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Original Article

Optimal Allocation of Custom Power Devices in Radial Distribution Network Using Chaos Game Optimization

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Abstract *- Recently, there has been rising concern regarding the demand for uninterrupted power with good power quality. Custom Power Devices (CPD), passive, active, and hybrid filters are used to maintain these. Along with the increasing use of renewable energy sources as well as nonlinear loads, power quality issues are rising. These renewable energy sources and power electronic loads are extremely efficient; however, power electronic loads exhibit nonlinear behavior. This results in variances in voltage, current, or frequency that are not in line with the standard, which can cause malfunction or failure of the equipment being used. In this paper, these concerns are solved using Chaos Game Optimization (CGO) for optimal allocation and sizing of CPD in a Radial Distribution Network (RDN). The objective function's design is to lower overall costs and losses in order to raise annual net savings. For the validation of the proposed algorithm, 34 and 85 bus RDN have been used. The benefits of the proposed algorithm are demonstrated by comparing the results it obtained with those of existing algorithms like PSO.*

Keywords *- Chaos Game Optimization (CGO), Particle Swarm Optimization (PSO), Radial distribution network, Optimal placement, Custom Power Devices (CPD).*

1. Introduction

Electricity is a basic need for everyone today. Hence, there has been a significant surge in demand. Numerous challenges arise in addressing the energy needs of individuals within our current power infrastructure, particularly in relation to the transmission grid. Out of the total power generated, 27% of power is dissipated as ohmic loss at the distribution level.

Voltage constraints and stability concerns hinder the use of transmission lines to their maximum capacity. Hence, the utilization of compensators is necessary to enhance the capacity of transmission lines. Utilizing FACTS) devices inside the power system are proposed as a viable approach for achieving this objective [1]. The diverse capabilities exhibited by FACTS devices have facilitated the establishment of distinct objectives for the purpose of ascertaining their optimal location and position [2-4].

Installing shunt CPD at appropriate spots helps reduce these losses, along with improvements in the voltage profile, power factor, and overall system stability [5]. Therefore, the precise size and strategic placement of these CPDs play a crucial role in distribution networks [6]. In recent years, numerous methods and strategies have been developed to identify appropriate positions and optimal ratings of CPD. The work [7] presents the application of Simulated Annealing (SA) to attain optimal arrangements of capacitors. Nevertheless, it is crucial to acknowledge that this method does not offer a guarantee of attaining the most favourable cost and may become trapped in a locally optimal solution. The problem of capacitor locations is addressed by the introduction of Tabu Search (TS) in [8]. Although this optimization method appears to be beneficial for the design problem, its efficiency is diminished when complex goal functions and a large number of optimized parameters are utilized. Furthermore, this approach is characterized by its time-consuming nature.

In [9], a Genetic Algorithm (GA) was designed to achieve optimal placement and sizing of capacitors. However, the algorithm's runtime is quite long and varies depending on the scale of the system being analysed. Additionally, it leads to the recurrence of revisiting the same suboptimal options. The application of Particle Swarm Optimization explains this problem as demonstrated in reference [10].

However, it suffers from the drawback of partial optimism. Additionally, the method has sluggish convergence during the refined search phase, limited ability to do local search, and the potential for becoming trapped in local minimum solutions. The Direct Search Algorithm (DSA) for capacitance compensation in RDN is addressed in [11].

However, this reference does not take into account the expenses related to installation and maintenance. The PSO

[10], Plant Growth Simulation Algorithm [12], Wild Horse Optimizer [13] and Genetic Algorithm [14] have been proposed as solutions to the problem of allocating capacitors in distribution networks. Nevertheless, these algorithms yielded favourable outcomes by utilizing continuous values of capacitors rather than discrete values. In addition, they utilize Loss Sensitivity Factors (LSF) to determine optimal placements. However, it is not guaranteed to yield the most optimal locations, as stated in [15].

The Artificial Bee Colony (ABC) algorithm addresses the same problem, but it exhibits delayed convergence due to conflicting processes of exploration and exploitation [16]. Ant Colony Optimization (ACO) is employed to address the same problem, albeit its theoretical analysis is challenging because the probability distribution changes with each iteration [17].

The Firefly Algorithm (FA) [18] is employed to address this problem, but the reference utilizes the Levy Flight Strategy (LFS). Furthermore, the expenses related to installation and maintenance are not being considered. Recently, many studies have been carried out for optimal capacitor placement in the unbalanced distribution network [19-22].

A sensitivity analysis with the objective of minimizing the VDI and the STATCOM cost using Mixed Integer Distributed Ant Colony Optimization (MIDACO) on IEEE 14-bus, IEEE 57-bus, and IEEE 118-bus standard test systems [23]. A similar study is presented in [24] using a modified Capuchin Search Algorithm (mCapSA) with a Sensitivity Index Algorithm (SIA) for the Optimal Allocation of DSTATCOM in the 33-bus and 118-bus RDS. In [25], an investigation of the improvement of power quality for a hybrid energy system using D-STATCOM was conducted using grasshopper optimization.

1.1. Contribution of the Proposed Work

The following is a description of the key findings from this research:

- This paper utilizes the chaos game optimization algorithm to find the optimal sitting and sizing of custom power devices.
- The primary objective of this research work is to minimize the overall cost of the system by reducing the loss by injecting reactive power by installing CPDs in the RDN.
- To highlight the superiority of CGO, a comparative analysis was performed using the PSO algorithm.

1.2. Organization of Paper

The paper's hierarchy is set up as follows: The problem formulation is represented in Section 2. Section 3 explains the methodology. The results and the discussion are in Section 4, and the paper is concluded in Section 5.

