

## ORIGINAL RESEARCH ARTICLE

# Optimal DG allocation by Garra Rufa optimization for power loss reduction

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## ABSTRACT

The rapid growth of distributed generation (DG) units has necessitated their optimization to address the increasing complexity of power grids and reduce power losses. The need for optimization of distributed generation (DG) units has been growing rapidly over the past few years. To minimize such losses, the optimal allocation of DG units needs to be correctly identified and applied. On the other hand, Garra Rufa optimization (GRO) is a mathematical optimization technique that is used to determine the high effective and efficient way to solve very complex problems to achieve optimal results. In this work, Garra Rufa optimization is used to identify the optimal placement and size of DG units in order to meet specific power loss requirements. A comparison between genetic algorithm (GA), particle swarm optimization (PSO), and GRO is done using MATLAB to validate the proposed method. The comparison shows that GRO is better than the other methods in DG allocation, especially in more than two DGs. The optimization techniques are evaluated using the IEEE standard power system case, specifically the 30-bus configuration.

**Keywords:** distribution generation; GRO; PSO; GA; power losses; optimization

## ARTICLE INFO

Received: 25 June 2023

Accepted: 19 July 2023

Available online: 28 August 2023

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## 1. Introduction

Although Artificial Intelligence (AI) optimization can be used to achieve acceptable solutions to most engineering problems, there are several challenges associated with the optimization process<sup>[1-3]</sup>. One of the main challenges is that the optimization process can be time-consuming and computationally intensive, depending on the complex problems<sup>[4]</sup>. Additionally, the optimization process can be hampered by the availability of data, as it requires accurate and up-to-date information in order to identify the most efficient way to identify the solution<sup>[5-8]</sup>. Generally, intelligent methods are inspired by nature, whether a physical phenomenon or the movement of a primitive or highly evolving being<sup>[9-13]</sup>. The latest developments in software engineering related to AI offer new opportunities and challenges for scientists to address extremely complicated problems that are challenging to answer using traditional methods<sup>[14-16]</sup>.

On the other hand, the power system is one of the most complex issues that need solving with fast with accurate results<sup>[17-20]</sup>. Problems like losses, stability, economic dispatch, voltage profile, reliability, or control, in addition to the huge number of buses and branches, are the sector behind the complexity of the power system<sup>[21-25]</sup>. For acceptable power system quality, all the above indices must be in a specific limits. The active power losses played an essential role in power system

transmission efficiency and economic operation<sup>[26,27]</sup>. The proper DG allocation in the distribution system leads to reduce the power losses in to the minimum value<sup>[28,29]</sup>. Several AI methods have been used for power losses reduction in last decade. For example, Adepoju et al.<sup>[28]</sup> used MATLAB to simulate the DG location effecting on the total power losses by particle swarm optimization (PSO) optimization. A part of Nigerian electricity distribution system of 34 bus and 11 kV was the application to prove the losses reduction. GA is also examined for estimation the DG implementation to save more power with acceptable minimum and maximum voltage values. Four cases of IEEE-34 standard were used to validate the GA algorithm<sup>[29]</sup>. Muthukumar and Jayalalitha<sup>[30]</sup> reduced the power losses using a hybrid between harmony search and bee colony algorithms. Two systems were tested which were 33 and 119 buses for determining the optimal DG placement. Accipitridae prey was the base of the optimization technique that introduced by Kanagasabai for power losses reduction<sup>[31]</sup>. The power loss of the IEEE 30 bus system was improved using the method that proposed by Kanagasabai. Particle swarm optimization with enhanced pseudo gradient pursuit was used by Polprasert et al.<sup>[32]</sup> to tackle the issue. The problem was resolved by an Operational Metaheuristic Method by Duong et al.<sup>[33]</sup>. For optimizing the D-STATCOM by finding the location of the DGs, by GA method with a fuzzy controller approach have been examend<sup>[34]</sup>. Three of the power system's indexes were being improved using the fuzzy-GA method in a 33-bus radial distribution standard system. The Dragonfly approach was used by Suresh and Belwin<sup>[8]</sup> to determine the ideal DG size for a multi-objective function. The algorithm performance was examined by IEEE 15, 33, and 69. Using the IEEE 30 bus standard's and analysis program and electrical transient model and increasing the active power loss and volt-age profile, Ogunsina et al.<sup>[9]</sup> identified the DG impact. Artificially intelligent colony optimization was the technique adopted. Marimuthu et al.<sup>[35]</sup> used a combination of time varying acceleration coefficients and PSO to determine the ideal size and placement of DGs. The aim was to improve a 69-node power system's voltage stability while still achieving the other four objectives. Montoya et al.<sup>[36]</sup> proposed a master slave approach using a GA modification known as the Chu Beasley GA as a solution for the DGs allocation. Sayed et al.<sup>[37]</sup> created a PSO technique for deciding where to place and how big to make the DG. To validate the development of the swarm technique for lowering losses and enhancing busses voltage stabilities, the IEEE14 standard system was applied. Using the 52-bus of Hamadan's power networks, the strategy was evaluated.

