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Optimal DG Location and Sizing to Minimize Losses and Improve Voltage Profile Using Garra Rufa Optimization

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Abstract: Distributed generation (DG) refers to small generating plants that usually develop green energy and are located close to the load buses. Thus, reducing active as well as reactive power losses, enhancing stability and reliability, and many other benefits arise in the case of a suitable selection in terms of the location and the size of the DGs, especially in smart cities. In this work, a new nature-inspired algorithm called Garra Rufa optimization is selected to determine the optimal DG allocation. The new metaheuristic algorithm stimulates the massage fish activity during finding food using MATLAB software. In addition, three indexes which are apparently powered loss compounds and voltage profile, are considered to estimate the effectiveness of the proposed method. To validate the proposed algorithm, the IEEE 30 and 14 bus standard test systems were employed. Moreover, five cases of DGs number are tested for both standards to provide a set of complex cases. The results significantly show the high performance of the proposed method especially in highly complex cases compared to particle swarm optimization (PSO) algorithm and genetic algorithm (GA). The DG allocation, using the proposed method, reduces the active power losses of the IEEE-14 bus system up to 236.7873%, by assuming 5DGs compared to the active power losses without DG. Furthermore, the GRO increases the maximum voltage stability index of the IEEE-30 bus system by 857% in case of the 4DGs, whereas GA rises the reactive power of 5DGs to benefit the IEEE-14 bus system by 195.1%.

Keywords: distribution generation; Garra Rufa ptimization; PSO; GA; power system

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1. Summary

The interconnection of generation, transmission, and distribution with a centralized control increases the power system complexity with the increase in the number of nodes and branches. To overcome centralized control and long-distance power transmission, distributed generators (DGs) are among the most common clean energy solutions introduced in the last 20 years [1–4]. Their advantages are not limited only to reduce the complexity and enhance the environment as in the smart city. They are also extended to other indexes, such as the economy, environment, quality, stability, losses, voltage profile, and sensitivity. Those benefits have positively increased with the corresponding proper selection of each benefit. On the other hand, within the context of intelligent optimization and control, the huge thinking of the maximum economic operation and high efficiency, the researchers spotlighted and paid attention to the intelligent behavior of nature [5–9]. The new artificial intelligence (AI) advances in software engineering are related to all scientific topics which provide new opportunities and challenges for scientists for tackling highly complex issues that are difficult to solve with conventional techniques [10,11]. The nature-inspired algorithms ranked the highest in predicting the exact solutions, efficiency, and speed even in multi-objective functions. Since intelligent optimization led the way in engineering science, several studies have been conducted on the topic of determination of DG location and size which are listed in the references [12–23]. For instance, Suresh and Belwin [12] used the Dragonfly algorithm to optimal DG size for multi-objective function. IEEE 15, 33, and 69 examined the algorithm performance. Ogunsina et al. [13] determined the DG effect using the electrical transient and analysis program (ETAP) model for the IEEE 30 bus standard via enhancing the active power loss and voltage profile. The used method was artificially intelligent colony optimization. The optimal size and sitting of DGs were estimated by Marimuthu et al. [14] by a hybrid of particle swarm optimization (PSO) and time-varying acceleration coefficients. The voltage Stability with other four objectives were the goal for enhancing a 69-node power system. Montoya et al. [15] suggested a solution for the DGs allocation by employing a master-slave technique using a modified genetic algorithm (GA) that named the Chu-Beasley genetic algorithm. The master-slave solved the mixed-integer nonlinear identification problem in the complex system and the slave determined the optimal power flow using MATLAB. Another attempt of GA for optimizing the allocation was introduced by Chandel et al. [16]. The differential evolution was the comparison base that was selected to enhance five objective functions of the IEEE 18 standard system. Elhosseny et al. [17] developed a PSO technique for selecting the location and the size of DG. The IEEE14 standard system was implemented to validate the build-up of the PSO method for reducing power losses and improving voltage stability. The power loss was reduced by using the Bat algorithm during the optimal selection of DG size in [18]. The IEEE 33-bus standard was the only system that has been tested to validate the system. Suresh and Edward [19] considered the hybridization of fuzzy and one-rank cuckoo search algorithms as the best method to allocate DG. The power losses and voltage profile were the objectives to improve IEEE 15-bus, 33-bus, and 69-bus test systems. Abedini and Saremi [20] proposed a hybrid of two intelligent methods, PSO and GA, to locate the DG with a fuzzy optimization idea to transfer the multi-objective into a single objective problem. The method was tested using the 52-bus of Hamadan power networks. A fuzzy logic control method with GA has been tested to optimize the D-STATCOM by optimizing the allocation of the DG [21]. A radial distribution standard of 33-bus was the system that examined the Fuzzy-GA method to improve three of the indexes of the power system.