2. Problem Formulation

The Loss Sensitivity Index (LSI) helps determine the optimal position for CPD deployment in a distribution network. It decreases the search space, which allows for quicker computation throughout the optimization process. For the *l*th line between the "l" and "l + 1" buses, the real and reactive power loss is expressed as

$$P_{l,loss}(l) = \frac{(P^2_{real,\sup plied}(l+1) + Q^2_{reactive,\sup plied}(l+1)) \times r_l}{(V^2(l+1))} \tag{1}$$

$$Q_{l,loss}(l) = \frac{(P^2_{real,\sup plied}(l+1) + Q^2_{reactive,\sup plied}(l+1)) \times x_l}{(V^2(l+1))} \tag{2}$$

Where, $P_{real}(l+1)\, \&\, Q_{reactive}(l+1)$ are total real and reactive power supplying ahead of the node "l+1'' respectively. $P_{real}(l+1)\, \&\, Q_{reactive}(l+1)$ are evaluated with the help of BIBC given below:

$$P_{real}(l+1) = BIBC \times P_{real,power,matrix} \tag{3}$$

$$Q_{reactive}(l+1) = BIBC \times Q_{reactive,power,matrix} \tag{4}$$

BIBC=Bus injected to branch current.

Now, the Loss Sensitivity Index is calculated by following the formula for different standard IEEE buses:

$$\frac{\partial P_{l,loss}}{\partial P_{real}} = \frac{2 \times P_{real}(l+1) \times r_l}{(V^2(l+1))} \tag{5}$$

$$\frac{\partial P_{l,loss}}{\partial Q_{reactive}} = \frac{2 \times Q_{reactive}(l+1) \times x_l}{(V^2(l+1))} \tag{6}$$

Thus, using LSI, we can find the most appropriate bus for the placement of CPD. The buses with larger LSI values are considered the most suitable buses for the placement of CPD using the optimization algorithm. In this paper, a comparative analysis of PSO and CGO algorithms has been conducted to highlight the superiority of CGO over PSO.

2.1. Objective

In this research work, the objective function that is to be minimised by optimally placing the CPD considers the expenses associated with power losses of the system and the costs related to operation, depreciation, and installation. The optimal placement problem of CPD aims to minimize the cost, subject to specific operational constraints in the distribution system, to reduce the system's yearly cost. The cost of operating and maintaining the CPDs installation in the distribution system is considered in the following mathematical equation:

$$\text{Cost} = [(C_p * P_{loss} * T) + D_f (C_1 * C_{BUS} + C_c * \sum_j^{C_{BUS}} Q_{cj}) + C_0 C_{BUS}] \tag{7}$$

Where,

C_p = Cost per KW-hour,
P_{loss} = After compensation the overall loss,
D_f = Depreciation factor,
C_1 = Cost per installation,
C_{BUS} = The number of compensated buses,
C_C = The cost per hour,
Q_{Cj} = Reactive power (KVAr),
C_0 = Represents operating cost.

The following equality and inequality constraints have been utilised to minimise the above equation.

2.2. Equality Constraint

2.2.1. Load Flow Constraint

The Forward-backwards sweep load flow algorithm is used to solve the load flow problem of distribution systems. This is a power balance equation which gives the equality constraints in a power flow in RDN.

$$P_{Swing} = \sum_{i=1}^{L} P_{Line\_Loss}(i) + \sum_{q=1}^{N} Pd_d(q) \tag{8}$$

2.3. Inequality Constraints

2.3.1. Voltage Constraint

$$V_{\min} \le |V_i| \le V_{\max} \tag{9}$$

The above equation is the constraint of voltage at each bus. Here, V_{min} = 0.9p.u. minimum bus voltage and V_{max} = 1.1p.u. maximum bus voltage.

The reactive power injected is restricted by following the equation to withstand the working of the power system with leading and lagging.

$$\sum_{a=1}^{CA} Q_c(b) \le \sum_{q}^{N} Qd(q) \tag{10}$$

2.3.2. Constraint for the Power Factor

The entire system's power factor (pfsys) should be more than the lowest and less than the maximum, as shown by the following equation:

$$pf_{\min} \le pf_{sys} \le pf_{\max} \tag{11}$$

2.3.3. Line Capacity Constraint

Any line's complex power must be smaller than its rating value. This is determined as per the below equation:

$$Q_{cpd\_\min} \le Q_{cpd} \le Q_{cpd\_\max} \tag{12}$$

2.3.4. Custom Power Devices Rating Constraints

The following equation describes the injected reactive power by the installed CPDs. A distinct value of 50 kVAr is considered to be the step size of CPD size:

$$Q_{cpd\_\min} \le Q_{cpd} \le Q_{cpd\_\max} \tag{13}$$

Furthermore, the cost of CPD can vary significantly depending on several factors, including the specific requirements of the application and the quality of the components used. Here are some key factors that can influence the cost of CPD.

3. Methodology

A CGO technique has been proposed for the sizing and placement of CPDs in IEEE 34 and 85 RDN. It is an effective method for optimal site selection. The quality of the search algorithm depends on three factors:

- The number of sides of polygons.
- The number of point's samples.
- Distance between each jump.

All these three factors greatly determine the ability of the CGO optimization. As the number of polygons increases, the number of points samples rises, and the region increases the accuracy of results obtained. Similarly, based on the optimization requirement, the distance between the vertex and the points that determine the jump to the next point greatly determines the quality of results obtained. To apply the proposed approaches, MATLAB R2020b was installed on a personal laptop equipped with an Intel (R) Core I5 CPU GB of RAM. Thus, to determine the optimal value of points, the sample and distance give the position and size of CPD. Here, the based-on variation of sample points and distance defined the CGO optimization.

3.1. PSO Optimization

PSO is a computational method used to solve optimization problems by iteratively improving candidate solutions. It involves a population of particles moving in the search space. This movement of the particles is based on mathematical formulas that consider each particle's velocity and position [26].

The movement of particles is influenced by their local best-known positions and best-known positions in the search space, aiming to converge towards the best solutions. PSO is a bio-inspired algorithm that differs from other optimization methods as it only requires the objective function and has few hyperparameters.