However, varieties of optimum algorithms are treated in the literature, each of which has its own disadvantages. For instance, GA has issues with slow convergence, problematic parameter determination and premature dependence convergence<sup>[38,39]</sup>. The last iterations converge of PSO gradually and quickly reach a solution of locally optimal<sup>[23,38]</sup>. The bee colony's slow convergence rate and PSO of the local optimal point issue are both present. The ant colony convergence typically depends on parameter selection and is hilly<sup>[38]</sup>. The system becomes more complex as a result of the modified and hybrid approaches<sup>[23]</sup>. These restrictions are mostly caused by the GRO technique used to choice the best location and size of DGs.

In this paper, GRO technique is used to minimize power losses by allocating the optimal amount of DG units to meet specific power requirements. The principles of the optimization process are treated to identify the size and location of the DG. To predict the optimal size and location of DGs in distribution network, it's using Garra Rufa optimization (GRO) technique, the proposed technique, with used system is introduced, applying important factor in single objective function which is real power losses minimization. The applied method used the 30-bus standard system with five cases of DG. GRO intelligent technique is compared with two nature inspired techniques in order to clarify the tracking performances via the real losses. By checking the best allocation of three techniques, the performance validation is completed using power losses of the above standard system.

## 2. Related work

### 2.1. GA algorithm

GA algorithm reflects the processes of natural selection where the best individuals are selected for reproduction to produce the next generation's offspring.

A string population representing a number of practical solutions of problems enhances the next generation used by the population search method defined as GA<sup>[13]</sup>. Generally, when using GA to solve optimization problems, this method has similarity that improves its seeking ability and speeds up the finding of the optimal. In order to find the global best functions, parameters, GA has an effective way to determine the point based on optimization techniques that have been generally applied in several technical problems<sup>[4,29]</sup>.

GA is better from basic methods of search steps and optimization as shown:

- 1) GA generally activates with parameter coding instead of the parameter itself.
- 2) It uses objective functions methods instead of using information such as their derivatives.
- 3) GA depends on the probabilistic transference principles, not deterministic principles.

The advantages of GA are:

- 1) No need for learning of gradient data about the response.
- 2) GA usually resistant to becoming restricted in local optimal then could be used for a set of issues.
- 3) It can speedily search a great set of solution.
- 4) No good suggestions do not affect the end of set solution badly as they are clearly neglected.
- 5) It doesn't have to learn any basics of the issues. It acts by its own internal basics. For the characteristics of searching mechanism, parallel screening and robust screening based on the base of normal evolution, GA has found uses in many fields and has become one of the large effective optimization techniques.

### 2.2. PSO algorithm

PSO has been inspired by the behaviors of birds in wildlife. In several issues, PSO is generally described as a clearly searching algorithm, naturally in the particle's movement, and computationally perfect method.

The advantages of PSO as shown below.

- 1) According to the techniques of swarm intelligence, PSO can be used into engineering, medical, economic, and other scientific researches.
- 2) PSO has a characteristic of a very speed convergence rate in comparison with GA.
- 3) The PSO process is done without mutation calculation and overlapping. The seeking can be achieved by the velocity of the particle, such as in comparison with GA technique.
- 4) Through the development of the next generations, only the more optimist particle can send data on to the other particles, and the probable velocity of the researching is fast.
- 5) Calculations in PSO is easy. Compared with the exiting developing calculations, it occupies a perfect optimization capability.
- 6) The code number taken by PSO is real, and it is determined by the problem resolution. The dimension number is equal to the solution constant.

