and δ wolves are assumed to have better knowledge about the location of the prey. The remaining wolves randomly update their positions according to the position of the best search agent as follows [36]:

$$D_\alpha = |C_\alpha \cdot X_\alpha - X|, D_\beta = |C_\beta \cdot X_\beta - X|, D_\delta = |C_\delta \cdot X_\delta - X|, \quad (33)$$

$$X_1 = X_\alpha - A_\alpha \cdot D_\alpha, X_2 = X_\beta - A_\beta \cdot D_\beta, X_3 = X_\delta - A_\delta \cdot D_\delta. \quad (34)$$

In the conventional GWO algorithm, the wolves update their position as an average of the three best grey wolves α , β , and δ . This leads to premature convergence and poor quality of the solutions on complex and nonconvex optimization problems [10]. Consequently, the weighted distance criterion proposed in [10] is employed in this article to improve the performance of the conventional GWO algorithm, especially in complex and nonconvex optimization problems. So, the updated position is weighted in each iteration and formulated as follows [10]:

$$w_1 = A_\alpha \cdot C_\alpha, w_2 = A_\beta \cdot C_\beta, w_3 = A_\delta \cdot C_\delta, \quad (35)$$

$$X(t+1) = \frac{w_1 \cdot X_1 + w_2 \cdot X_2 + w_3 \cdot X_3}{w_1 + w_2 + w_3}. \quad (36)$$

When the algorithm reaches the desired number of iterations, the search is completed.

3.2. Particle Swarm Optimization

PSO algorithm is a stochastic population-based metaheuristic optimization technique first introduced by Eberhart and Kennedy in 1995 [21]. This algorithm is based on a simple concept and can be easily implemented with computer codes. The idea of this metaheuristic procedure came from the observation of the behavior of natural organisms to find food and it works with a swarm of particles [19,21].

In the PSO algorithm, each particle represents a candidate solution for the optimization problem in the decision space and has two characteristics: its own position and velocity. The position represents the current values in the solution, whereas the velocity defines the direction and the distance to optimize the position at the next iteration. Their positions are changed with time-based on their present velocity, previous experience, and the experience of their neighbors. Firstly, the initial population is generated randomly within the search domain in the PSO method. For each particle i , its own past best position (PBest $_i$) and the entire swarm best overall position (GBest) are remembered. The updated velocity and position of each particle in the $(t + 1)$ th iteration are calculated using the following equations [19]:

$$v_i^{t+1} = W^t v_i^t + c_1 r_1 (PBest_i^t - x_i^t) + c_2 r_2 (GBest^t - x_i^t), \quad (37)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1}. \quad (38)$$

The inertia weight is updated for swarm exploration, exploitation, and fast convergence using the following formulation:

$$W^t = W^t * (1 - \mu). \quad (39)$$

The search continues until an optimum result is achieved or a maximum predefined number of iterations is reached. It mainly consists of five steps: initialization, updating particle velocity, updating particle position, and stopping criteria [19]. The advantages of the PSO algorithm in comparison with other optimization algorithms are as follows [21]:

- PSO is a simple algorithm and users could easily develop this algorithm with basic mathematical and logic operations.
- Its implementation is easy and computation is efficient in terms of both memory requirements and speed.
- It does not require a good initial solution to start its iteration process.
- PSO is much faster for power system optimization.

3.3. Hybrid Enhanced GWO-PSO (EGWO-PSO)

In this proposed method, the enhanced version of the GWO algorithm is utilized to support the PSO algorithm to reduce the possibility of falling into a local minimum. The main idea to adapt hybridization is to improve the ability of exploitation in PSO with the facility of enhanced exploration in GWO to increase quality and stability for the solution further. The initial population is updated by enhanced GWO and the updated solutions are again updated by PSO. The global best position is returned to the enhanced version of GWO and the algorithm continues to run until the optimal solution is obtained. However, the running time is extended since the PSO algorithm is also employed in addition to the enhanced GWO algorithm. Nevertheless, when the success of the results and the amount of extra time needed are taken into consideration, the extended time can be regarded as tolerable depending on the optimization problem solved. The implementation of the proposed EGWO-PSO algorithm for determining the optimal allocation of DGs and CBs is summarized in the following steps and described through the flowchart presented in Figure 1 (EGWO algorithm is executed first followed by the PSO algorithm).

Enhanced GWO operation

- Step 1: Initialize the search agents, maximum iterations, dimension, and boundaries of the problem.
- Step 2: Search agent population is generated randomly by the EGWO and the positions of α , β and δ wolves' are initialized.
- Step 3: The random size of CB/DG units for each search agent is placed at buses identified by the LSF method and the objective function is calculated.
- Step 4: The components of " a_0 " are determined using the modified Equation (32) and the parameters A and C are calculated using Equations (30) and (31), respectively.
- Step 5: The positions of α , β , and δ wolves are updated using Equations (33) and (34).
- Step 6: The positions of search agents are weighted in each iteration using Equations (35) and updated using Equation (36).
- Step 7: The above steps are repeated for all the positions of search agents.

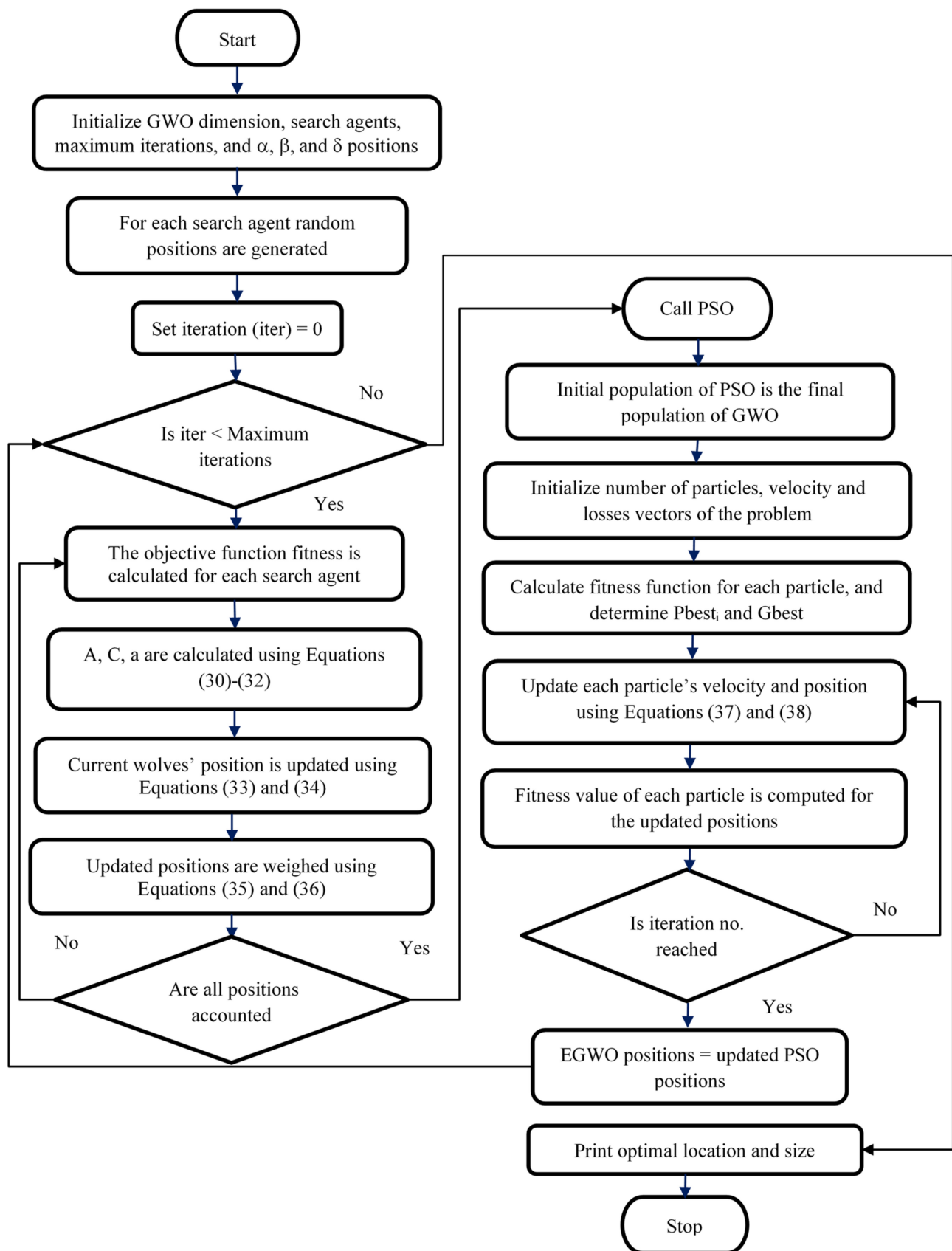


Figure 1. Flowchart of the proposed enhanced grey wolf optimizer and particle swarm optimization (EGWO-PSO) method.

PSO operation

- Step 8: Initialize the number of particles, velocity, and losses vector of the problem.
- Step 9: The final population of EGWO is the initial population of PSO.
- Step 10: The CB/DG size for each particle is assigned to the same buses considered for EGWO and the fitness function of all the particles is evaluated.
- Step 11: Individual $PBest_i$ and global $GBest$ are computed.
- Step 12: Using Equations (37) and (38), each swarm velocity and swarm position are updated.
- Step 13: The fitness value of each particle is computed for the updated sizing of CBs/DGs placed at the best nodes obtained in step 11.
- Step 14: Steps 12 and 13 are repeated for all the particles until maximum iterations are reached.
- Step 15: The improved positions are returned to step 3 of enhanced GWO.
- Step 16: Steps 3 to 15 are repeated till the stopping criterion is reached.

