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Research article

Enhancement of power distribution efficiency through optimal capacitor placement using adaptive simulated gorilla troop optimizer

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Abstract: This paper proposes an Adaptive Simulated Gorilla Troop Optimizer (ASGTO) to minimize the cost of switched capacitor placement in the IEEE 34-bus radial distribution network. The novelty of this work lies in the enhancement of the standard Gorilla Troop Optimizer (GTO) through the integration of circle chaotic mapping and step adaptive simulations, which improve the global optimization performance. The ASGTO adopts a two-step approach: a loss sensitivity analysis identifies candidate buses, followed by the determination of the optimal capacitor locations and sizes by ASGTO. The optimization process is validated using a backward-forward sweep power flow analysis based on standard IEEE data. Comparative results reveal the superiority of the proposed ASGTO method, thereby achieving a 27.9% reduction in active power loss, a 28.09% decrease in reactive power loss, and an annual energy cost saving of $9,122.32. The optimal placement of the capacitors significantly enhances the voltage stability, thereby maintaining voltage levels between 0.9505 per unit (p.u) and 0.9952 p.u. The results confirm the effectiveness of the ASGTO in reducing losses and costs while improving voltage profiles, thereby supporting the development of more efficient and sustainable distribution networks.

Keywords: capacitor; optimization; algorithm; distribution network; metaheuristic

1. Introduction

In modern power distribution systems, efficient energy management is critical to meet increasing electricity demands while ensuring system reliability and cost-effectiveness [1]. Radial distribution networks (RDNs), characterized by their unidirectional power flow from a central substation to end-users, are particularly susceptible to power losses and voltage instability due to their topology [2]. To mitigate these challenges, shunt capacitor banks are commonly deployed for power factor correction, voltage support, and loss minimization [3].

The optimal placement and sizing of capacitors in RDNs have long been recognized as a complex combinatorial optimization problem [4]. Various deterministic, heuristic, and metaheuristic techniques have been explored in the literature to address this issue [5,6]. For instance, Power Loss Index (PLI) methods have been combined with algorithms such as the sine cosine algorithm (SCA) [7], fuzzy logic with simulated annealing (SA) [8], and particle swarm optimization (PSO) [9] to enhance the identification of capacitor locations and their corresponding ratings. Other metaheuristic strategies including bacterial foraging [10], gravitational search [11], the firefly algorithm [12], teaching learning-based optimization [13], big bang-big crunch optimization [14], harmony search variants [15,16], the genetic algorithm (GA) [17], golden jackal [18], and the grey wolf optimizer [19] have been employed to effectively solve the capacitor placement problem.

Recent research has proposed enhanced hybrid techniques to improve the convergence behavior and cost-effectiveness, especially for large-scale and complex distribution systems. For example, [20] presented a two-stage approach combining Loss Sensitivity Factor (LSF) to identify candidate buses and the Cuckoo Search Algorithm (CSA) for fine-tuning capacitor sizing and placement, thus achieving notable reductions in power loss and compensation costs. Similarly, [21] utilized LSF followed by the Reptile Search Algorithm (RSA) to determine the optimal capacitor parameters, thus highlighting improvements in annual savings and voltage enhancement. A case study on the distribution network of Duhok city, simulated using an Electrical Transient and Analysis Program (ETAP), demonstrated significant enhancements in voltage stability and a reduction in losses through strategic capacitor deployment.

Furthermore, [22] integrated the GA with forward and backward sweep (FBS) load flow techniques to optimize solar-based distributed generation (DG) and capacitor placement, and showed performance improvements on IEEE benchmarks and a real network in Nepal. In [23], a modified PSO was introduced with sensitivity-based candidate screening, validated on IEEE 15, 33, and 69-bus systems, and yielded robust annual net savings. A comparative study in [24] between the Bat Algorithm and CSA further demonstrated their efficacy in optimizing capacitor placement for loss reduction and cost savings.

Despite these advancements, there remains a need for more robust and adaptive optimization frameworks that ensure fast convergence and effective scalability. In response, this study proposes a hybridized method that combines a Loss Sensitivity Index (LSI) for candidate bus selection with an adaptive variant of the Gorilla Troop Optimizer (GTO), termed the Adaptive Simulated GTO (ASGTO). The LSI is employed to identify buses with the highest potential for power loss reduction through capacitor integration, while the ASGTO determines the optimal sizing and placement of capacitors.

The GTO algorithm, inspired by the intelligent social behavior of gorillas [25], has shown high flexibility and potential in solving complex optimization tasks. In this study, its adaptive variant incorporates parameter control mechanisms that improve the balance between exploration and exploitation, making it well-suited for capacitor placement problems in RDNs [26].