The main problems of PSO are:

- 1) The method readily suffers from the small optimism, due to the less right at the regulation of its direction and the speed.
- 2) The method may not active out exactly the issues of the non-coordinate method, such as the solution to the electric power and the basic important rules in moving of the particles in the electric power area.

Both of the previous algorithms could be largely used to inspect optimal DG positioning. The complex

model of the distribution generation systems has settled the problems of discontinuity and irregularity. The single objective functions that organized by the GA have a better feature of adaptability compared to other nature inspired algorithms<sup>[40]</sup>. PSO is more efficient compared to GA and has a balanced technique to develop global and local reconnaissance abilities<sup>[41,42]</sup>.

## 2.3. GRO algorithm

The optimization method which was introduced by Jaber et al.<sup>[43]</sup>, is a process that involves the use of mathematical principles and algorithms to identify the optimal way to find problem solutions. The process begins by defining an objective function, which is typically related to several engineering issues<sup>[4,10,44,45]</sup>, then determining a set of constraints and parameters that must be met in order to achieve the desired result. Once these have been defined, the software can then start the optimization process, which involves the use of mathematical algorithms to identify the most effective and efficient parameter value to solve the problem. The optimization process is iterative, meaning that it will adjust the allocation of resources until the optimal solution is found. The GRO process can be done by three parts, which are GRO initialization, leaders' crossover, and followers' crossover.

### 2.3.1. GRO initialization

The fundamental tenet of GRO is to separate each particle into many groups, each of which has a unique set of guides for both the global and local optimal group positions. The GRO approach also requires the use of starting assumptions, such as the notion that each fish may act as a follower or a guide depending on the associated global optimal point for each group. A portion of the followers will switch the very weak leader to the strong leader who achieves the greater ideal value before the following iteration. It is necessary to first assume this maximum portion of the followers as a percentage. Additional initial parameters must be assuming like the acceleration coefficients ( $c_1$ ,  $c_2$ ) and the inertia weight ( $\omega$ ). As can be seen, the initialization Equation (1) is stated<sup>[4,43-45]</sup>.

$$followers\ number = \frac{total\ umber\ of\ partcles - number\ of\ groups}{number\ of\ groups} \quad (1)$$

### 2.3.2. Leaders crossover of GRO

The GRO technique involves two leader crossover processes that need to be considered. The first process entails selecting new leaders for each group, while the second process involves choosing the superior leader who can lead the maximum number of followers. These phases serve as guiding principles that establish the method's crucial attribute, providing flexibility to this technique.

### 2.3.3. Followers crossover of GRO

The likelihood of finding the best solution in the problem space is great because of the flexible motion between the groups. Any optimization strategies that have an inflexible nature to going between one search spaces to another one may become confused by the extremely complicated problems. This issue arises as a result of the numerous parameters and high deferential equation order in complex issues. GRO employed a method to continue searching in the larger field space of the issue, using the follower crossover between the groups. A random selection of fish from every group will first move to the strong leader. Second, one step must be taken in the direction of each leader by calculating the velocity ( $v_i$ ) and position ( $X_i$ ) using the standard Equations (2) and (3), respectively.

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

$$X_i(t + 1) = X_i(t) + v_i(t + 1) \quad (3)$$

The fitness function from the group figures will be recalculated include all leaders and followers. Equations (4) and (5) represent new technique steps of GRO.

$$\text{moving followers}_i = \text{integer}(\mathcal{E} * \text{random}) \quad (4)$$

$$\text{followers}_{ij} = \text{Max}((\text{followers}_{ij-1} - \text{moving followers}_i), 0) \quad (5)$$

where  $\mathcal{E}$  is highest probable of moving fish.

### 2.3.4. GRO implementation steps

1) Choose the initial values (particles initialization number of this technique, leaders number, limits of fitness function)

2) Followers number =  $n/\text{leaders number}$

3) Calculate fitness function for  $n$  of particles, with sort fitness function

4) While  $t < \text{iteration}$  do

5) For  $i = 1$  to number of leaders

6) Update particles for the followers for leaders ( $i$ ) using optimization method

7) End for

8)  $i = 2$  to number of leaders

9)  $\text{Random} \times \mathcal{E} = \text{fishes of mobile } (i)$

$\text{Followers } (i) = \text{Max}(0, \text{followers } (i) - \text{mobile fishes}(i))$

10) Total number of mobile fishes = total number mobile fishes + fishes of mobile ( $i$ )

11) End for

12) Followers (1) = total number of mobile fishes + Followers (1)

13) Determine the solution of sub global for every leader

14) Calculate the solution of global

15) End while

In this work, PSO and GA optimization techniques are used for finding the optimal DG location and size compared to GRO. The fundamental equations for PSO, GA, and GRO from Kennedy and Eberhart (PSO)<sup>[46]</sup>, Abedini and Saremi (GA)<sup>[17]</sup>, and Jaber et al. (GRO)<sup>[43]</sup> are implemented without any additional adjustments.