However, each of the optimal algorithms that is used in the literature has its own drawback. For example, GA suffers from premature dependence convergence, slow convergence, and difficulty in parameter determination [24,25]. The last iterations of PSO converge slowly and drop easily into a locally optimal solution [24,26]. The convergence rate of the bee colony is slow convergence, also has the same problem of PSO of the local optimal point. The ant colony convergence is normally slow, and hilly dependent on parameter selection [24]. The modified and the hybrid methods are more complex and increase the complexity of the system [26]. These limitations are due mainly to the use of Garra Rufa optimization (GRO) for estimating the size and location of DGs. The high flexibility feature of GRO may lead to solving the DGs issues. First of all, a simplified view of the DG, the proposed method, and the used systems are introduced. Secondly, applying three factors in one objective function that are active and reactive power losses minimization, and voltage stability index enhancement. The three objectives were weighted depending on the corresponding priority of each index on the power system's economic and quality. Moreover, the proposed method is applied to the 14 and 33-bus bar standard systems with PSO and GA algorithms with five cases of distribution generator numbers.

Finally, the proposed optimization technique is compared with PSO and GA in order to show its tracking performance via the active power losses, reactive power losses, and voltage profile. By examining the optimal allocation of each method, the performance validation is conducted by analyzing the IEEE of 14-bus and 30-bus.

2. Related Work

A population of strings representing several potential solutions makes up the population used by the population-based search technique known as GA [27]. As a result, when it's used to solve challenging optimization issues, GA has latent parallelism that improves its search capabilities and speeds up the discovery of the optima. In order to discover a globally optimal solution, GA is an effective point-based optimization technique that has been widely used in a variety of engineering issue.

Another evolutionary computation method is used to validate the proposed method is (PSO). PSO has been inspired by the behaviors of wildlife like swarming fishes and flocking birds. In several cases, PSO is typically described as a clear, simple-to-use, and computationally efficient technique.

The GA and PSO can be widely used to investigate optimal DG placement. The non-linear model of the power system, as settled, has problems of irregularity and discontinuity. The objective function organized by the genetic algorithm has a high feature of adaptability compared to PSO [28]. PSO is more effective than GA and has a balanced method to improve local and global exploration capabilities [29,30]. However, some shortcomings have been found in the performance of most of the basic algorithms, such as GA, ABC, ACO, CKO, and PSO [31]. Figures 1 and 2 represent the intelligent algorithms for GA and PSO respectively.

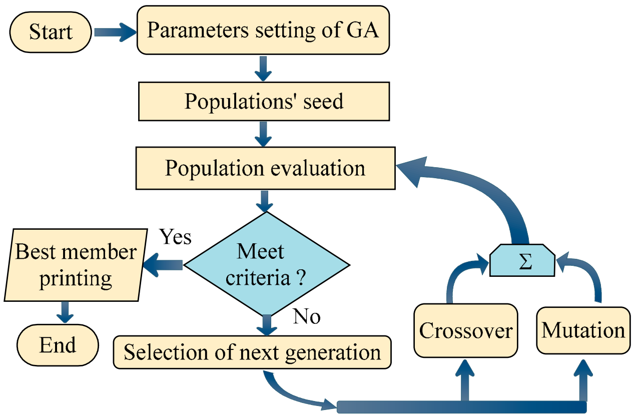


Figure 1. GA algorithm.

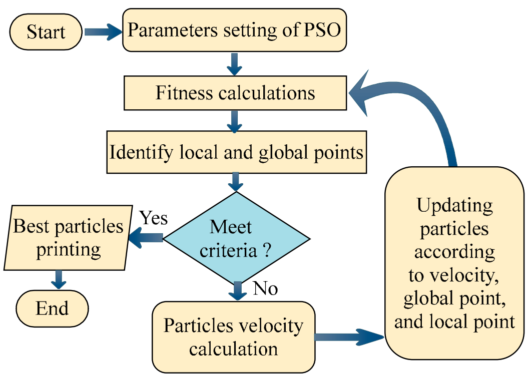


Figure 2. PSO algorithm.

To overcome the drawback of many of the intelligent optimization methods, GRO is one of the most flexible and efficient methods introduced to solve the highly complex issues [32,33]. To understand the GRO mechanism, the algorithm could be simplified in three steps. Step one is initialization, step two is the leaders' crossover, and group followers' crossover is the last step.