In the proposed work, the stop criteria are set as the maximum number of iterations. The simulation will be stopped when the criterion is satisfied, and the optimum location and size of DG/CB units satisfying all the specified constraints of the distribution system can be obtained.

4. Test Systems and Cases

4.1. Test Distribution Systems

The superiority of the proposed EGWO-PSO is realized on IEEE standard 33- and 69-bus radial distribution systems, as shown in Figures 2 and 3, respectively [6]. The power flow calculations are carried out in MATLAB using MATPOWER (an open-source software package) [39].

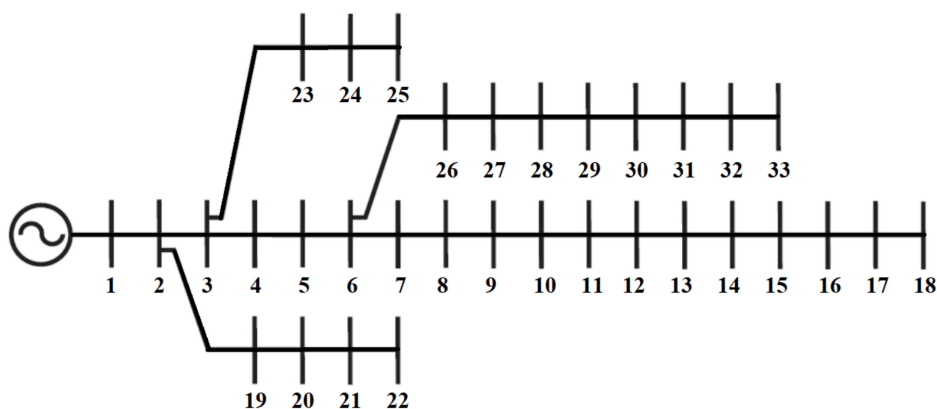


Figure 2. IEEE 33-bus distribution systems.

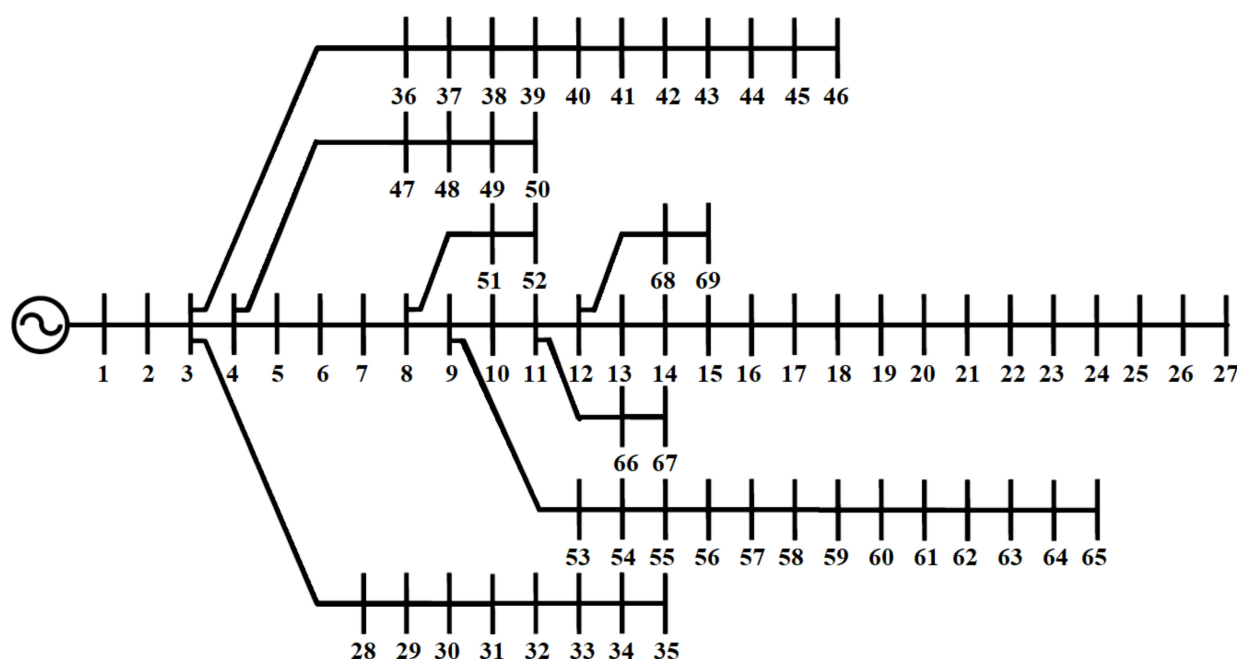


Figure 3. IEEE 69-bus distribution systems.

4.2. Case Study

Six operational cases are introduced to demonstrate the effectiveness of the proposed EGWO-PSO for the placement sizing of DGs and CBs as follows:

Case 1: Optimal placement and sizing of CBs alone

The reactive power losses in the distribution system can be reduced by optimally installing CBs. The candidate nodes for CBs location are obtained from the LSF method and the maximum number of CBs (N_C) considered are three. To avoid overcompensation, the size of CBs (Q_{Ci}) is less than the total reactive power demands of the distribution systems.

Case 2: Optimal placement and sizing of DGs at UPF

DGs operating at unity power factor (UPF) can inject only active power. Moreover, the LSF method is adapted to select the candidate nodes. The total number of DGs allotted are three with a maximum capacity that is less than the total active power demands of the distribution systems.

Case 3: Optimal placement and sizing of the combination of CBs and DGs at UPF

The integrated operation of DGs and CBs provides superfluous advantages for the distribution systems. It is the combination of both cases 1 and 2. The criteria for candidate nodes, maximum number, and sizing of CBs and DGs, are the same as mentioned in the above two cases.

Case 4: Optimal placement and sizing of DGs at LPF

In cases 2 and 3, DGs are allowed to supply only active power, but in this case, the DGs are permissible to supply both real and reactive powers. The LSF nodes and total number of DGs considered are the same as case 2. The real and reactive power capacities of DGs are less than the total active and reactive power demands of the distribution systems respectively.

Case 5: Optimal placement and sizing of the combination of CBs and DGs at LPF

The combined operation of CBs and DGs at LPF provides maximum benefits to the distribution systems. It is the combination of cases 3 and 4. The selection of candidate nodes, maximum number, and capacity of CBs and DGs, is the same as considered in cases 3 and 4.

For all cases (1 to 5), three technical objectives (of_1 , of_2 , of_3) are considered. The multiobjective function can be expressed as follows:

$$MOF_1 = \min (of_1, of_2, of_3). \quad (40)$$

Case 6: Optimal placement and sizing of multi-CBs and DGs

In case 6, multiple DGs and CBs are considered for realizing maximum benefits. DGs are controllable units to supply active and reactive power. Moreover, technical, economic, and environmental objectives (of_1 , of_4 , and of_5) are optimized, and therefore, the MOF can be formulated as follows:

$$MOF_2 = \min (of_1, of_4, of_5). \quad (41)$$

The economic and environmental properties of DGs are dependent on their type. To increase the DGs penetration level, three types of DGs are considered (PV, WT, and GT) as illustrated in Table 2. Furthermore, generated power costs at substations are considered to be 0.044 \$/kWh and e_i and C_{ci} are taken equal to 1000 and 30 \$/kVAR, respectively [6].

Table 2. DG characteristics.

DG Type	Rated Capacity (MW)	Life Time (year)	Capital Cost (\$/kW)	O&M Costs (\$/kWh)	Fuel Cost (\$/kWh)	Emission Factors (lb/MWh)		
						NO _x	SO ₂	CO ₂
Grid	25	25	-	-	0.044	5.06	11.6	2031
PV	1	20	3985	0.01207	-	-	-	-
WT	5	20	1822	0.00952	-	-	-	-
GT	3	12	1224	0.06481	0.0667	0.279	0.93	1239.2

5. Result and Discussions

The above-discussed test systems (IEEE 33-bus and IEEE 69-bus RDSs) are demonstrated to prove the effectiveness of the proposed algorithm for optimal allocation of CBs and DGs. Further, two types of DG units (Type I and Type III) are considered for the analysis. The total number of DGs location is three and the further increase of DGs show marginal variation in system parameters that also incur additional investment cost [7]. The population size or the number of wolves considered is 30. The stopping criterion is also adapted based on the maximum number of iterations, i.e., fixed as 50. For PSO, inertia weight and social and cognitive acceleration weights are 1, 2, and 2.0, respectively [40]. Moreover, all calculations are done in per unit (p.u.) system. The EGWO-PSO approach and the load-flow solution are implemented using MATPOWER 7.0 [39] in MATLAB version 2018a software on a personal computer with a 64-bit, i5 processor, 1.6 GHz, and 8 GB RAM. The results of these test cases are discussed in the following sections.

5.1. Results of 33-Bus Network

This RDS has 33 buses and 32 distribution lines and the total real and reactive power demands are 3.72 MW and 2.3 MVAR, respectively [6]. The base values are 100 MVA and 12.66 kV. The voltage keeps decreasing from the source to the end due to the presence of loads at the buses, as shown in Figure 2. The voltage profiles of the buses may be improved by connecting CB and DG units to the buses to take up part of the load demand, thereby reducing the current flow and losses. The uncompensated or base case power loss for this system is 202.68 kW.

Case 1: Optimal placement and sizing of CBs alone

The first case establishes the optimal placement and sizing of CBs using the proposed algorithm. The results of this case are compared with, WCA, FPA, PSO, PGSA, and CSA, as illustrated in Table 3. The results show that the proposed algorithm is efficient in finding

the optimal solution except for WCA and CSA. However, analysis of VDI and VSI is not discussed by the authors for this case. Three capacitors are installed at buses 13, 24, and 30 that decrease the real power losses from 202.68 kW to 132.17 kW for the total installed CBs capacity of 2.134 MVAR. The minimum voltage magnitude is enhanced from 0.913 p.u. to 0.9377 p.u. at bus 18. Moreover, VDI is minimized from 0.1171 p.u. to 0.0551 p.u. and the maximization of VSI is attained from 0.6968 p. u. to 0.775 p. u.