## 3. Proposed model

A large number of parameters with equations for a nonlinear high-order system makes up the power system model and its networks, according to the work cited above. Thus, an evident objective function is required in order to solve the DGs problem of predicting their location and size. Every DG allocation's objective function could be one or more. Using the formulation based on the load flow and many types of power system variables. The quality of the electrical power system has been improved with the presentation of significant indices. The location and size of each DG are chosen to be two of the most significant issues in the endeavor of power loss reduction. The base index formula for the objective function is represented by the active power losses index.

### 3.1. Objective function

A precise evaluation for the objective function has been chosen. The main goal of the proposed method is to determine the best locations and size for DG resources by minimizing function, related to project aims. The main goal is taken into considerations to calculate the objective formula that is used in point of start. The main objective of the problem is to reduce the real power losses. Furthermore, the fitness function is determined as in Equation (6).

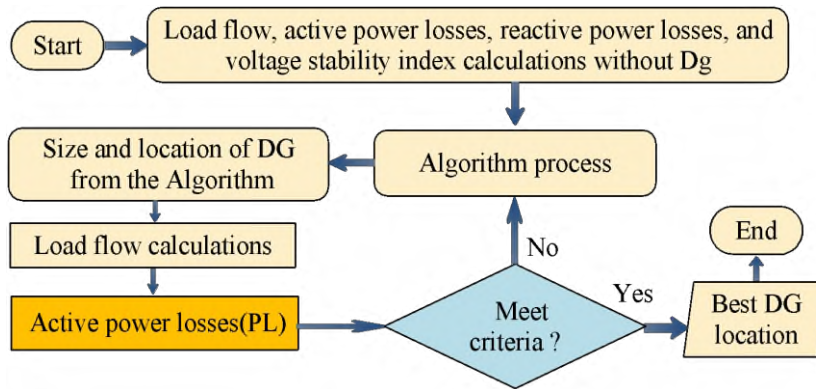
$$\text{Objective function} = \text{Minimize}(P_L) \quad (6)$$

### 3.2. Power losses minimization

The overall power losses have a significant impact on the total amount of power generated, which could increase the benefits to the economy and environment. The most significant objective function,  $P_L$ , which is represented by these currents and has a mathematical model as an Equation (7), is the total power losses as following.

$$P_L = \sum_{line=1}^{N_u} G_{line} (V_i^2 + V_s^2 - 2V_i V_s \cos(\alpha_i - \alpha_s)) \quad (7)$$

where  $V_s$  and  $V_i$  are the absolute values of the receiving and transmitting ends voltage,  $N_u$  is the total number of transmission lines in the system,  $G_{line}$  is the conductance of the line, and  $\alpha_i, \alpha_s$  are angles of the end voltages. The computation of the objective function using the AI method is shown in **Figure 1**.



**Figure 1.** The objective function.

## 4. Result and discussion

The authors of this work were obviously motivated to use the algorithm to determine the size and position of DGs in order to minimize actual power losses by the high flexibility and high efficiency of GRO in solving extremely complicated problems.

MATLAB has simulated tests and methods to carry out the outcomes and performances of the prepared scenario. The 30 bus IEEE standards are used to test the optimization techniques as well.

Also, according to the problem case and system as stated in **Table 1**, the objective function is built using GA, PSO, and GRO with the same varied number of iterations and amount of population for fair comparisons.

**Table 1.** Algorithm parameters.

DGs-number	1	2	3	4	5
Particles	25	30	40	40	40
Iterations	30	30	35	40	40

To determine the effectiveness of the DG of the objective function, one to five DGs are supposed to be added to the chosen IEEE 30 bus system. Different numbers of DG are added to construct situations with multiple levels of complexity. Moreover, the Newton-Raphson method was used to calculate the load flow in all circumstances. **Table 2** shows the three approaches' dimensions and placement.