2.1. GRO Initialization

The main principle of GRO is to divide the total particles into more than one group, each group has its' own guide to the local and global optimal group points. Moreover, initial assumptions must be assumed in the GRO algorithm such as each fish could be either a guide or a follower according to the corresponding global optimal point of each group. Before the next iteration, a percentage of the followers will move from the weak leader to the stronger one that got the best optimal value. This percentage must be initially assumed. Other initial parameters are the inertia weight (ω) and acceleration coefficients (c_1, c_2). The initialization equation is listed as shown [31].

$$followers\ number = \frac{total\ umber\ of\ partcles - number\ of\ groups}{number\ of\ groups} \tag{1}$$

2.2. GRO Leaders' Crossover

Two types of leaders' crossovers are assumed in the GRO algorithm, firstly, a new leader (guide) is elected for each group. Secondly, select the best leader to lead the number one group which has the maximum number of followers. These steps are considered the basis paving the way for the most important step, which gives flexibility to the method of GRO.

2.3. GRO Followers' Crossover

The flexible movement for the sleeve fish between the groups is more probability to search in the problem space. The highly complex problems can cause disorientation for all the intelligent optimization algorithms that have inflexible nature of moving from one search space to another. This issue occurs due to a large number of ripples and the multiplicity of parameters of complex problems. By the follower crossover between the groups, GRO found a way to keep searching in the wider area space of the problem by applying three steps. First of all, a random number of fish will move to the strong leader from all other groups. Secondly, one step is moving toward each leader which must be done by determining the velocity (v_i) and the position (X_i) using the classical Equations (2) and (3).

$$v_i(t+1) = \omega v_i(t) + c_1 r_1 (p_i(t) - X_i(t)) + c_2 r_2 (G_i(t) - X_i(t)) \tag{2}$$

$$X_i(t+1) = X_i(t) + v_i(t+1) \tag{3}$$

After that, the fitness of the new groups' figures will be recalculated, including all followers and leaders. Equations (4) and (5) represent the novelty steps of GRO.

$$moving\ folwoers_i = integer\ (£ * random) \tag{4}$$

$$followers_{ij} = Max\left(\left(followers_{ij-1} - moving\ folwoers_i\right), o\right) \tag{5}$$

where £ is the highest possible number of moving fish. Figure 3 shows the algorithms flowchart of GRO method.

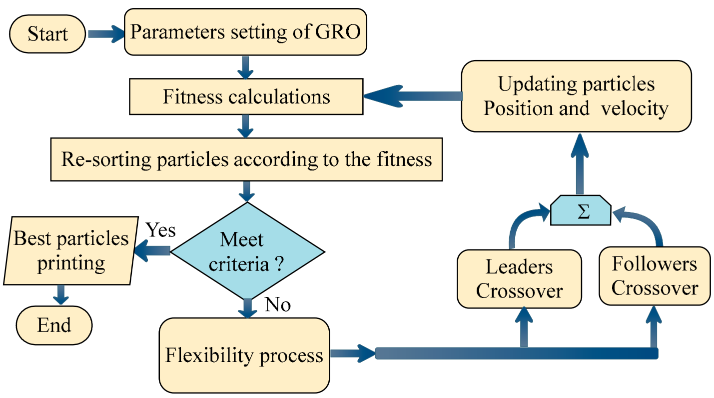


Figure 3. GRO algorithm.

In this paper, particle swarm (PSO) and GA optimization algorithms will be used for comparison with GRO to optimize the size and location of the DGs. The PSO, GA, and GRO basic fundamental equations are implemented without any further modifications according to Kennedy and Eberhart (PSO) [34], Abedini (GA) [20], and Jaber [31].

3. Proposed System Model

As previously mentioned, power system models and their networks comprise a nonlinear high-order system of equations that arise from a large number of parameters.

Thus, prior to solving the DGs problem of estimating their size and location, an obvious objective function is required. The objective function of any DG allocation could be one or more.

According to the power flow using the formulation that contained the different types of power system variables (active reactive power, voltage, and power angle), important indexes have been introduced to improve the power system quality, e.g., power losses, voltage profile, reliability, stability, and economic issues. In this paper, three of the most important challenges in DG topic are selected to determine the size and location of each DG. The following indexes represent the base indexes formulas of the objective function.