Table 3. Optimal allocation of CBs for the 33-bus system.

Techniques	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	202.68	0	0.913 (18)	0.1171	0.6968
WCA [6]	0.3973 (14), 0.4511 (24), 1.0 (30)	1.8484	130.912	35.41	0.951 (18)	–	–
FPA [15]	0.25 (6), 0.4 (9), 0.95 (30)	1.6	134.47	33.65	0.9365	–	–
PSO [41]	0.9 (2), 0.45 (7), 0.3 (15), 0.45 (29), 0.45 (31)	2.55	132.48	34.64	0.945	–	–
PGSA [42]	1.2 (6), 0.76 (28), 0.2 (29)	2.16	135.4	33.19	0.9463	–	–
CSA [41]	0.6 (11), 0.45 (24), 0.6 (30), 0.3 (33)	1.95	131.5	35.12	0.943	–	–
EGWO-PSO	0.4238 (13), 0.5663 (24), 1.1439 (30)	2.134	132.17	34.79	0.9377 (18)	0.0551	0.775

Case 2: Optimal placement and sizing of DGs at unity PF

Table 4 summarizes the simulation results of the proposed technique in comparison with existing optimization methods for this case. It is observed that the proposed method delivers the most cooperating results for the multiobjective optimal size and site of DG allocation at possible DG injection compared to the available methods, namely, WCA, I-DBEA, comprehensive TLBO (CTLBO) ϵ -method, TLBO, quasi-oppositional TLBO (QOTLBO), GA/PSO, hybrid GA/PSO, FWA, HSA, ACO-ABC, IMOEOH, and TM. The proposed EGWO-PSO offers the least active power loss of about 71.457 kW. Three DGs are installed at buses 14, 24, and 30 with penetration of 0.754, 1.099, and 1.071 MW, respectively. The minimum voltage level of 0.9687 p. u. is obtained at node 33. However, the proposed method offers trivial deviations of VDI (0.0135 p. u.) and VSI (0.8813 p. u.) compared with existing methods. Nonetheless, an extensive reduction of real power losses diminishes these trifling limitations.

Table 4. Optimal allocation of DGs at unity power factor (UPF) for 33-bus system.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	202.68	0	0.913 (18)	0.1171	0.6968
WCA [6]	0.8546 (14), 1.1017 (24), 1.181 (29)	3.1373	71.052	64.94	0.973 (33)	–	–
I-DBEA [7]	1.098 (13), 1.097 (24), 1.715 (30)	3.9131	94.8514	53.21	–	0.0007	0.9650
CTLBO [31]	1.0364 (13), 1.1630 (24), 1.5217 (30)	3.7211	85.9595	57.59	–	0.0026	0.9481
CTLBO ϵ -method [31]	1.1926 (13), 0.8706 (25), 1.6296 (30)	3.6928	96.1732	52.54	–	0.0009	0.9638
TLBO [43]	1.1826 (12), 1.1913 (28), 1.1863 (30)	3.5602	124.6950	38.47	–	0.0011	0.9503

Table 4. Cont.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
QOTLBO [43]	1.0834 (13), 1.1876 (26), 1.1992 (30)	3.4702	103.4030	48.97	–	0.0011	0.9530
GA [44]	1.50 (11), 0.4228 (29), 1.0714 (30)	2.9942	106.3	47.55	0.981 (25)	0.0407	0.9497
PSO [44]	1.1768 (8), 0.9816 (13), 0.8297 (32)	2.9881	105.3000	48.05	0.980 (30)	0.0335	0.9256
GA/PSO [44]	0.925 (11), 0.863 (16), 1.200 (32)	2.988	103.4	48.98	0.980 (25)	0.0124	0.9508
FWA [45]	0.5897 (14), 0.189 (18), 1.0146 (32)	1.2036	88.68	56.25	0.968	–	–
HSA [46]	0.5724 (17), 0.107 (18), 1.0462 (33)	1.7256	96.76	52.26	0.967 (29)	–	–
ACO-ABC [47]	0.7547 (14), 1.0999 (24), 1.0714 (30)	2.9260	71.4	64.77	–	–	–
IMOEOH [48]	1.057 (14), 1.054 (24), 1.741 (30)	3.8520	95.0000	53.13	–	0.0008	0.9673
TM [49]	0.5876 (15), 0.1959 (25), 0.783 (33)	1.5665	91.305	54.95	0.958 (30)	–	–
EGWO-PSO	0.754 (14), 1.099 (24), 1.071 (30)	2.924	71.457	64.74	0.9687 (33)	0.0135	0.8813

Case 3: Optimal placement and sizing of a combination of CBs and DGs at UPF.

Table 5 exemplifies the outcomes of Case 3 that displays a superior power loss reduction compared with Cases 1 and 2 due to the influence of the proposed technique. It recommends installing three DGs at nodes 14, 24, and 30 and three CBs at nodes 11, 23, and 29. It is noted that there is a significant power loss reduction of about 15.157 kW when compared to WCA, and GA. The improved minimum voltage level of 0.9941 p.u. is obtained at bus 22. Further, VDI is diminished and VSI is enhanced from their base value to 0.00036 p.u. and 0.9786 p.u., respectively.

Table 5. Optimal allocation of DGs at UPF and CBs for the 33-bus system.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	–	–	202.68	0	0.913 (18)	0.1171	0.6968
WCA [6]	0.563 (11), 0.973 (25), 1.04 (29)	2.576	0.535 (14), 0.465 (23), 0.565 (30)	1.565	24.688	87.82	0.980 (33)	–	–
GA [50]	0.25 (16), 0.25 (22), 0.50 (30)	1	0.30 (15), 0.30 (18), 0.30 (29), 0.60 (30), 0.30 (31)	1.8	71.25	64.85	0.971	–	–
EGWO-PSO	0.746 (14), 1.078 (24), 1.048 (30)	2.873	0.528 (11), 0.712 (23), 1 (29)	2.241	15.157	92.52	0.9941 (22)	0.00036	0.9786

Case 4: Optimal placement and sizing of DGs at LPF

DGs are inadmissible to inject reactive power to the distribution network in the preceding study cases (Cases 2 and 3) for the optimization of considered objective functions. In the presented case, the proposed EGWO-PSO technique is applied to obtain the best site and capacity of 3 DGs operating at LPF. The simulation results of the proposed technique for 33-bus RDS associated with the present approaches in the literature are summarized in Table 6. It shows that the EGWO-PSO offers the best results for optimal size and site of the DG allocation problem at possible DG injection compared to the available methods. It offers the least power loss and VDI reduction and maximizes VSI compared to methods in I-DBEA, LSFSa, IMOCHO, and IA. The suggested technique optimized the real power losses extensively from 202.68 kW to 11.68 kW (94.24% reduction). Further, the minimum voltage is also enhanced from the base case to 0.9926 p.u. at the bus no. 8. The value of VDI is decreased from 0.1171 p.u. to 0.00062 p.u. and the maximization of VSI is achieved from 0.6968 p.u. to 0.9707 p.u. Although the proposed method offers a marginal reduction of VDI and minor improvement of VSI compared to existing techniques, significant minimization of real power losses shrinks the negligible effects of VDI and VSI.

Table 6. Optimal allocation of DGs at LPF for the 33-bus system.

Techniques	DG Location, Size (MW), and Power Factor	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	202.68	0	0.913 (18)	0.1171	0.6968
I-DBEA [7]	(13, 0.7491, 0.85), (24, 1.0420, 0.85), (30, 1.2395, 0.85)	3.0307	14.570	92.8081	–	0.0002	0.9733
LSFSa [51]	(6, 1.383, 0.85), (18, 0.552, 0.85), (30, 1.063, 0.85)	2.9980	26.700	86.8300	–	0.0013	0.9323
IMOCHO [48]	(13, 0.929, 0.85), (24, 1.181, 0.85), (30, 1.473, 0.85)	3.5830	14.900	92.6000	–	0.0003	0.9814
IA [52]	(6, 1.059, 0.85), (14, 0.741, 0.85), (30, 1.059, 0.85)	2.8590	23.100	88.6000	–	–	–
EGWO-PSO	(13, 0.7793, 0.905) (24, 1.0723, 0.89) (30, 1.0356, 0.715)	2.8872	11.68	94.24	0.9926 (8)	0.00062	0.9707

Case 5: Optimal placement and sizing of a combination of CBs and DGs at LPF

From the results of Case 5 (Table 7), it is clear that the optimal placement and sizing of DGs (with LPF) and CBs can be very effective in achieving the technical multi-objective (MOF₁). The proposed EGWO-PSO method remarkably enhanced all the objective functions such as power loss, VDI, and VSI. The proposed technique optimized the real power losses from 202.68 kW to 14.994 kW greatly compared to WCA (19.848 kW). The value of VDI is minimized from 0.1171 p.u. to 0.000343 p.u. and VSI is improved from 0.6968 p.u. to 0.9788 p.u. for the total DG size of 2.8841 MW and CB size of 2.2159 MVAR. Further, the minimum voltage is enhanced to 0.99408 p.u. at the bus no. 22.

Table 7. Optimal allocation of DGs at LPF and CBs for the 33-bus system.