It is known for its simplicity and effectiveness in finding optimal solutions. In this approach, a population of particles is regarded as a swarm. The current goal is to find the global optimum among an entire particle as quickly as feasible. This optimization method uses what is called a swarm population of particles. Our current goal is to quickly identify the global optimum among all of the particles. Beyond its sluggish convergence, PSO has several additional limitations. In the past, this yielded an accurate answer, which was a disadvantage because it was almost entirely devoid of adaptive accelerators for the velocity updating formula [10].

The weighting elements in particle swarm optimization are assumed to be constants. Here, r_1 and r_2 are random variables. Also, C_1 and C_2 determine the acceleration rating of each particle at each step. The particles in PSO are the same size and step size/ratio. However, we may change the PSO's weight to achieve quicker movement, more sensitivity, and an acceleration of the convergence rate; hence, we can refer to this as adaptable.

The primary criterion for determining the minimal function value that we employ in each iteration is the minimum value of the objective functional value, which shows how much better current particle movement is compared to the previous particle movement. The accelerators are chosen based on variations in the goal function's values during the several rounds.

$$V_i^k = WV_i^k + C_1 r_1 (pbest_i^k - x_i^k) + C_2 r_2 (gbest_i^k - x_i^k) \tag{14}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{15}$$

Here, V_i^k, X_i^{k+1} are velocity and position updates.

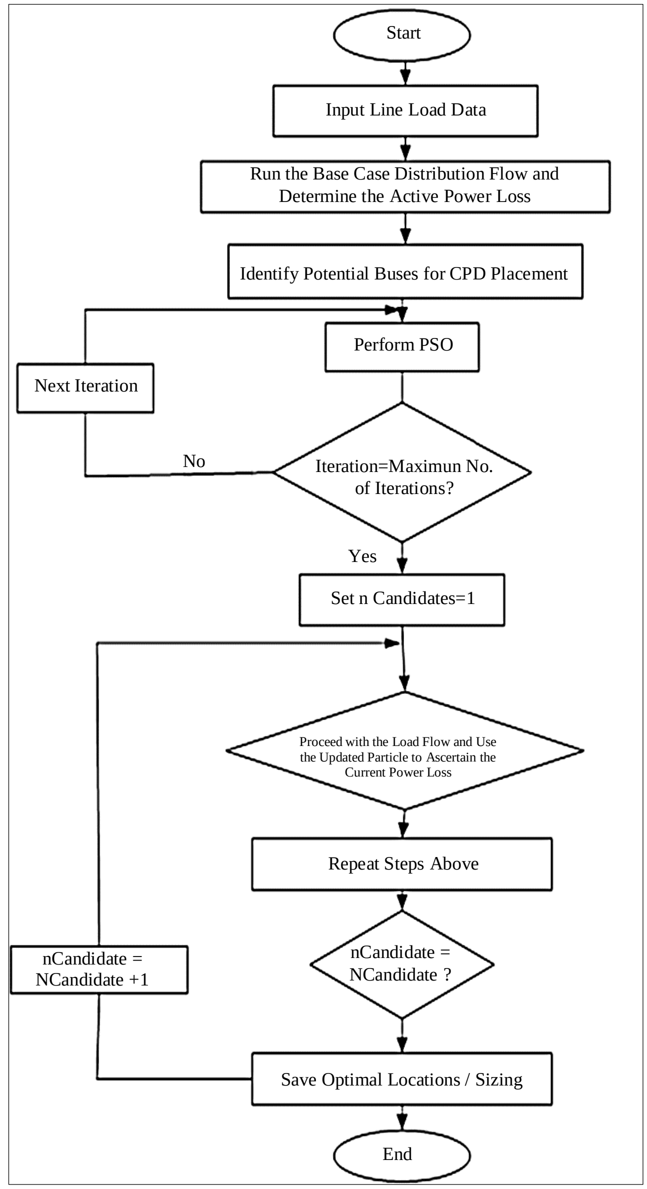

Fig. 1 Flow chart for the PSO optimization

3.2. CGO Optimization

Chaos game theory, often referred to as the "Chaos Game," is a mathematical and computational concept that is used to generate fractal patterns. Because chaos touches on a wide range of disciplines, research on the applications of chaos-based systems has piqued the curiosity of many scholars.

Recently, Chaos Game Optimisation (CGO), a novel metaheuristic based on the fractal theorem, was suggested [27]. As such, it is predicated on the fundamental idea that depends on certain principles of chaos theory, whereby self-similarity issues of fractals and the organisation of fractals through the concept of chaotic games are demonstrated [28].

The chaotic game theory is a key to the CGO algorithm. The basic idea behind the chaos game is as follows:

- Start with a closed geometric shape, often a triangle, but it can be any polygon.
- Select a random point within or on the boundary of the shape as your initial point.
- Choose a fixed set of transformation rules, typically involving the vertices of the shape. For example, in the case of a triangle, you might have rules that say:
  - Move halfway toward vertex A.
  - Move halfway toward vertex B.
  - Move halfway toward vertex C.
- Now, for each iteration, randomly select one of the transformation rules and apply it to the current point. This

means you are moving the point halfway toward one of the vertices.

- Repeat this process for a large number of iterations. As you do, the points generated will trace out a self-replicating pattern known as a fractal.

The resulting fractal pattern will depend on the specific transformation rules, the initial point, and the number of iterations. The process can be visually fascinating and is used in mathematics and computer graphics to create intricate and beautiful fractal designs. The chaos game is a simple but powerful concept that demonstrates how complex and detailed structures can emerge from deterministic and repetitive processes. It is not typically used for solving mathematical problems or optimization tasks but is more of an illustrative tool for studying fractals and self-similarity in geometry.