3.1. Minimization of Total Active Power Losses

The total losses have a substantial effect on the total power generation, thus could grow the economic and environmental merits. Two power systems are used to estimate the current flow in the lines between the buses of those systems. These currents result in power losses (P_L) that represent the most important objective function which has a mathematical model as (6).

$$P_L = \sum_{line=1}^{N_u} G_{line}(V_i{}^2 + V_s{}^2 - 2V_iV_s\cos(\alpha_i - \alpha_s)) \tag{6}$$

where N_u is the total number of transmission lines in the system, G_{line} is the conductance of the line, V_i and V_s are the magnitudes of the sending end voltages and receiving end voltages of the line, α_i and α_s are angles of the end voltages.

3.2. Minimization of Reactive Power Losses

Q_L are referred to as the complex part of the apparent power losses. The amount of reactive power losses (Q_L) has a significant impact on conductor capacity and voltage profile. In addition, the QL reduction could increase the stability and reliability indexes. The second objective function in this study can be mathematically written as (7).

$$Q_L = \sum_{line=1}^{N_u} B_{line}(V_i{}^2 + V_s{}^2 - 2V_iV_s\sin(\alpha_i - \alpha_s)) \tag{7}$$

where N_u is the total number of transmission lines in the system, B_{line} is the susceptance of the line, V_i and V_s are the magnitudes of the sending end voltages and receiving end voltages of the line, α_i and α_s are angles of the end voltages.

3.3. Voltage Stability Index Improvement

In order to satisfy the modern power system quality, the improvement of voltage stability is essential that it is concerned with the power capability for maintaining acceptable voltages at all buses in both normal and up normal conditions. In this paper, the voltage deviation index is used to estimate the voltage stability index which is based on the power flow calculations [35,36]. The described voltage stability index (VSI) is formulated as follows:

$$\mathrm{VSI} = \sum_{Bus=1}^{N_b}\left(V_{ref} - V_{bus}\right) \tag{8}$$

where N_b is the number of buses; V_{ref} is the reference voltage; and V_{bus} is the bus voltage.

From the other hands, the weights are selected to give the corresponding priority to each impact indices of DGs allocation objective functions [37,38]. The appropriate weight selection also relies on the experience of power system researchers and the heeds of distribution side utilities. Nowadays, total power loss reduction in both of its components is one of the major concerns in the power system operation and control due to its impact on the economy, stability, and environment, while the voltage stability index is less important than the power loss reduction. Hence, the weights for P_L, Q_L, and VSI (w_1, w_2, and w_3) have been taken as 0.50, 0.15, and 0.35, respectively.

Moreover, in order to make the maximum and minimum values and the possible changes of each index as a result of adding the DG homogeneous in terms of units and influence, a corresponding base index was chosen that represents the same of each index without adding the DG. Figure 4 represents the objective function calculation according to the AI algorithm. Furthermore, the optimization problem is given by Equation (9)

$$\text{objective} = \text{minimize}\left(w_1 * \frac{P_L \text{ with } DG}{P_L \text{ without } DG} + w_2 * \frac{Q_L \text{ with } DG}{Q_L \text{ without } DG} + w_3 * \frac{VSI \text{ with } DG}{VSI \text{ without } DG}\right) \tag{9}$$

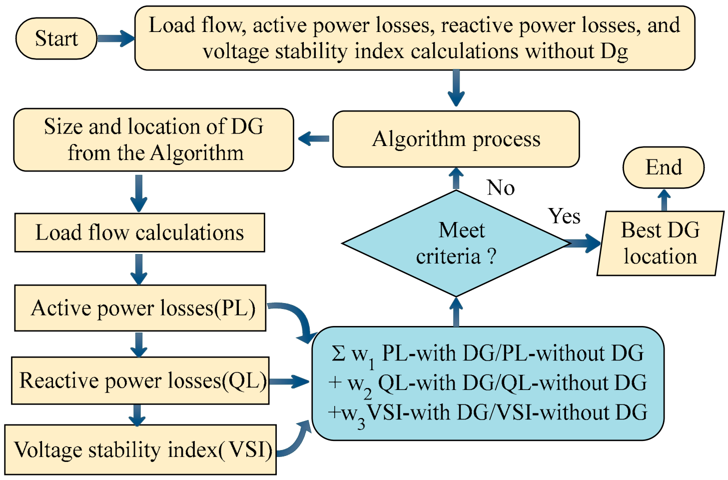


Figure 4. The objective function.