Techniques	DG LOCATION, Size (MW), and Power Factor	Total DG Size (MW)	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	-	-	-	-	202.68	0	0.913 (18)	0.1171	0.6968
WCA [6]	(11, 0.9917, 0.905) (31, 0.9823, 0.985) (24, 1.652, 0.959)	3.626	0.325 (19), 0.3116 (23), 0.5432 (30)	1.1798	19.848	90.207	0.989 (18)	0.041	0.985
EGWO-PSO	(13, 0.77762, 1) (24, 1.072, 0.996) (30, 1.0345, 0.999)	2.8841	0.5235 (11), 0.6925 (23), 1 (29)	2.2159	14.994	92.602	0.99408 (22)	0.000343	0.9788

Case 6: Optimal placement and sizing of multi-CBs and DGs.

Table 8 presents the technical, economic, and environmental benefits (MOF₂) of simultaneous placement of DGs and CBs in a 33-bus distribution system. It reveals that the overall performance of the EGWO-PSO shows superior performance to WCA. The total emission is reduced by 71.47% due to the penetration of renewable DGs (PV with 0.1728 MW (at node 32) and 1.3008 MW (at node 27); WT with 0.7751 MW (at node 25); GT with 0.4719 MW (at node 13)). Moreover, the generated power cost is reduced by 25% and the distribution power loss is reduced to 19.217 kW.

Table 8. Multiobjective placement and sizing for a 33-bus system.

Techniques	Grid Location, Active Power (MW), and Reactive Power (MVAR)	PV Location, Active Power (MW), and Reactive Power (MVAR)	WT Location, Active Power (MW), and Reactive Power (MVAR)	GT Location, Active Power (MW), and Reactive Power (MVAR)	CB Location and Reactive Power (MVAR)	Power Loss (KW)	Loss Reduction (%)	Cost (\$/h)	Emission (lb/h) ($\times 10^6$)
Base case	-	-	-	-	-	202.68	0	304.8966	8.0267
WCA [6]	(1, 1.541, 0.6572)	(32, 0.7149, 0.4385) (27, 0.6397, 0.2776)	(25, 0.6476, 0.1467)	(18, 0.2008, 0.0516)	(15, 0.3) (19, 0.45) (26, 0)	28.9615	85.71	249.3429	3.4045
EGWO-PSO	(1, 1.0136, 0.2434)	(32, 0.1728, 0.83568) (27, 1.3008, 0.07421)	(25, 0.7751, 0.42202)	(13, 0.4719, 0.0212)	(15, 0.3) (19, 0.45) (26, 0)	19.217	90.52	227.372	2.2899

Additionally, a comparative analysis between bus voltage profiles of different cases and power losses is illustrated in Figures 4 and 5 respectively. It is observed that the addition of CB and DG units operating at LPF (Case 5) increases the voltage profile of the buses across the network. Furthermore, the real power losses are reduced significantly in all the lines for the Case 5 configuration. To demonstrate the convergence characteristics of the proposed scheme, EGWO-PSO is compared with EGWO and PSO for Case 5 (CBs and DGs of Type III). It can be seen that hybridization of the EGWO with PSO produces considerable improvement in both the speed of convergence and optimality of the solution (Figure 6).

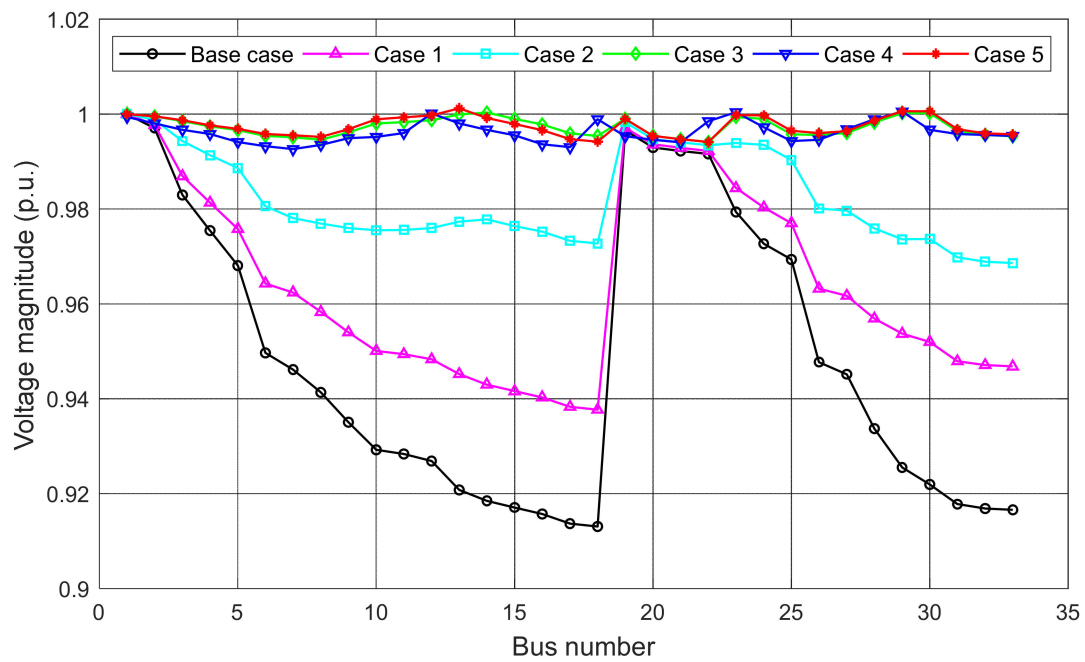


Figure 4. Voltage profiles of different cases for the 33-bus system.

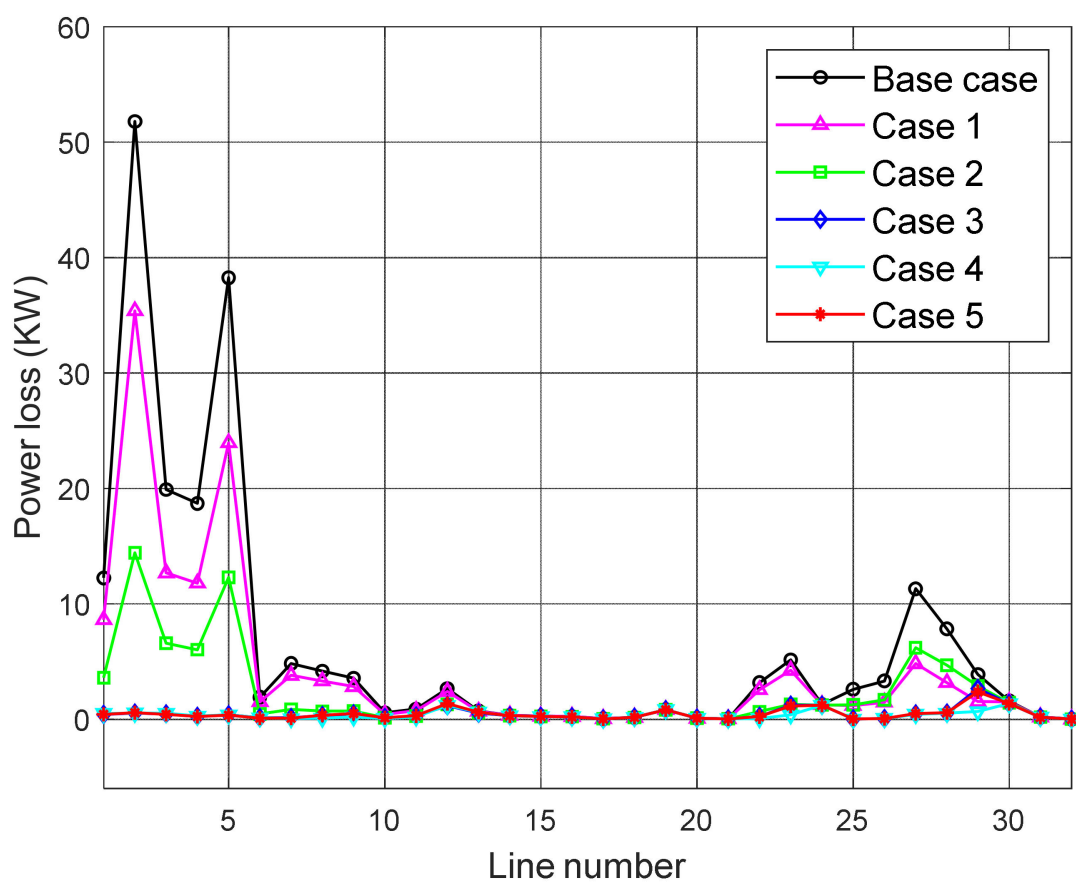


Figure 5. Power losses at each line for different cases of the 33-bus system.

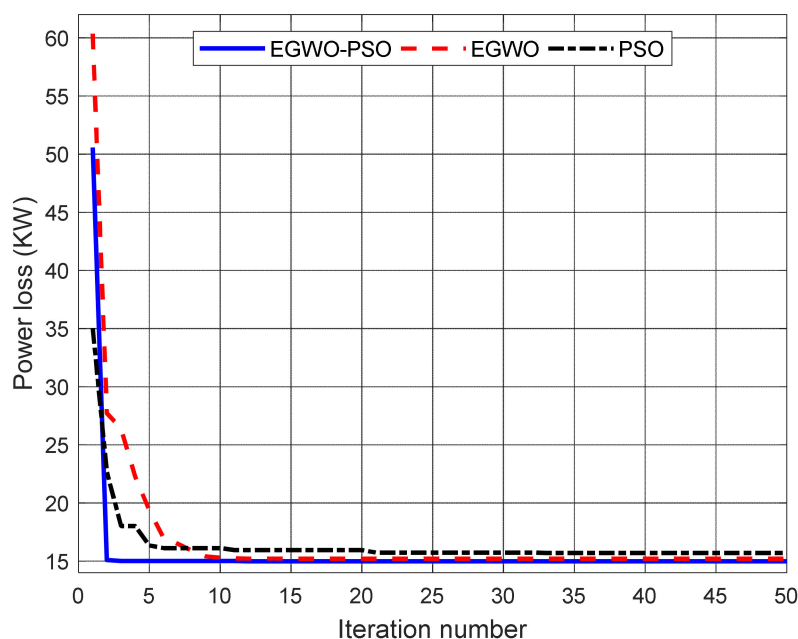


Figure 6. Convergence characteristics of case 5 for the 33-bus system.