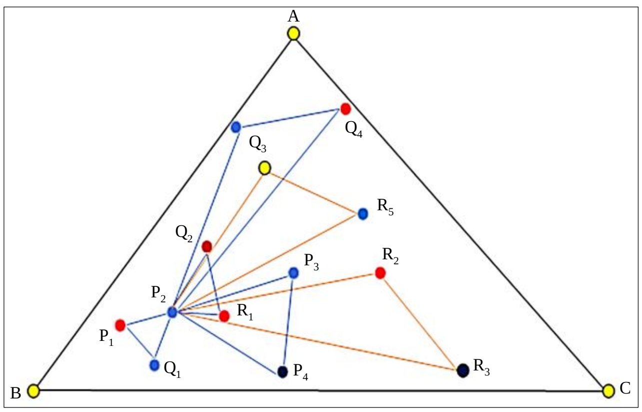

Fig. 2 There are two ways that sub-triangles might form outside the exploration field, and inside it

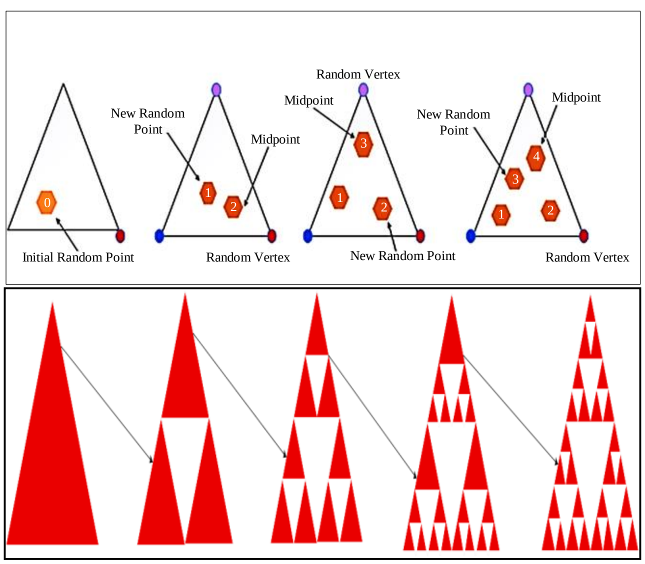

Fig. 3 There are steps (inside) from and to (outside)

3.3. Background of CGO

According to the chaos theory, even little adjustments to the starting circumstances can influence how a dynamic system behaves. This theory states that a system's approximate instantaneous state cannot predict a system's future position, but the system's current state may. To create a form with a similar style throughout a range of values, the main goal is to obtain a set of points with a recurring attitude. An example from the field of chaotic game theory that helps us comprehend it better is a Sierpinski fractal triangle.

In this case, as Figure 3 illustrates, the triangle is the outcome of selecting three points for the main fractal structure. The chosen vertices have highlights added to them in red, green, or blue. In this case, the die in question has to have two blue, two red and two green sides. The first seed of the fractal is selected at random. With each roll of the dice, the seed is moved from its original place to the vertex that corresponds to that colour. To do this, roll the die once more and start new replications of the seed at its new position. The dice are finally rolled several times before the Sierpinski triangle eventually shows.

3.4. Mathematical Model

According to the CGO algorithm, a collection of candidate solutions (C) represents the seeds. Each possible solution (C_i) has a few movable variables ($C_{j,i}$) that reflect the position of the seed. The region used to seek solutions is known as the Sierpinski triangle. Here is the mathematical representation:

$$C = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_i \\ \vdots \\ C_n \end{bmatrix} = \begin{bmatrix} c_1^1 & c_1^2 & \cdots & c_1^j & \cdots & c_1^d \\ c_2^1 & c_2^2 & \cdots & c_2^j & \cdots & c_2^d \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ c_i^1 & c_i^2 & \cdots & c_i^j & \cdots & c_i^d \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ c_n^1 & c_n^2 & \cdots & c_n^j & \cdots & c_n^d \end{bmatrix} \qquad (16)$$

$$\begin{Bmatrix} i & = & 1,2,\ldots\ldots n \\ j & = & 1,2,\ldots\ldots d \end{Bmatrix}$$

Here, n and d are indicating the size of the exploration field's population and problem dimension. The following is how the seeds are randomly initialised:

$$c_i^j(0) = c_{i,\min}^j + rand.(c_{i,\max}^j - c_{i,\min}^j), \begin{Bmatrix} i & = & 1,2,\ldots\ldots n \\ j & = & 1,2,\ldots\ldots d \end{Bmatrix} \qquad (17)$$

Where, cji(0) is the starting population, rand is taken between 0 and 1, and cji min and cji max are the minimum and maximum values for the jth design variable. To complete a triangle, the mathematical model produces several seeds inside its upper and bottom boundaries. Here is a makeshift triangle made of three seeds:

- Global Best (GB).
- Mean Group (MV_i), which is the average value of the random seeds.
- i_{th} solution candidate (C_i).

The points of the triangle are GB, MV_i, and C_i. To generate fresh seeds and complete a new triangle, a temporary triangle is formed for each starting seed. The basic designs for the temporary triangle structure are shown in Figure 3.