4. Result and Discussion

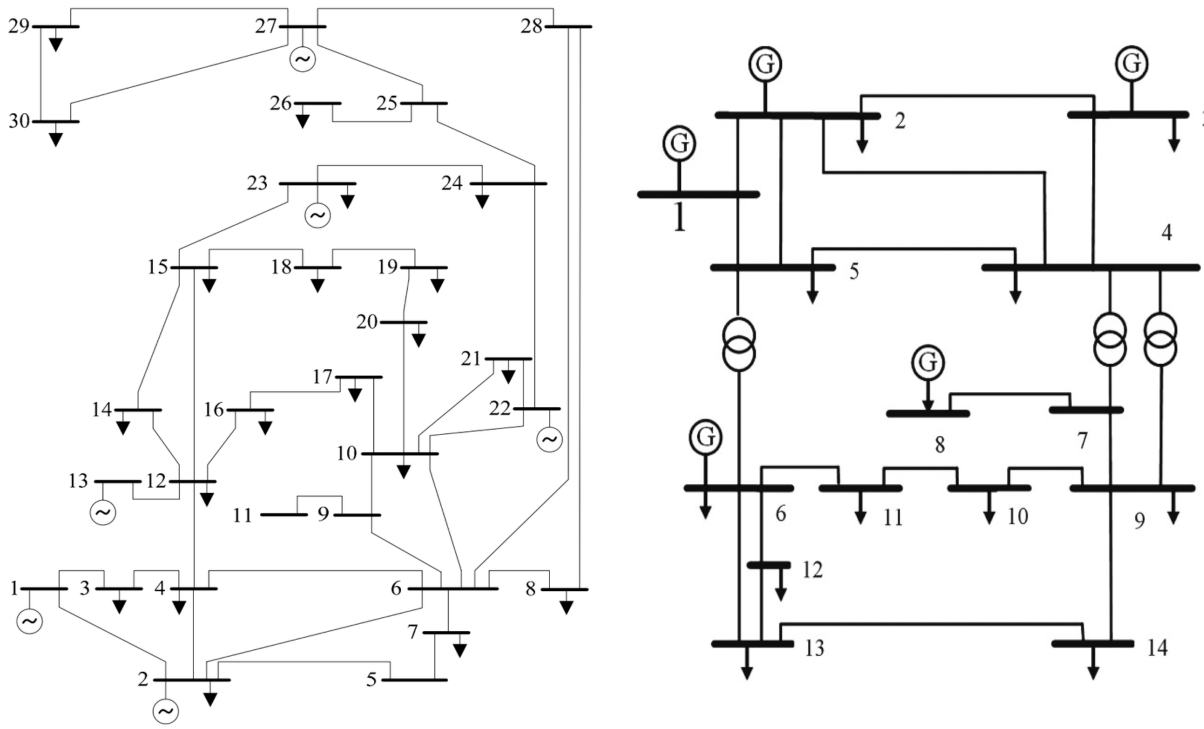
The discovery of the high efficiency and flexibility of GRO in highly complex issues inspires the authors of this paper to utilize the algorithm to estimate the location and size of DGs in order to reduce active and reactive losses of power and improve voltage stability.

To achieve the results and performances of the prepared scenario, all tested cases and algorithms have been simulated by MATLAB. Additionally, the optimization algorithms are tested with the 30 and 14 bus IEEE standards which are shown in Figure 5.

Besides, for fair comparisons, the objective functions are implemented using GRO, PSO, and GA with the same different numbers of population and iterations depending on the problem case and the system, as shown in Table 1.

Table 1. Algorithm parameters.

System	30 Bus	30 Bus	30 Bus	30 Bus	30 Bus	14 Bus	14 Bus	14 Bus	14 Bus	14 Bus
DGs-number	1	2	3	4	5	1	2	3	4	5
Particles	25	30	40	40	40	20	20	20	20	20
Iterations	30	30	35	40	40	20	20	30	30	30



(**a**) (**b**)

Figure 5. Tested systems (**a**) IEEE 30 bus system (**b**) IEEE 14 bus system.

4.1. Test Case 1: IEEE-14 Bus Standard

Between 1 and 5 DGs are assumed to be added to the selected IEEE systems to find the effectiveness of DG of the objective functions. The addition of different numbers of DG is create multi complexity cases. Furthermore, the load flow calculations for all the cases have been done using the Newton–Raphson method. Table 2 shows the size and location for the three methods.

Table 3 describes some of the important directories for the changes in Loss saving and voltage profile improvements by the three used methods. It can be noted from Table 3 that all three methods have an impact on the apparent power losses and improve the stability voltage index but in different values. In cases of single, two, and three generators, there is no significant noted advance of GRO on the objective value, while the effectiveness of the proposed method is clearly shown in the four and five DGs allocation problem solutions.

4.2. Test Case 2: IEEE-30 Bus Standard

In order to validate the proposed method, the same procedure sequence is followed with a higher complex system of the IEEE system instead of the IEEE-14 bus. The IEEE-30 bus consists of six generators and 41 lines between the 30 buses. Tables 4 and 5 illustrate the DGs locations for the five cases of the number of generators and the three cases of the optimization methods.