5.2. Results of 69-Bus System

The effectiveness of the proposed scheme is tested with 69 RDS. It consists of 69 buses and 68 distribution lines and the base values are taken as 10 MVA and 12.7 kV. The system has a total real power demand of 3.802 MW and a total reactive power demand of 2.694 MVAR [6]. Among 69 buses, bus 3 has three branches and buses 4, 8, 9, 11, and 12 have two branches, while the other buses have only one branch connected to their next bus. The uncompensated or base case power loss for this system is 225 kW.

Case 1: Optimal placement and sizing of CBs alone

The total power loss obtained by the proposed algorithm is better than those obtained by other methods such as FPA, PSO, PGSA, GSA, DE, DE-PS, CSO, DSA, TLBO, Fuzzy GA, Heuristic, Hybrid, and New Heuristic (Table 9). Three CBs are installed at buses 11, 20, and 61 with sizes of 0.4232 MVAR, 0.2543 MVAR, and 1.4112 MVAR respectively. For the total capacity of 2.0887 MVAR, a net power loss is decreased from 225 kW to 145.13 kW. The minimum voltage is enhanced from 0.9092 p.u. to 0.93142 p.u. at node 65. Moreover, VDI is reduced from 0.0993 p.u. to 0.01729 p.u. and the maximization of VSI is achieved greatly from 0.6850 p.u. to 0.87344 p.u.

Table 9. Optimal allocation of CBs for the 69-bus system.

Techniques	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	225	0	0.9092 (65)	0.0993	0.6850
WCA [6]	1.2882 (61), 0.2134 (69), 0.27 (18)	1.7716	144.53	35.76	0.95 (65)	–	–
FPA [15]	1.35 (61)	1.35	150.28	33.2	0.9333	–	–
PSO [53]	0.241 (46), 0.365 (47), 1.015 (50)	1.621	152.48	33.2	–	–	–
PGSA [42]	1.2 (57), 0.274 (58), 0.2 (61)	1.674	147.4	34.48	–	–	–
GSA [54]	0.15 (26), 0.15 (13), 1.050 (15)	1.35	145.9	35.16	0.952	–	–

Table 9. Cont.

Techniques	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
DE [55]	0.2 (16), 0.7 (60), 0.5 (61)	1.4	147.96	34.24	0.9296	–	–
DE-PS [56]	0.95 (61), 0.2 (64), 0.50 (65), 0.15 (59), 0.3 (21)	1.650	146.13	35.02	0.9327 (65)	–	–
CSO [57]	1.2 (62), 0.25 (21)	1.45	147.95	34.24	0.930	–	–
DSA [58]	0.9 (61), 0.45 (15), 0.45 (60)	1.800	147	34.64	–	–	–
TLBO [59]	0.6 (12), 1.050 (61), 0.150 (64)	1.800	146.35	34.92	0.9313 (65)	–	–
Fuzzy GA [60]	0.1 (59), 0.7 (61), 0.8 (64)	1.600	156.62	30.4	0.9369	–	–
Heuristic [61]	0.6 (8), 0.15 (58), 1.05 (60)	1.8	148.48	34	0.9305	–	–
Hybrid [17]	1.19 (61), 0.25 (18), 0.33 (11)	1.770	145.2	35.47	–	–	–
New heuristic [5]	1.21 (61), 0.226 (21), 0.32 (12)	1.756	145.3	35.42	–	–	–
EGWO-PSO	0.4232 (11), 0.2543 (20), 1.4112 (61)	2.0887	145.13	35.50	0.93142 (65)	0.0461	0.78415

Case 2: Optimal placement and sizing of DGs at unity PF

The simultaneous installation of 3 DGs operating at UPF at different buses of the 69-bus network is performed and the observed results are illustrated and compared with existing techniques (Table 10). The proposed method offers more power loss reduction and VDI along with VSI enhancement in contrast to the methods presented by WCA, I-DBEA, CTLBO ϵ -method, TLBO, QOTLBO, GA/PSO, hybrid GA/PSO, FWA, HSA, EA, MTLBO, KHA, Hybrid, CVSI, and New Heuristic. It is also clear from Table 10 that I-DBEA, CTLBO ϵ -method, TLBO, QOTLBO, GA, PSO, and hybrid GA/PSO inject more DG power than EGWO-PSO. The proposed method reduced the total active power loss from 225 kW to 69.428 kW (reduction of 69.14%). It achieves the utmost cooperating results to find the best size and site of DG allocation problem compared with HGWO, MINLP, Exhaustive OPF, EA-OPF, and ACO-ABC. The proposed method installs three DGs with penetration of 0.5268 MW, 0.3803 MW, and 1.719 MW at buses 11, 18, and 61, respectively. The minimum voltage level is attained at node 65 of about 0.979 p.u. Moreover, VDI and VSI are improved from their actual value to 0.0052 p.u. and 0.9205 p.u., respectively. Though the proposed algorithm endows minimal VDI reduction and slighter VSI improvement compared to the existing methods, the minimization of power loss is commendable.

Table 10. Optimal allocation of DGs at UPF for the 69-bus system.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	225	0	0.9092 (65)	0.0993	0.6850
WCA [6]	0.775 (61), 1.105 (62), 0.4380 (23)	2.318	71.5	68.22	0.987 (65)	–	–
I-DBEA [7]	2.1487 (61), 0.4717 (19), 0.7126 (11)	3.320	78.347	65.17	–	0.0002	0.9772
CTLBO [31]	0.5603 (11), 0.4274 (18), 2.1534 (61)	3.1411	76.372	66.04	–	0.0008	0.9770
CTLBO ϵ -method [31]	0.9658 (12), 0.2307 (25), 2.1336 (61)	3.3301	79.660	64.57	–	0.0003	0.9770

Table 10. Cont.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
TLBO [43]	1.0134 (13), 0.9901 (61), 1.1601 (62)	3.1636	82.172	63.46	–	0.0008	0.9745
QOTLBO [43]	0.8114 (15), 1.1470 (61), 1.0022 (63)	2.9606	80.585	64.17	–	0.0007	0.9769
GA [44]	0.9297 (21), 1.0752 (62), 0.984 (64)	2.9897	89.000	60.42	–	0.0012	0.9706
PSO [44]	1.1998 (61), 0.7956 (63), 0.9925 (17)	2.9879	83.200	63.01	–	0.0049	0.9676
GA/PSO [44]	0.8849 (63), 1.1926 (61), 0.9105 (21)	2.988	81.100	63.90	–	0.0031	0.9768
FWA [45]	0.2258 (27), 1.1986 (61), 0.4085 (65)	1.8329	77.85	65.4	0.974 (62)	–	–
HSA [46]	0.1018 (65), 0.3690 (64), 1.3024 (63)	1.7732	86.77	61.43	0.9677	–	–
ACO- ABC [47]	0.559 (11), 0.346 (21), 1.715 (61)	2.622	69.429	69.14	–	–	–
HGWO [11]	0.527 (11), 0.380 (17), 1.718 (61)	2.625	69.425	69.14	–	–	–
MINLP [62]	0.530 (11), 0.380 (17), 1.720 (61)	2.630	69.426	69.14	–	–	–
Exhaustive OPF [63]	0.527 (11), 0.380 (18), 1.719 (61)	2.626	69.43	69.14	–	–	–
EA-OPF [63]	0.527 (11), 0.380 (18), 1.719 (61)	2.626	69.43	69.14	–	–	–
EA [63]	0.467 (11), 0.380 (18), 1.795 (61)	2.642	69.62	69.06	–	–	–
MTLBO [64]	0.493 (11), 0.378 (18), 1.672 (61)	2.544	69.539	69.09	–	–	–
KHA [65]	0.496 (12), 0.311 (22), 1.735 (61)	2.542	69.56	69.08	–	–	–
Hybrid [17]	0.510 (11), 0.380 (17), 1.670 (61)	2.560	69.52	69.10	–	–	–
CVSI [66]	1.895 (61)	1.895	83.18	63.03	0.968 (27)	–	–
New heuristic [5]	1.689 (61), 0.312 (21), 0.471 (12)	2.472	69.7	69.02	–	–	–
EGWO-PSO	0.5268 (11), 0.3803 (18), 1.719 (61)	2.6261	69.428	69.14	0.979 (65)	0.0052	0.9205

Case 3: Optimal placement and sizing of a combination of CBs and DGs at UPF

Table 11 shows the placement of DGs at UPF and CBs. It is observed that there is a reduction in a total power loss of 7.8554 kW by the proposed EGWO-PSO compared to WCA (33.339) with active power penetration using DGs at nodes 11 (0.4957 MW), 17 (0.3804 MW), and 61 (1.6554 MW). Furthermore, three CBs at nodes 61, 64, and 69 are considered with reactive power penetration levels of 1 MVAR, 0.4134 MVAR, and 0.4759 MVAR, respectively. Therefore, the optimal DGs/CBs placement enhances the power loss reduction and maximizes the energy utilization of the distribution system. The VDI and VSI are further enhanced to 0.000198 p.u. and 0.9794 p.u., respectively.

Table 11. Optimal allocation of DGs at UPF and CBs for the 69-bus system.