The i^{th} iteration combines the seeds from the previous one in the three corners of a Sierpinski triangle. On the fresh seeds, the temporary triangle is placed. They toss the die. Either the GB or the MV_i receive the seed from C_i, depending on the hue that is generated. A random integer function is used to simulate this. It produces two numbers, 0 or 1, so that the user may select between green or red faces. The chaotic game suggests that there should not be much movement of the seeds. Numerous constructed factorials are used in this situation. The mathematical representation of the defined procedure of the first seed is as follows:

$$Seed_i^1 = C_i + \alpha_i \times \left(\beta_i \times GB - \gamma_i \times MV_i\right), i = 1, 2, ..n \quad (18)$$

Here, Ci is the i_{th} candidate, α_i denotes the random value that restricts the movement of the seeds, and β_i and γ_i are random numbers of 0 or 1 that indicate the likelihood of rolling certain dice. The 2nd seed (GB) is a two-sided dice with blue and red sides. The GB changes into either Ci or MV_i. It depends on the colour of the dice roll result. The seed travels in the direction of the MV_i when a red face is raised and in the direction of the Ci when a blue face is lifted. A point on the arcs connecting Ci and MV_i is the target of the second seed. The following equation may be used to express this quantitatively:

$$Seed_i^2 = GB + \alpha_i \times \left(\beta_i \times C_i - \gamma_i \times MV_i\right), i = 1, 2, ..n \quad (19)$$

For generating 3rd seed, the dice are rolled. The seed advances in the direction of the C_i or GB, which only produces two integrals, 0 and 1, based on the resulting hue. According to the equation, the seed will go in the direction of the Ci and GB's connecting lines.

$$Seed_i^3 = MV_i + \alpha_i \times \left(\beta_i \times C_i - \gamma_i \times GB\right), i = 1, 2, ..n \quad (20)$$

Again, the fourth is created by adding a mutation step to the updated location of the seeds. The change in the position is dependent on the adjustments to the selected choices. The following is the mathematical representation of the proposed method:

$$Seed_i^4 = C_i\left(c_i^k = c_i^k + R\right), k = \left[1, 2, ..., d\right] \quad (21)$$

Where, k represents a random integer ranging from 1 to d, and R represents a random value between 0 and 1.

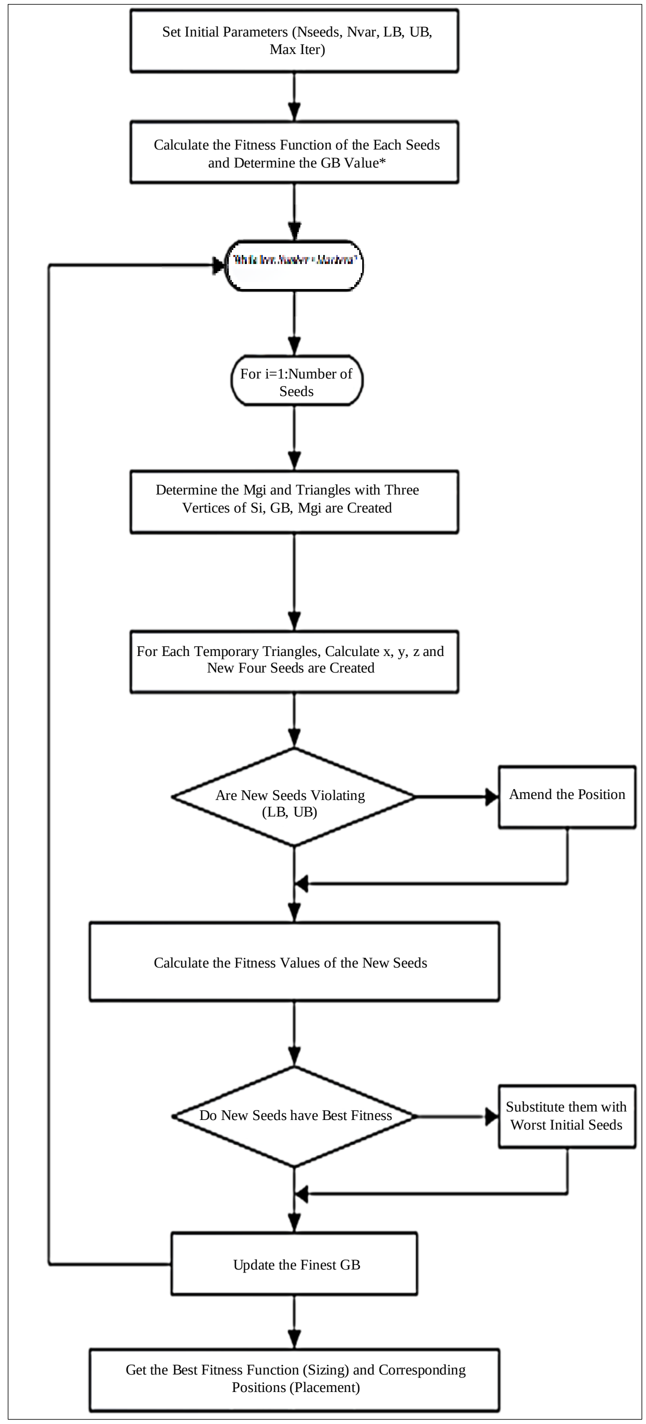

Fig. 4 Flow chart diagram for the CGO

The exploration and exploitation rate of the CGO algorithm may be tracked and modified using the four formulations of αi that regulate the grain mobility limits as follows:

$$\alpha_i = \left(c_i^k + R\right)\begin{Bmatrix} Random \\ 2\times Random \\ (\delta\times Random)+1 \\ (\varepsilon\times Random)+(\sim\varepsilon) \end{Bmatrix} \tag{22}$$

Where, Random depicts a random number between 0 & 1. While δ and ε stand for random values ranging between 0 & 1. These new applicants' levels of fitness are compared to the existing pool; one with the highest score is kept, while those who score poorly are eliminated.