The specific underlined values seen in Tables 3 and 5 show the best optimal values of each optimization method for all the classes. To clarify those distinction of these optimization methods, Figures 6–8 illustrate samples of power system improving in power losses and voltage profile.

Table 2. DGs allocation of IEEE-14 bus.

Dg Number	1DG			2DG			3DG			4DG			5DG		
Method	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**
Location	**7**	**7**	**8**	**12,8**	**9,5**	**3,7**	**6,5,4**	**2,4,5**	**2,6,13**	**2,3,12,10**	**9,2,2,3**	**2,2,8,11**	**2,3,10,11,2**	**2,7,2,5,4**	**11,10,2,2,3**
size	17.771	20.85	20.848	17.381 21.432	20.850 20.010	20.837 20.707	46.174 41.925 45.954	49.685 51.350 50.850	50.789 43.203 49.329	15.652 17.134 13.558 38.021	20.850 8.048 17.471 20.85	1.582 20.849 20.777 20.825	11.352 39.087 25.309 12.051 10.112	6.725 20.211 20.309 20.850 20.850	20.754 20.812 16.147 20.835 20.828

Table 3. IEEE-14 bus objective functions.

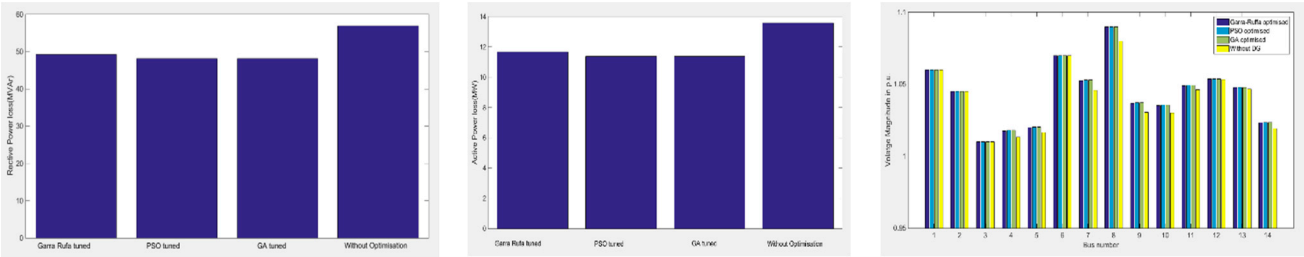
Dg Number	1DG			2DG			3DG			4DG			5DG		
Method	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**
P_{LOSS}	<u>15.055</u>	14.324	13.961	11.695	11.716	11.453	6.7	8.427	7.051	6.795	8.087	7.85	<u>4.034</u>	4.786	4.190
Q_{LOSS}	<u>61.259</u>	58.986	57.859	35.931	35.558	36.541	22.04	26.057	24.758	26.126	27.724	27.383	21.565	19.347	<u>19.281</u>
$\mid VSI \mid$	<u>0.2707</u>	0.2210	0.1916	0.1062	0.0866	0.1330	0.0294	0.0334	0.13685	0.0626	0.0470	0.0994	<u>0.0107</u>	0.2150	0.1990
Objective	<u>0.547</u>	0.545	<u>0.547</u>	0.459	0.471	0.435	0.323	0.358	0.410	0.280	0.400	0.423	<u>0.212</u>	0.361	0.329

Table 4. DGs allocation of IEEE-30 bus.

Dg Number	1DG			2DG			3DG			4DG			5DG		
Method	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**
Location	**5**	**16**	**2**	**19, 14**	**14, 18**	**18,14**	**3,4,9**	**17,28,13**	**29,17,8**	**6,23,9,7**	**17,27,15,9**	**17,29,18,10**	**5,10,21,25,24**	**28,24,2,16,29**	**7,11,28,18,12**
size	44.641	61.054	70.076	48.608 52.589	47.358 63.882	52.719 40.175	22.123 72.297 101.7	46.051 70.850 58.858	9.562 69.359 67.387	56.195 26.217 25.888 66.511	30.850 30.850 30.850 26.487	30.849 22.015 30.839 30.756	98.468 47.781 35.144 7.556 7.448	98.468 47.781 35.144 7.556 7.448	50.819 42.210 46.125 10.804 46.461