**Table 2.** Location and size of selected system.

DGs-number	One-DG			Two-DGs			Three-DGs			Four-DGs			Five-DGs		
	Methods	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO
Location	27	15	2	13, 25	7, 20	28, 3	17, 22, 7	9, 18, 14	21, 9, 4	2, 27, 18, 11	4, 20, 2, 20	20, 15, 15, 3	5, 8, 23, 6, 14	22, 2, 4, 22, 12	3, 24, 19, 15, 10
Size	78.7	80.85	80.85	76.14, 49.49	80.85, 50.96	80.84, 80.84	52.88, 36.49, 66.91	80.85, 34.10, 26.55	42.58, 72.40, 80.47	64.05, 35.65, 41.21, 65.62	80.85, 39.01, 80.85, 40.83	34.31, 3.74, 56.65, 80.73	80.83, 49.15, 28.87, 74.34, 8.41	72.36, 55.77, 68.21, 41.59, 52.06	46.28, 21.33, 14.86, 35.16, 77.46

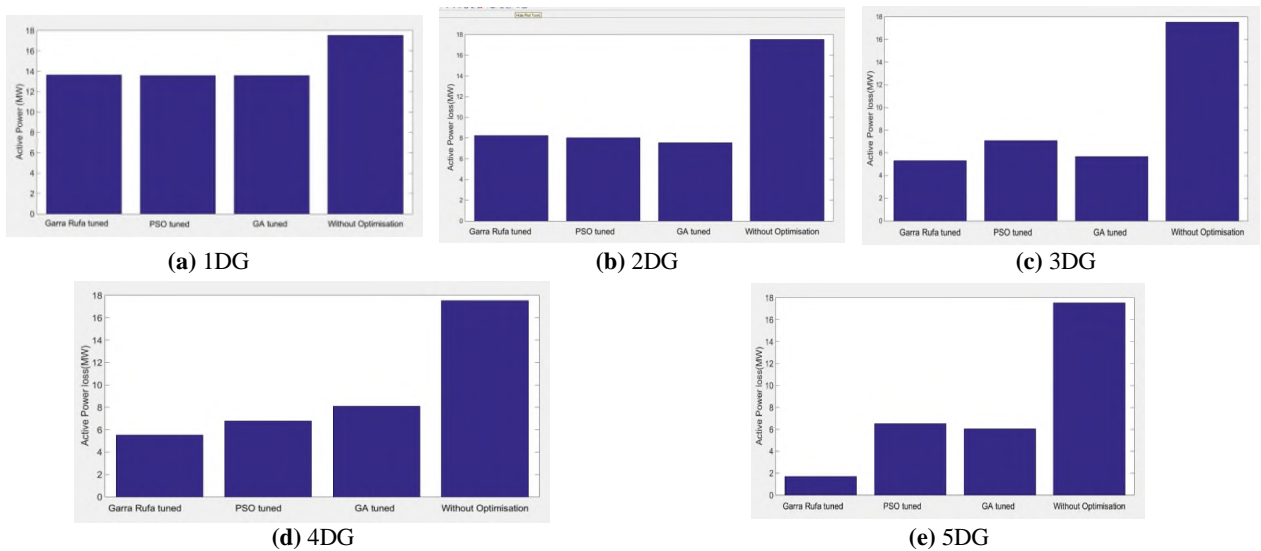
Some of the key directories for the three commonly used approaches' changes in loss saving are listed in **Table 3**. **Table 3** shows that all three techniques have an effect on real power losses, albeit to varying degrees. The objective value is not much advanced in the cases of a single generator or a pair of generators, whereas the solutions to the allocation problems involving three, four, and five DGs clearly demonstrate the efficacy of the proposed strategy.

**Table 3.** Objective function.

DGs-number	One-DG			Two-DGs			Three-DGs			Four-DGs			Five-DGs		
	Methods	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO	GA	GRO	PSO
$P_{Loss}$	<u>12.45</u>	11.21	13.58	8.85	6.61	7.55	<u>5.32</u>	7.09	5.68	5.53	6.79	8.10	<u>1.69</u>	6.51	6.04

The precise values that are highlighted in **Tables 3** demonstrate the best results for the GRO approach with various connections of DG for all classes. **Figure 2** shows examples of power systems improving in active power losses and compared without DG, helps to highlight the differences between these proposed optimization methods to decreased active power with increased number of DG in distribution system.