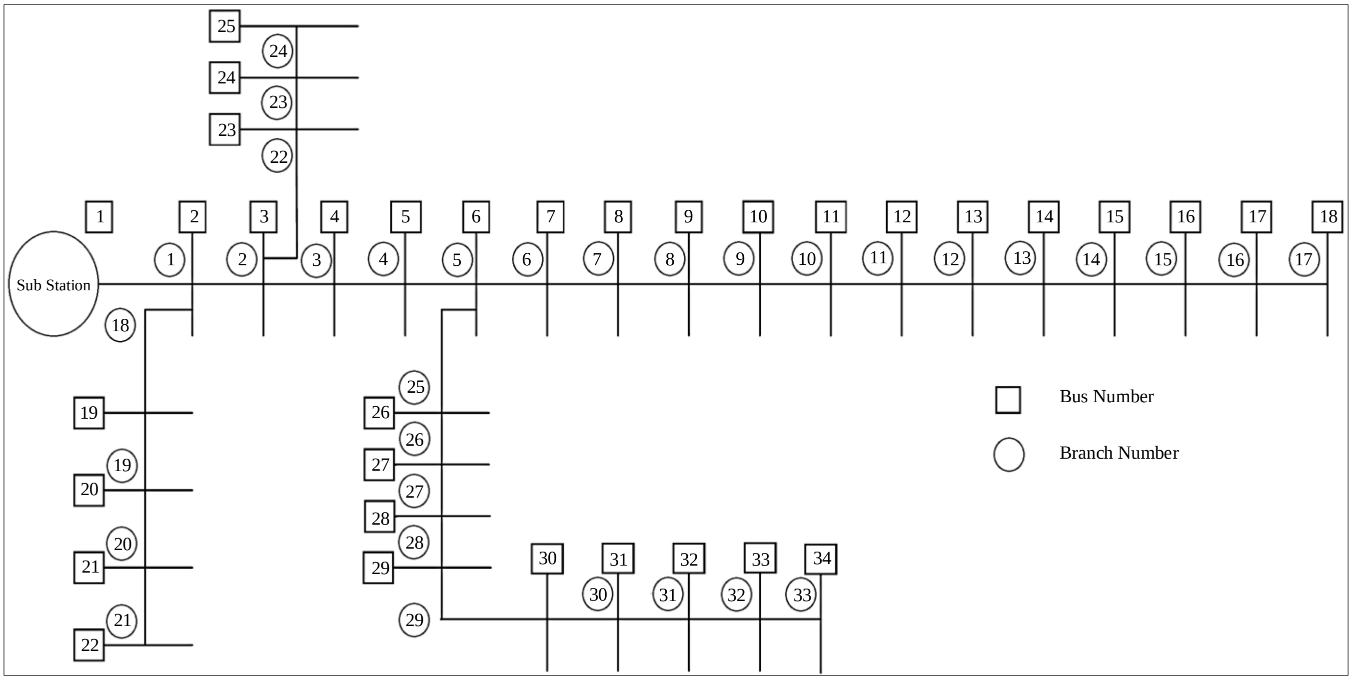

Fig. 5 IEEE-34-bus RDN

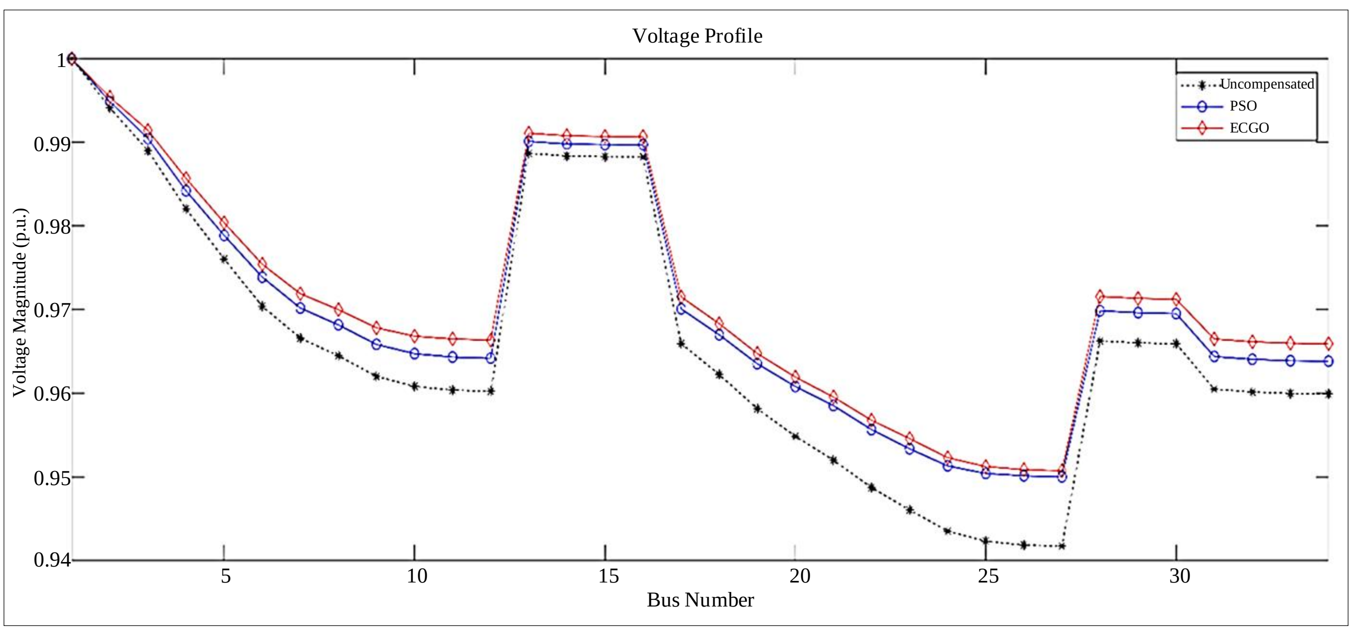

Fig. 6 Voltage profile of the 34-RDN bus voltage vs bus number

4. Results and Discussion

4.1. IEEE-34 Bus Distribution System

The IEEE-34 bus system is shown in Figure 5. Four laterals, or sub-feeders, plus a main feeder, make up this system. In Figure 5, the single-line figure is displayed. The feeders' line, load statistics, the system's rated line voltage, and system data are provided in reference [29]. The overall load for this system is 2873.5 kilovolt-amperes with a power factor of 0.7. The uncompensated losses amount to 221.754 kW. The minimum voltage is 0.9424 per unit. The yearly expense amounts to $37248. 9438. A comparison between two different optimization methods was conducted, and their results are shown in Table 1. The different optimization algorithms determine the best location and sizes of the CPDs. This method has been recommended in this research due to its superior cost and loss response. The efficacy of the enhanced CGO is validated on IEEE-34 RDN. The installed capacity of CPD with PSO and CGO algorithms are 1728.35 KVAr and 1650 KVAr, respectively. Also, net savings yearly with PSO and CGO are $8646.2407 and $10386.6124, respectively. The minimum voltage has been raised to 0.9574 per unit. The losses have been reduced to 51.4657 kW with PSO and 61.8251 kW with CGO, as indicated in Table1. By using the CGO optimization method, losses have been reducing 10.3601 kW more than the PSO method.