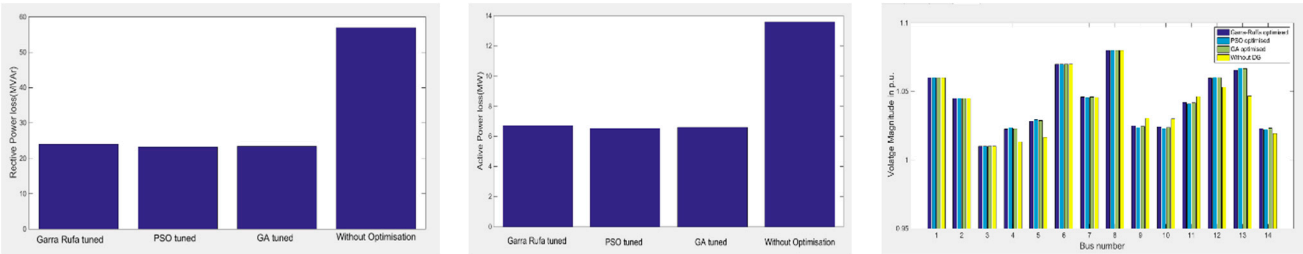
Table 5. IEEE-30 bus objective functions.

Dg Number	**1DG**			**2DG**			**3DG**			**4DG**			**5DG**		
Method	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**	**GRO**	**PSO**	**GA**
P_{LOSS}	11.671	11.371	11.371	9.268	9.022	8.961	6.708	6.518	6.595	8.697	9.621	8.841	5.531	7.72	6.889
Q_{LOSS}	49.266	48.157	48.157	40.092	39.34	39.081	23.964	23.164	23.446	33.58	39.033	36.448	23.624	32.691	27.842
$\vert$VSI$\vert$	0.1737	0.2990	0.6672	0.1527	0.1430	0.6922	0.4708	0.5261	0.5632	0.0955	0.3012	0.4576	0.2341	0.4215	0.2812
objective	0.507	0.544	0.685	0.4104	0.398	0.606	0.424	0.438	0.455	0.358	0.475	0.507	0.299	0.453	0.365



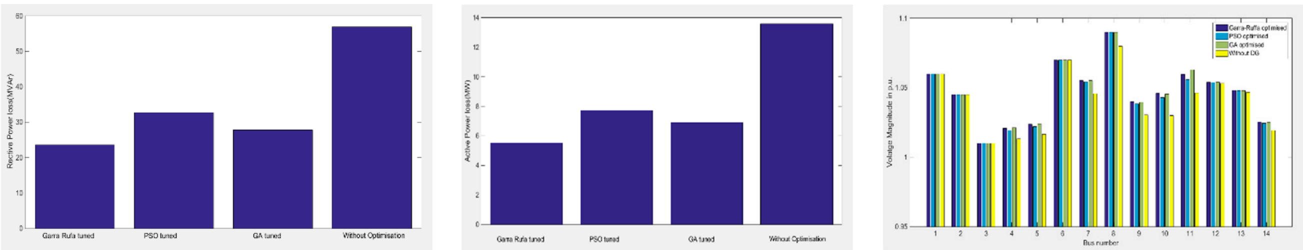
(**a**) (**b**) (**c**)

Figure 6. IEEE-14, 1-DG Power system improvement (**a**) reactive power, (**b**) active power, and (**c**) voltage profile.



(**a**) (**b**) (**c**)

Figure 7. IEEE-14, 3-DG Power system improvement (**a**) reactive power, (**b**) active power, and (**c**) voltage profile.



(**a**) (**b**) (**c**)

Figure 8. IEEE-14, 5-DG Power system improvement (**a**) reactive power, (**b**) active power, and (**c**) voltage profile.

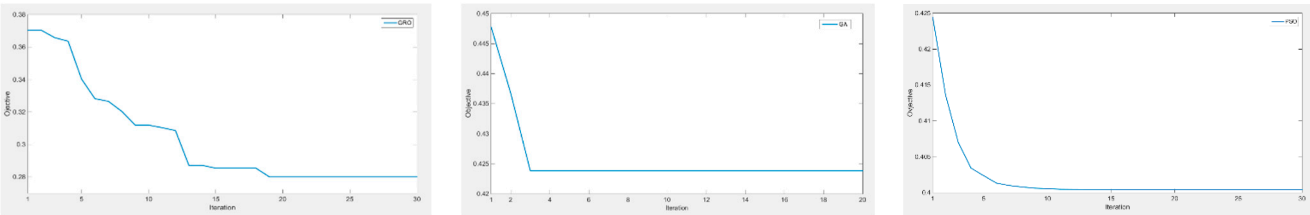
As observed in Tables 3 and 5, there are loss savings in all three methods. The maximum saving in the active power of the IEEE-14 bus system is 236.7873% in the case of the 5DGs GRO method, and the minimum benefit is –9.7576% in the 1DG GRO method, which means GRO failed in finding an acceptable solution. Moreover, the maximum saving in the reactive power of the IEEE-14 bus system is 195.1% in the case of the 5DGs GA method, and the minimum benefit is −7.1173% in the 1DG GRO method. Furthermore, the maximum saving in the voltage stability index of the IEEE-14 bus system is 515.2% in the case of the 5DGs GRO method, and the minimum benefit is 107.6 in the 1DG GRO method. While the best objective function is 0.212 in the case of the five DG GRO method, the worst value is 0.547 in both GA and GRO single DG.