Techniques	DG Size (MW) and Location	Total DG Size (MW)	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	–	–	225	0	0.9092 (65)	0.0993	0.6850
WCA [6]	0.5408 (17), 2 (61), 1.1592 (69)	3.7	1.1879 (2), 1.2373 (62), 0.2697 (69)	2.6949	33.339	85.18	0.994 (50)	–	–
EGWO-PSO	0.4957 (11), 0.3804 (17), 1.6554 (61)	2.5315	1 (61), 0.4134 (64), 0.4759 (69)	1.8893	7.8554	96.5087	0.99427 (50)	0.000198	0.9794

Case 4: Optimal placement and sizing of DGs at LPF

The simulation results of the proposed technique for the 69-bus network compared with existing techniques are shown in Table 12. The proposed method achieves significant real power loss reduction and VDI along with higher VSI compared to the method presented in I-DBEA, LSFSA, IMOHS, EA, Hybrid, PSO, KHA, and IPSO. It also shows that the proposed method achieves the utmost cooperating results for DG allocation compare with HGWO, MINLP, and EA-OPF. The suggested technique minimized the real power losses from 225 kW to 4.2676 kW (98.1% reduction). Furthermore, it improves the voltage profile about 0.99427 p. u. at bus no.50 and reduces the VDI from 0.0993 p.u. to 0.000128 p.u. with maximized VSI from 0.6850 p.u. to 0.9791 p.u. The proposed method stretches an exceptional enhancement in all technical objective functions.

Table 12. Optimal allocation of DGs at LPF for the 69-bus system.

Techniques	DG Location, Size (MW), and Power Factor	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	225	0	0.9092 (65)	0.0993	0.6850
I-DBEA [7]	(61, 1.50, 0.85), (59, 0.370, 0.85), (16, 0.575, 0.85)	2.4459	7.9660	96.45	–	0.000266	0.9774
LSFSA [51]	(18, 0.5498, 0.85), (60, 1.1954, 0.85), (65, 0.3122, 0.85)	2.0574	16.2600	92.77	–	0.002300	0.9678
IMOHS [67]	(61, 1.4552, 0.85), (11, 0.4769, 0.85), (21, 0.3124, 0.85)	2.2445	10.5000	95.33	–	0.001800	0.9468
HGWO [11]	(11, 0.614, 0.81), (18, 0.452, 0.83), (61, 2.056, 0.81)	3.122	4.26	98.11	–	–	–
MINLP [62]	(11, 0.607, 0.813), (50, 1.058, 0.82), (61, 1.058, 0.82)	3.123	4.26	98.11	–	–	–
EA-OPF [63]	(11, 0.611, 0.81), (18, 0.456, 0.83), (61, 2.067, 0.81)	3.134	4.27	98.1	–	–	–
EA [63]	(11, 0.668, 0.82), (18, 0.458, 0.83), (61, 2.113, 0.82)	3.239	4.48	98.01	–	–	–

Table 12. Cont.

Techniques	DG Location, Size (MW), and Power Factor	Total DG Size (MW)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Hybrid [17]	(18, 0.480, 0.77), (61, 2.060, 0.83), (66, 0.530, 0.82)	3.070	4.30	98.09	–	–	–
PSO [17]	(11, 0.600, 0.83), (18, 0.460, 0.81), (61, 2.060, 0.81)	3.120	4.61	97.9	–	–	–
KHA [65]	(11, 0.560, 0.86), (22, 0.357, 0.86), (61, 1.773, 0.86)	2.690	5.91	97.37	–	–	–
IPSO [68]	(21, 0.375, 0.85), (61, 1.515, 0.85), (64, 0.353, 0.85)	2.243	12.80	94.31	–	–	–
EGWO-PSO	(11, 0.4945, 0.81), (18, 0.3792, 0.83), (61, 1.6743, 0.81)	2.548	4.2676	98.1	0.99427 (50)	0.000128	0.9791

Case 5: Optimal placement and sizing of a combination of CBs and DGs at LPF.

Multiobjective (MOF₁) optimal placement and sizing of CBs and type III DGs offer better results than WCA, as shown in Table 13. The proposed method provides an outstanding enhancement in all the objective functions. It optimized the active power losses from 225 kW to 7.2081 kW; VDI is reduced to 0.000115 p.u. and VSI is improved from its actual value to 0.9797 p.u. Further, the minimum voltage is improved to 0.99428 p.u. at bus no. 50. The proposed EGWO-PSO produces exceptional enhancement in all three technical objective functions.

Table 13. Optimal allocation of DGs at LPF and CBs for the 69-bus system.

Techniques	DG Location, Size (MW), and Power Factor	Total DG Size (MW)	CB Size (MVAR) and Location	Total CB Size (MVAR)	Power Loss (KW)	Loss Reduction (%)	Min. Voltage (p.u.)	VDI (p.u.)	VSI (p.u.)
Base case	–	–	–	–	225	0	0.9092 (65)	0.0993	0.6850
WCA [6]	(61, 1.82547, 0.877), (36, 1.0414, 0.916), (19, 0.1063, 0.904)	2.9732	0.0188 (15), 0.4578 (33), 0.5586 (22)	1.0352	18.7048	91.6867	0.994 (50)	0.0092	0.0313
EGWO-PSO	(11, 0.49369, 1), (18, 0.3789, 0.948), (61, 1.6532, 1)	2.5258	1 (61), 0.41341 (64), 0.47591 (69)	1.8893	7.2081	96.7964	0.99428 (50)	0.000115	0.9797

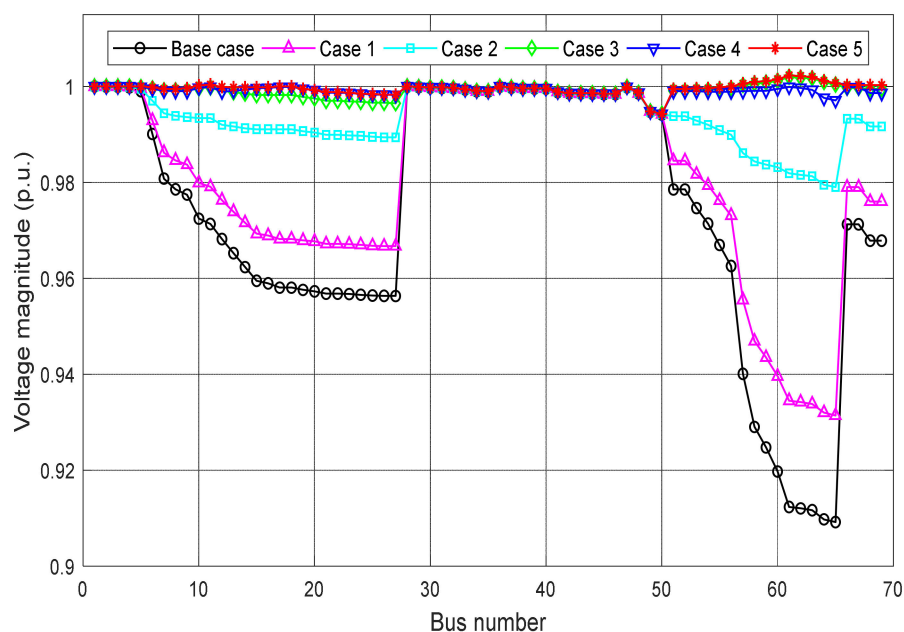
Case 6: Optimal placement and sizing of multi-CBs and DGs.

Table 14 shows the technical, economic, and environmental benefits (MOF₂) of simultaneous placement of DGs and CBs for the 69-bus distribution system. A high reduction in a power loss of about 8.837 kW and significant economic and environmental benefits are achieved compared to WCA. Notably, the economic benefits are achieved by reducing production costs from 309.7134 \$/h to 250.5372 \$/h, while the emissions pollution is reduced from 8.2508×10^6 lb/h to 2.992×10^6 lb/h.

Table 14. Multiobjective placement and sizing for 69-bus system.

Techniques	Grid Location, Active Power (MW), and Reactive Power (MVAR)	PV Location, Active Power (MW), and Reactive Power (MVAR)	WT Location, Active Power (MW), and Reactive Power (MVAR)	GT Location, Active Power (MW), and Reactive Power (MVAR)	CB Location and Reactive Power (MVAR)	Power Loss (KW)	Loss Reduction (%)	Cost (\$/h)	Emission (lb/h) ($\times 10^6$)
Base case	–	–	–	–	–	225	0	309.7134	8.2508
WCA [6]	(1, 1.7467, 0.2946)	(58, 0.1024, 0.0352) (66, 0.7314, 0.2913)	(63, 0.7030, 0.2742)	(64, 0.5405, 0.3130)	(23, 0.6) (62, 0.6) (42, 0.3)	22.36	90.06	297.47	4.247
EGWO-PSO	(1, 1.2885, 0.50695)	(11, 0.5470, 0.3546) (20, 0.3559, 0.0047)	(63, 1.3344, 0.0277)	(64, 0.2851, 0.4603)	(23, 0.3) (42, 0.45) (62, 0.6)	8.837	96.07	250.5372	2.992

The voltage magnitudes of different buses are compared for five cases along with the base values (Figure 7). It is observed that the voltage profile of the entire network is enhanced greatly by the addition of CBs and type III DG units, i.e., Case 5. Moreover, the power losses are reduced commendably in all the lines for Case 5 (Figure 8). Furthermore, the convergence characteristics of the EGWO-PSO, EGWO, and PSO are shown in Figure 9 for Case 5 of the 69-bus network. It is also perceived that the hybridization of the EGWO and PSO improves the optimality of the solution for higher-order systems. Further, the computation time of the proposed EGWO-PSO, EGWO, and PSO algorithms are evaluated and shown in Figure 10. It is observed that the convergence time of the proposed method is higher than the EGWO and PSO algorithms. Additionally, the computation time doubles when the system size is increased. This prolonged time can be considered tolerable when the success of the results is taken into the account.