4.2. IEEE-85 Bus Distribution System

According to the proposed algorithm, the IEEE-85 bus system has been tested. A diagram of the system is presented in Figure 7, which shows that there are seven branches and principal feeds. The data from the system are displayed in [29]. As can be shown in Table 3, the losses that occur without any compensation amount to 319.2494 kW. Additionally, the minimum voltage has been determined to be 0.8525p.u. The cost can be calculated to be 53633.7394 dollars per year.

Table 1. Results of IEEE standard 34 bus system

Number of items	Uncompensated	PSO	CGO
Total Active Loss in KW	221.7199	170.2542	159.8948
Total Annual Cost ($)	37248.9438	28602.7031	26862.3314
Minimum Voltage (volt in p.u)	0.94171 at Bus 27	0.95 at Bus 27	0.9574 at Bus 27
Maximum Voltage (volt in p.u)	0.99414 at Bus 2	0.9948at Bus 2	0.9984 at Bus 2
Optimal Location and Size in kVAr		1728.5 (Bus-23-1200, Bus-9-180.77, Bus-27-347.73)	1650 (Bus-23-450, Bus-17-400, Bus-25-350, Bus-9-450)
Total CD Cost ($)		1384.50	1275

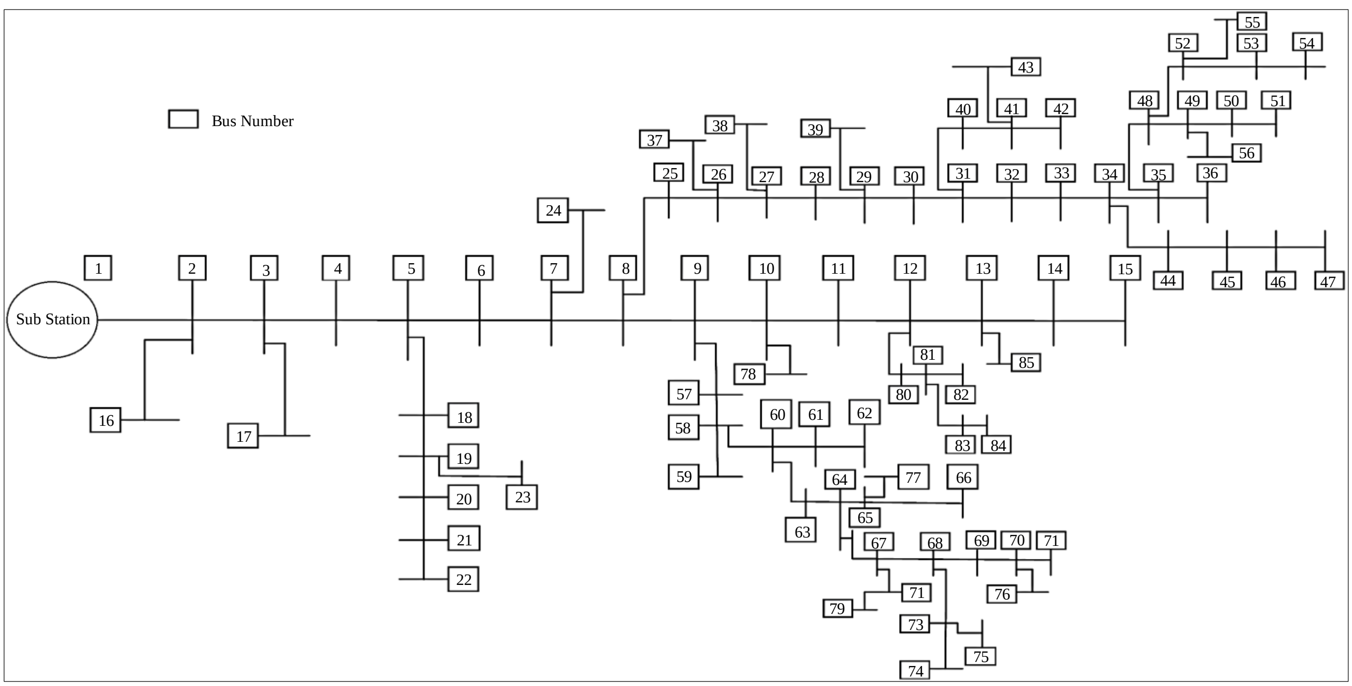

Fig. 7 IEEE-85-Bus RDN

4.3. Compensated Using PSO and Proposed Method

The proposed enhanced CGO's ability to find out the optimal location and size of CPD is confirmed by comparing it to the results obtained and shown in Table 3. Then, the proposed CGO method searches the different locations to place the required size of CPDs so that it improves each bus voltage profile, annual cost and net saving. For the 85-bus RDN [29]. The best potential places for the CPDs to be placed are shown in Table 2. Before compensation, the lowest and highest voltages were 0.8525 and 0.9952 p.u.; these values are now improved to 0.96571 and 0.9991 p.u, respectively. The comparison of the outcomes using the PSO approach is also displayed in Table 3. The ideal candidate locations using the proposed technique have less power loss than using the PSO method. Furthermore, the percentage decrease in losses is further improved to 35.38%. Furthermore, the minimum voltage has been raised to 0.937 per unit. The installed capacity of CPD with PSO and CGO algorithms are 3975.55 kVAr and 3600 KVAr, respectively. It can be seen that the yearly net saving with PSO is $24768.2769, while the net saving using CGO is $28896.1052, which is 16.66% more net saving. Further, the total active loss by PSO is 159.9135 kW, while that from CGO is 147.2478 kW, as indicated in Table 3. Using the CGO optimization method, losses have been reducing 12.6657 kW more than the PSO method, which is nearly 7% more than PSO.