The maximum saving in the active power of the IEEE-30 bus system is 216.6% in the case of the 5DGs GRO method, and the minimum benefit is 50.07% in the 1DG GRO method. Moreover, the maximum saving in the reactive power of the IEEE-30 bus system is 193.8% in the case of the 3DGs GA method, and the minimum benefit is 39.79% in the 1DG GRO method. Furthermore, the maximum saving in the voltage stability index of the IEEE-30 bus system is 857% in the case of the 4DGs GRO method, and the minimum benefit is 32.04% in the 2DG GA method. While the best objective function is 0.299 in the case of the five DG GRO method, and the worse value is 0.606 in both GA 2DGs.

Of the ten cases that were selected to study the new method which represents a multi-level of complexity, seven of the cases were advanced via the objective function using GRO, while two and one cases are optimized better by using PSO and GA, respectively. Moreover, all the high levels of complexity had a better solution using the proposed method.

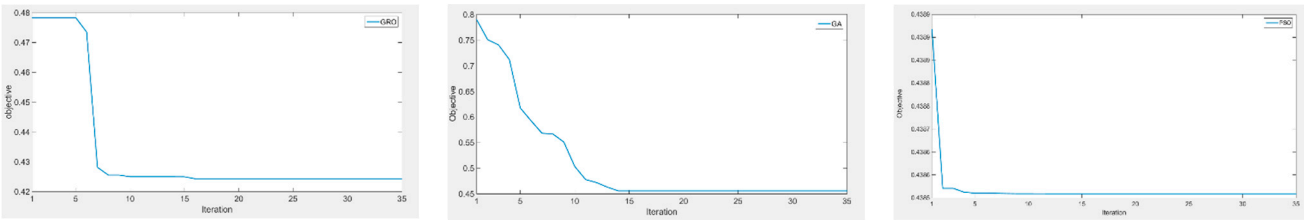
Converge mechanism of the proposed optimization methods by searching in several areas in the problem space is the reason behind the overcome of GRO method in most cases. The convergence for two cases of each optimization method is shown in Figures 9 and 10. Additionally, all the other load flow results and figures can be shown in Supplementary Materials.

From Figures 9 and 10, it can be noted that for the assumed iterations and the same number of search particles, GRO converges more effectively than the others (GA, PSO) in terms of the minimum objective function. Moreover, in Figure 10, GRO could find a better solution even after five constant iterations (from 10 to 15). This gives the impression that GRO may be successful in skipping in falling into a single optimal point.



(**a**) (**b**) (**c**)

Figure 9. IEEE-14, 4-DG algorithm convergence (**a**) GRO, (**b**) GA, and (**c**) PSO.



(**a**) (**b**) (**c**)

Figure 10. IEEE-30, 3-DG algorithm convergence (**a**) GRO, (b) GA, and (**c**) PSO.

5. Conclusions

In this work, the GRO, a recent nature-inspired algorithm, has been utilized to specify DGs' location and size in power network distribution. The proposed method was investigated on two well-known IEEE14 and IEEE30 bus standards by DG, 2DGs, 3DGs, 4DGs, and 5DGs installation and succeeded in terms of loss reduction improvement in voltage stability. Three algorithms, including GA, PSO, and GRO, were applied to solve the assigned issue for comparative aims. As a result of proper DG allocation using the proposed methods, the active and reactive power losses were reduced and the voltage stability index was enhanced up to 236.7873%, 857%, and 195.1% respectively. Moreover, there was a single case where the GRO was unable to find a proper solution, which was reducing the reactive power in a single DG and IEEE 14-bus standard. The GRO mechanism and its superior exploration and exploitation features over other swarm intelligence methods for solving highly complex engineering optimization issues were conveyed. In the end, it is expected that the GRO may provide efficient solutions to existing highly complex power engineering issues, such as load forecasting or load frequency control. On the other hand, the newly proposed method can be modified to be able to solve low-complex problems with more accuracy.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15021156/s1.

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