**Figure 7.** Voltage profiles of different cases for the 69-bus system.

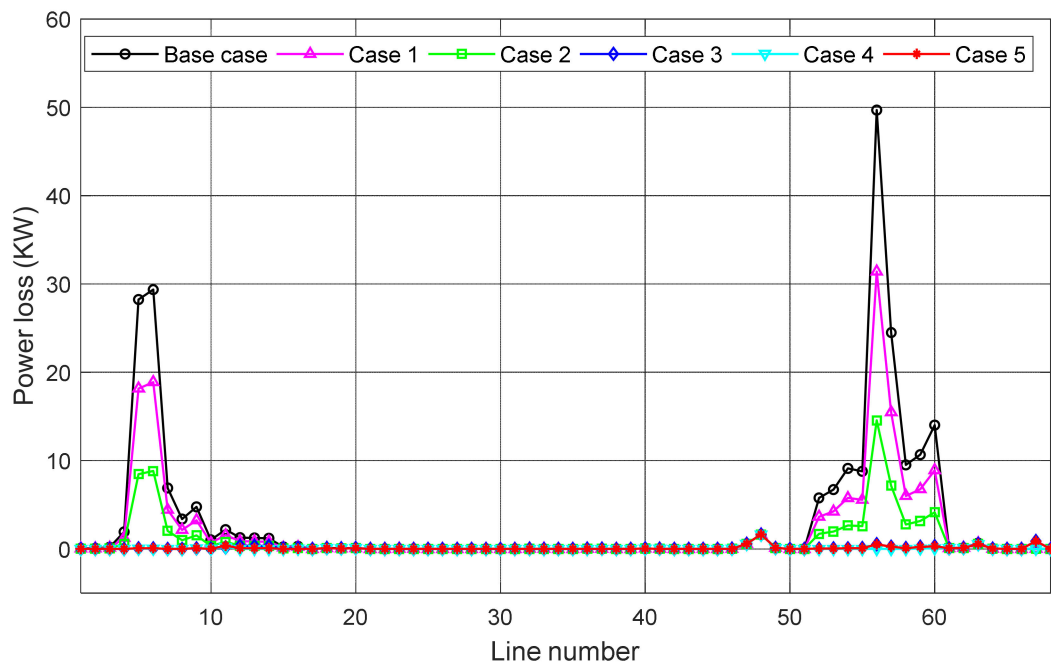


Figure 8. Power losses at each line for different cases of the 69-bus system.

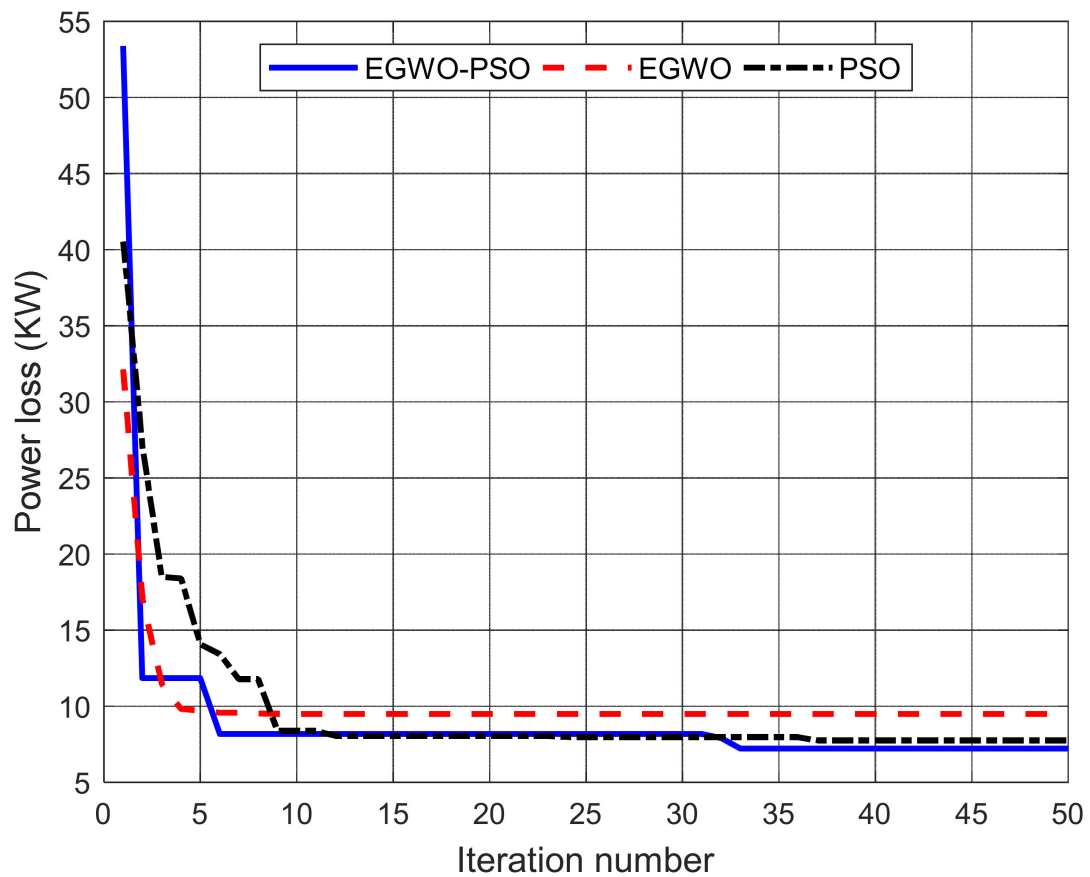


Figure 9. Convergence characteristics of Case 5 for 69-bus system.

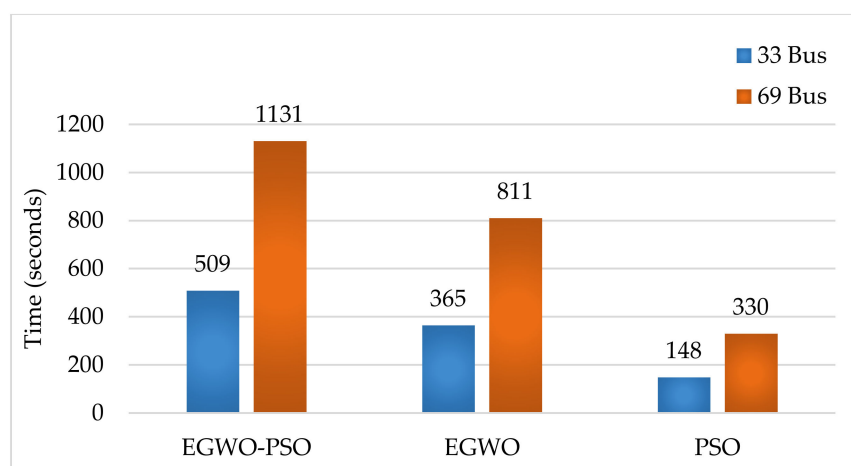


Figure 10. Computation time of proposed EGWO-PSO and other algorithms.

A comparative analysis of technical multiobjective functions such as real power loss, VDI, and VSI improvement for all the five cases of standard IEEE 33 and 69 radial distribution networks along with low voltage bus magnitude is shown in Figure 11. The above simulation results show that the minimum bus voltage improved beyond the smallest restriction limit following the optimal CBs/DGs allocation. In both 33 and 69-bus test systems, significant real power loss reduction is obtained when DGs are operating at LPF (Case 4). Whereas, least VDI and maximum VSI are attained for optimal allocation of CBs and DGs at LPF (Case 5). Furthermore, it can be observed that the DGs are capable of injecting both real and reactive power (type III) with CBs (Case 5) in a 69-bus distribution network significantly that minimize a notable line loss and voltage deviation index along with the high value of VSI compared to 33-bus system. This is because of the availability of its reactive power capacity.

The EGWO-PSO solves the problem in a minimum number of iterations. The convergence curves show that the EGWO-PSO method had fewer convergence fluctuations and achieved a lower loss rate than the EGWO and PSO. Furthermore, the proposed hybrid technique provides the best improvement for both optimal solution and convergence speed. Among the various methods available in the literature, the EGWO-PSO algorithm has a significant outcome of conflicting technical objective functions, i.e., minimization of active power losses, VDI, and maximization of VSI, economic, and environmental objective functions in most of the cases studied. Particularly, emission and cost are reduced commendably due to the effectiveness of the proposed hybrid EGWO-PSO technique.