Table 2. Obtained location and size of CPD using PSO and CGO algorithm

PSO		CGO	
BUS	**Size (KVAr)**	**BUS**	**Size (KVAr)**
69	182..02	78	300
78	1200	23	300
23	1200	53	300
30	1200	17	150
53	375.55	26	300
		28	150
		74	150
		55	150
		57	600
		61	150
		62	150
		44	300
		79	150
		40	450

Table 3. Results of IEEE standard 85 bus system

Number of Items	Uncompensated	PSO	CGO
Total Active Loss in Kw	319.2494	159.9135	147.2478
Total Annual Cost ($)	53633.739	28865.463	24737.634
Minimum Voltage (volt in p.u)	0.8525 at bus 76	0.9075 at bus 76	0.9074 at bus 76
Maximum Voltage (volt in p.u)	0.99414 at Bus 2	0.9948at bus 2	0.9984 at bus 2
Optimal Location and Size in kVAr		3975.55	3600
Total CPD Cost ($)		6805	6675

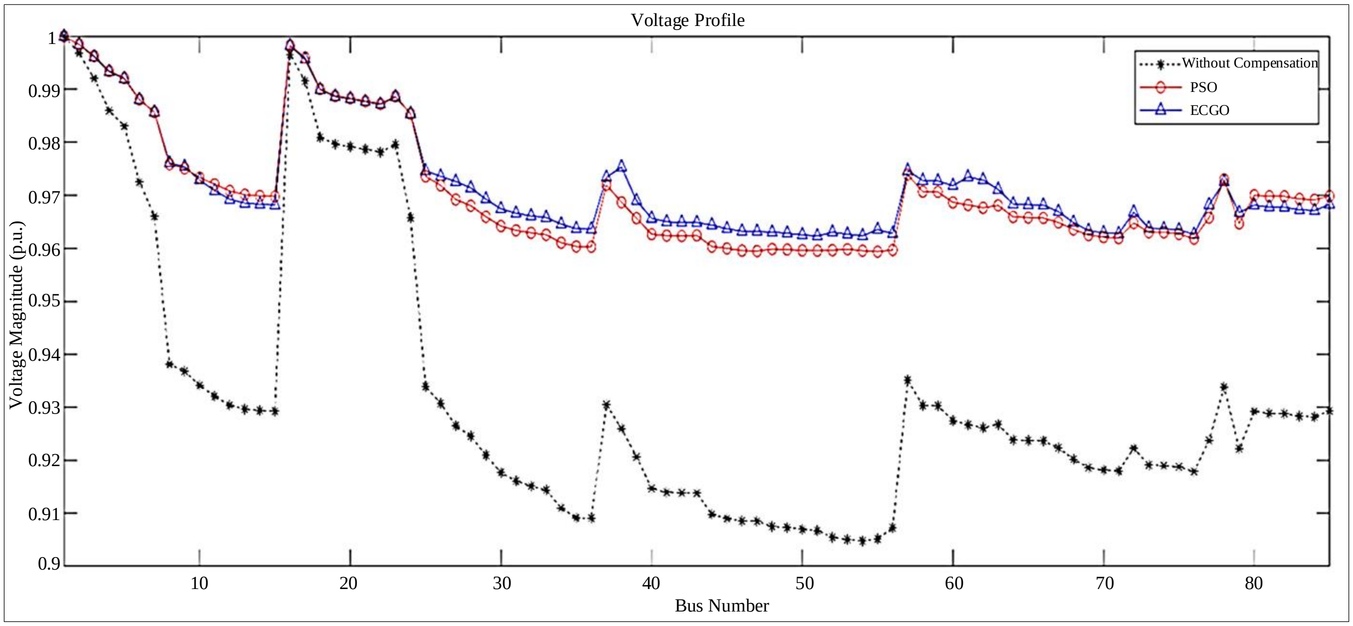

Fig. 8 Voltage profile of the 85-RDN bus voltage vs bus number

5. Conclusion

This study presents the effective use of CGO to address the issue of CPD size and optimal placements in distribution networks. It has been determined that this problem is an optimisation challenge that involves estimating power losses, installation and operating costs, and injected variables power. Assessing the cost-benefit, total power losses, and voltage profiles, it can be said that CPDs are highly cost-effective devices utilized in distribution networks for reactive compensation. In this research, the CPDs are strategically placed to minimize distribution system losses and maximize cost savings. Simulation tests were conducted on the IEEE 34 and 85 bus RDS. The results demonstrate the high efficiency of CGO in determining global optimal location and its ability to generate superior results compared to the PSO method. When considering 34 bus RDS, it is found that the total active power loss is reduced by 51.4657 kW using the PSO algorithm; however, when the purposed CGO algorithm is used for the optimal placement of CPD, the losses are reduced by 61.3546 kW, which means that around 19.21% more active power can be saved using CGO when compared to PSO algorithm. Similarly, for 85 bus RDS, the total active loss is reduced to 159.9135 kW using PSO for optimal placement of CPD, while when the CGO algorithm is utilized, the total losses are reduced to 147.2478 kW. From the results, it can be seen that using the CGO optimization method leads to a higher loss reduction by about 7% when compared to PSO. Also, the total cost saving by optimal placement of CPD is 53.87% by CGO, while from PSO, it is around 49.90%. It can be inferred that the CGO algorithm produces improved results when compared to other algorithms in terms of overall cost, net savings, and losses.

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