There are loss saves in all three ways, as can be seen in **Table 3**. The largest reduction in the conventional system's active power is 1.69 losses for the 5DGs GRO technique, and the lower benefit is 12.45 losses for the 1DG GRO method, indicating that GRO was unable to come up with a workable solution. While the single DG of GA and GRO methods both have a worse value, the five DG for the GRO technique has the best objective function.

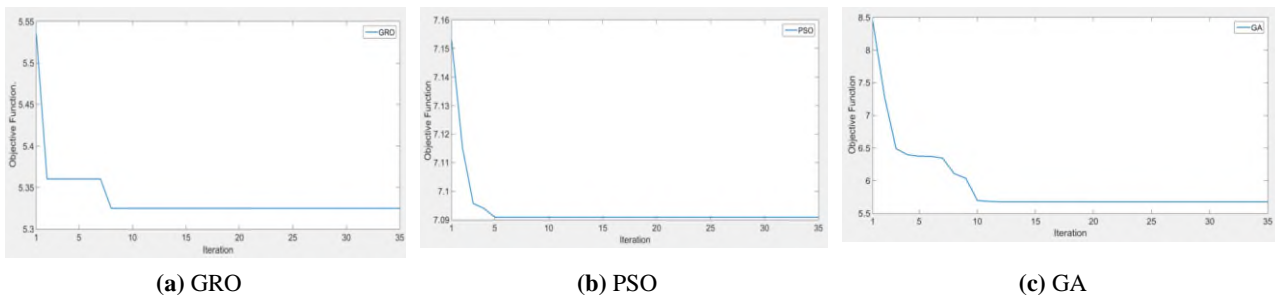
**Figure 2.** Power system improvement active power. (a) 1DG; (b) 2DG; (c) 3DG; (d) 4DG; (e) 5DG.



Three of the five examples, representing a multi-level of complexity, were progressed via the new objective function utilizing GRO, while other two cases are optimized more effectively using PSO. Also, utilizing the suggested strategy, a superior solution was found for all high degrees of complexity.

In most instances, the proposed optimization approaches outperform the GRO method due to a convergence mechanism that involves searching over many regions of the problem space. **Figure 3** illustrates how each optimization technique converges for the case of 3DG.

It can be shown from **Figure 3**, which depicts a new objective function for 3DG utilizing three optimization techniques, that in terms of the assumed number of search particles and iterations, GRO demonstrates faster convergence compared to the other two methods (GA and PSO), when it comes to minimizing the objective function. Nevertheless, even after seven iterations, GRO was still able to improve the answer. This suggests that GRO might be able to avoid collapsing into a single optimal location.



**Figure 3.** 3DG algorithms convergence. (a) GRO; (b) PSO; (c) GA.

## 5. Conclusion

In conclusion, Garra Rufa optimization is a powerful tool that can be used to minimize power losses and improve the efficiency of DG units. By using the principles and algorithms of the optimization process, the user can identify the most effective and efficient way to allocate DGs in order to minimize power losses. Additionally, it can be used to identify the optimal placement of DG units to meet specific power requirements. For comparative purposes, the assigned problem was solved using three algorithms: GA, PSO, and GRO. The total active power losses were decreased as a consequence of effective DG allocation utilizing the suggested approaches and improved up to 1.6 MW. Additionally, there was one instance in which the GRO was unable to come up with a suitable solution, and that involved lowering the in a single DG. It was explained that the GRO mechanism's superior exploitation and exploration capabilities over other swarm optimization intelligence approaches make it the best choice for resolving extremely challenging engineering optimization problems. In the end, it is anticipated that the GRO will be able to offer effective answers to some of the most difficult power engineering problems now in existence, such as load frequency regulation or load forecasting. furthermore, the recently proposed technique can be altered to more accurately answer low-complexity issues.

## Author contributions

Conceptualization, RKC, AS and MBS; methodology, AS; software, ASJ; validation, RKC, AS and MBS; formal analysis, RKC; investigation, ASJ, RKC; data curation, ASJ; writing—original draft preparation, RKC; writing—review & editing, ASJ, MBS; visualization, AS; supervision, AS; project administration, AS.

## Conflict of interest

The authors declare no conflict of interest.



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