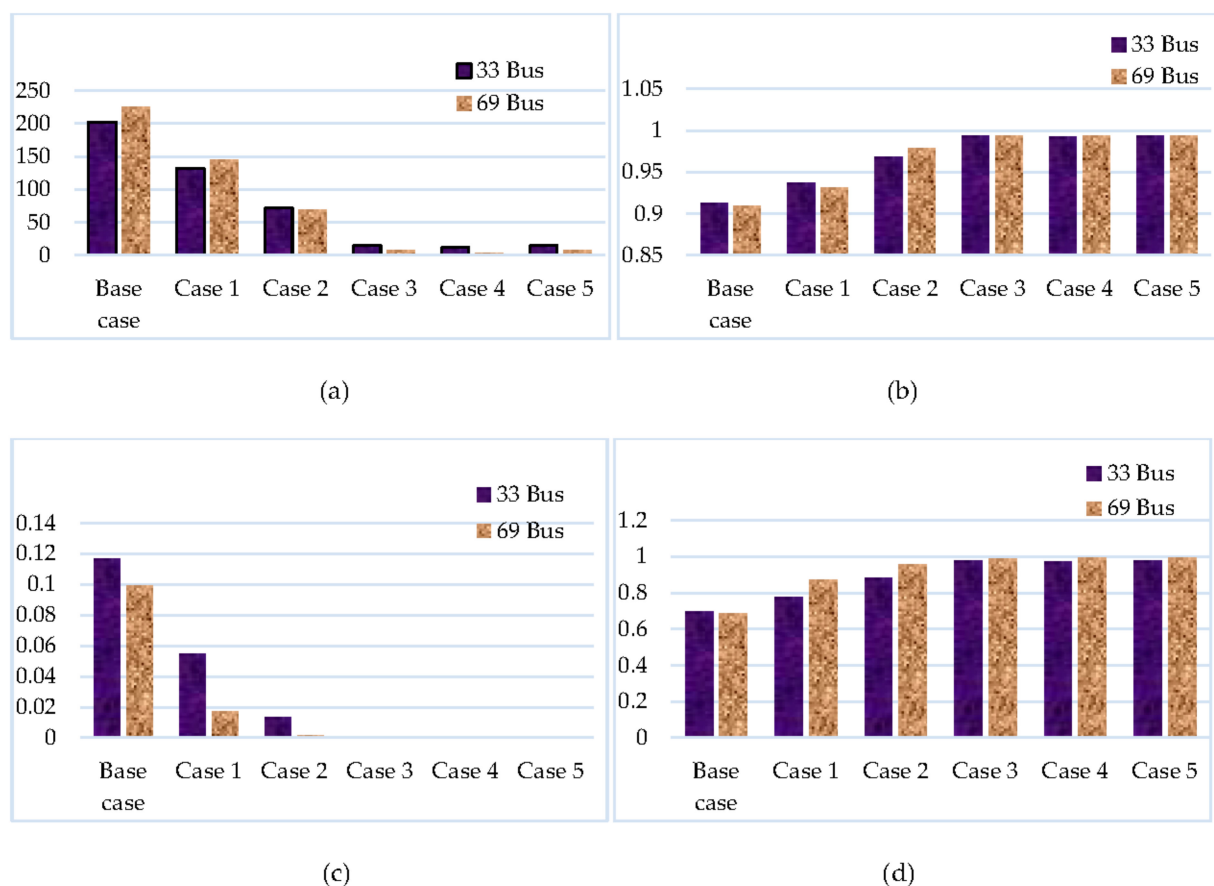


Figure 11. Comparative analysis: (a) power loss (kW); (b) minimum voltage in p.u.; (c) voltage deviation index in p.u.; (d) voltage stability index in p.u.

6. Conclusions

A hybrid EGWO-PSO algorithm has been proposed as a multiobjective framework for optimal placement and sizing of combined DGs/CBs in RDS. It is applied to two standard test systems such as IEEE 33-bus and 69-bus to validate its effectiveness for three key objectives: technical, economic, and environmental. From the simulation results, it can be examined that the EGWO-PSO technique can effectively solve the multiobjective problems and it is safe to trapping in the local extreme. Six operational cases of DGs and CBs have been applied and the observed results are compared with existing optimization techniques. Compared with the other methods, the proposed algorithm has a better convergence speed in a multiobjective optimization problem. The prominent conclusions of the proposed method have been summarized as follows:

- Real power loss of the system is reduced greatly up to 92.60% and 96.79% for 33 and 69 test systems, respectively, using the optimal placement and sizing of combined DGs and CBs.
- The voltage stability index (VSI) of the system is improved significantly from its base value of 0.6968 p.u. to 0.9788 p.u. for the 33-bus test system and 0.6850 to 0.9933 p.u. for the 69-bus test system.
- Excellent emission reduction has taken place up to 72%.
- Significant cost reduction of up to 25% is attained.
- Excellent convergence characteristics have been obtained for EGWO-PSO.

With these merits, the proposed method can be employed to solve any type of complex multiobjective problems and challenges met in practice.

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Nomenclature

a	Fixed generation cost coefficient
A and C	Coefficients of grey wolf optimizer (GWO)
a_0	Modified optimizer of enhanced GWO
b	Variable generation cost coefficient
c_1 and c_2	Control coefficients of particle swarm optimization (PSO)
C_{CB}	Investment cost of the capacitor bank (CB)
C_{Ci}	Purchase cost of i th CB
C_{DG_i}	Generation cost of i th distributed generation (DG) unit
C_{Grid}	Substation cost
CO_2 , NO_x and SO_2	Carbon dioxide, nitrogen oxides, and sulfur dioxide, respectively.
E_{Grid}	Emissions generated by the grid
e_i	Installation cost of i th CB
E_{PVi} , E_{WTi} and E_{GTi}	Emissions generated by the i th photovoltaic (PV), wind turbine (WT), and gas turbine (GT) power plants, respectively
$GBest$	Global best of PSO
Gr	Annual rates of benefit
I_i	Current magnitude of i th branch
LF	Load factor of DGs
$\min$ and $\max$	Lowest and highest permissible limits respectively.
n	Total number of buses in the system
N_C	Number of capacitor bank units
N_{DG}	Total number of DG units
n_L	Total number of branches
N_{PQ}	Total number of load buses
N_{PV} , N_{WT} and N_{GT}	Total number of PV, WT, and GT DG units, respectively
N_R	Number of installed reactive power resources
$O \& M$	Operation and maintenance
$PBest_i$	Personal best of i th particle of PSO
P_D	Total active power demand
P_{DG_i} and Q_{DG_i}	Active and reactive power the capacity of a DG unit at i th bus, respectively
P_d and Q_d	Active and reactive power demand, respectively
P_{gGrid}	Real power produced by the substation
$P_{ij \text{ loss}}$	Active power loss in the line between the nodes i and j
P_j and Q_j	Real and reactive power of load at j th node, respectively
P_{Lossj} and Q_{Lossj}	Active and reactive power line losses of j th bus, respectively
P_{PVi} , P_{WTi} and P_{GTi}	Active power generated by the PV, WT, and GT DG units at i th bus, respectively
P_{rGrid}	Generated power cost at the substation
P_s and Q_s	Real and reactive power of swing bus, respectively
Q_{Ci}	Reactive power capacity of i th CB

Q_d	Total reactive power demand
Q_{Ri}	Reactive power injection by CB and/or DG unit at ith node
r_1 and r_2	Random numbers
R_i	Resistance of ith branch
t	Current iteration
V_i and V_j	Voltage magnitude at ith and jth nodes, respectively
v_i	Velocity of the ith particle in PSO
V_{Li}	RMS value of ith load-bus voltage
W	Inertia weight of PSO
w	Weight coefficient of GWO
X	Location of a grey wolf
x_i	Position vector of the ith particle in PSO
X_{ij} and R_{ij}	Reactance and resistance of the line between nodes i and j, respectively
X_p	Position of the prey in GWO
α , β , δ , and ω	Fittest, second best, third best, and remaining solutions of GWO, respectively
ζ and θ	Control parameters of GWO
μ	Update coefficient of PSO
Abbreviations	
ABC	Artificial bee colony
ACO-ABC	Ant colony optimization and artificial bee colony
ALO	Ant lion optimization
BBBC	Big bang–big crunch
BPSO-SLFA	Binary particle swarm optimization-shuffled frog leap algorithm
BSA	Backtracking search algorithm
CB	Capacitor bank
Cf-PSO	Constriction factor particle swarm optimization
CSA	Crow search algorithm
CSO	Cuckoo search optimization
CTLBO	Comprehensive teaching learning-based optimization
CVSI	Combined voltage stability index
CWOA-LSF	Chaotic whale optimization algorithm and loss sensitivity factor
DE	Differential evolution
DE-PS	Differential evolution and pattern search
DG	Distributed generation
DS	Distribution systems
DSA	Direct search algorithm
EA	Efficient analytical
EA-OPF	Efficient analytical and optimal power flow
EGWO	Enhanced grey wolf optimizer
EGWO-PSO	Enhanced grey wolf optimizer and particle swarm optimization
FPA	Flower pollination algorithm
Fuzzy GA	Fuzzy genetic algorithm
FWA	Fireworks algorithm
GA	Genetic algorithm
GA-IWD	Genetic algorithm-intelligent water drops
GSA	Gravitational search algorithm
GWO	Grey wolf optimizer
GWO-PSO	Grey wolf optimizer and particle swarm optimization
HGWO	Hybrid grey wolf optimizer
HS	Harmony search
HSA	Harmony search algorithm
HSA-PABC	Harmony search algorithm and particle artificial bee colony
IA	Improved analytical
I-DBEA	Improved decomposition-based evolutionary algorithm
IEEE	Institute of Electrical and Electronics Engineers
IGWO	Improved grey wolf optimizer
IMDE	Intersect mutation differential evolution

IMOHO	Improved multiobjective elephant herding optimization
IMOHs	Improved multiobjective harmony search
IPSO	Improved particle swarm optimization
KHA	Krill herd algorithm
LPF	Lagging/leading power factor
LSF	Loss sensitivity factor
LSFSA	Loss sensitivity factor simulated annealing
MINLP	Loss sensitivity factor simulated annealing
MODE	Multiobjective differential evolution
MOF	Multiobjective functions
MOHTLBOGWO	Multiobjective hybrid teaching learning-based optimization-grey wolf optimizer
MOPSO	Multiobjective particle swarm optimization
MTLBO	Modified teaching learning-based optimization
of	Objective function
OPF	Optimal power flow
PBOA	Polar bear optimization algorithm
PF	Power factor
PGSA	Plant growth simulation algorithm
PSO	Particle swarm optimization
PV, WT, and GT	Photovoltaic, wind, and Gas turbine power plants, respectively
QOTLBO	Quasi-oppositional TLBO
RDS	Radial distribution systems
RGA	Refined genetic algorithm
SHO	Spotted hyena optimizer
SSA	Spring search algorithm
TLBO	Teaching learning-based optimization
TM	Taguchi method
UPF	Unity power factor
VDI	Voltage deviation index
VSI	Voltage stability index
WCA	Water cycle algorithm
WOA	Whale optimization algorithm

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