The proposed methodology is validated on the standard IEEE 34-bus test system. Simulation results confirm enhanced cost savings, reduced system losses, and improved voltage profiles compared to existing approaches. This research contributes a novel and scalable solution to the capacitor placement problem and offers valuable insights for distribution system planners that aim to optimize the operational performance and promote sustainable power delivery.

2. Method

2.1. The adaptive simulated gorilla troop optimizer (ASGTO)

2.1.1. The gorilla troop optimizer

Drawing inspiration from gorillas, the artificial GTO replicates the social behaviors of gorilla groups through an algorithm that imitates five key traits of gorillas: migration to new areas, interaction with other gorillas, moving to known locations, following the leader (silverback), and competition among mature males for females. These traits form the exploration and exploitation phases of optimization. The GTO employs a set of guiding rules for its metaheuristic process to achieve optimal solutions. The solution space encompasses the current position vector X of gorillas and candidate position vectors GX created in each GTO phase. These vectors define the parameters or variables being optimized. GX operates when its value surpasses the quality of the present solution and $X_{silverback}$ represents the global solution after each iteration.

$$GX(t+1) = \begin{cases} (ub - lb) \times r_1 + lb, & r < p \\ (r_2 - C) \times X_1(t) + L \times Z \times X(t), & r \geq 0.5 \\ X(t) - L \times (L \times (X(t) - X_1(t) + r_3 \times (X(t) - X_2(t)), & r < 0.5 \end{cases} \tag{1}$$

$$Z = [-C, C] \tag{2}$$

In Equation (1), the term $GX(t+1)$ represents the candidate position vector of the gorilla in the subsequent t iterations, $X(t)$ represents the current position of the gorilla, and r, r_1, r_2, r_3 are random numbers within [0,1]. The variable p is set at the initialization stage and has a value within [0,1]. It is employed to select which of the three mechanisms highlighted above must operate. ub and lb are the upper and lower boundaries of the variables of the problems being solved, respectively. X_1 and X_2 represent a randomly selected gorilla and its vector position, respectively. The variables C and L are calculated using (3) and (4), respectively.

Exploration phase:

In the exploitation phase, the gorillas search within their own search space based on two behaviors: gorillas follow the silverback gorilla, which is the best solution in the troop, or male gorillas compete amongst themselves for adult females. In the search process of the GTO, the selection of either of the two behaviors is randomly simulated with variables C and W, where C is defined according to (3) and W is a number between 0 and 1 chosen at the initialization of the GTO.

$$C = F \times \left(1 - \frac{t}{MaxIter}\right) \tag{3}$$

$$L = C \times l \tag{4}$$

$$F = cos(2 \times r_4) + 1 \tag{5}$$

The variable r_4 represents a number chosen at random within [0,1], the variable l is a number chosen at random from the range [-1,1], t holds a value representing the current iteration count, and $MaxIter$ represents the maximum number of iterations the algorithm should run. The rules for choosing either of the two behaviors using C and W are as follows.

Follow silverback

Gorillas begin to follow the silverback when the condition $C > W$ is met. This behavior is exhibited when the silverback is young, healthy, and strong enough to lead the troop, make decisions, determine the group's movement, and direct the troop toward a potential food source. In this state, members of the troop follow the silverback well and obey instructions given by the silverback. This is simulated according to (6).

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \tag{6}$$

$$M = \left(\left| \frac{1}{N} \sum_{i=1}^{N} GX_i(t) \right|^g \right)^{\frac{1}{g}} \tag{7}$$

$$g = 2^L \tag{8}$$

$$L = C \times l \tag{9}$$

Male gorillas compete for females

Male gorillas compete or fight amongst themselves for females when $C < W$. This occurs when young gorillas grow up and become stronger. The fight is violent and may last for many days. This behavior is simulated according to (7).

$$GX(i) = X_{silverback} - (X_{silverback} \times Q - X(t) \times Q) \times A \tag{10}$$

$$Q = 2 \times r_5 - 1 \tag{11}$$

$$A = \beta \times E \tag{12}$$

$$E = \begin{cases} N_1, rand \geq 0.5 \\ N_2, rand < 0.5 \end{cases} \tag{13}$$

In Equation (10), the variable Q represents the impact force with which the male gorillas compete. The variable r_5 represents a number generated at random from the range [0,1], and variable A represents a coefficient vector that is meant to determine the degree of violence in the fight among the gorillas. β is a parameter selected at the initialization of the algorithm, and E is a parameter modeled to simulate the impact of violence on the dimensions of the solutions. The exploitation phase of the original GTO algorithm is completed with a group formation, where the cost or function values associated with all GX solutions are determined and compared to the cost or function value of X. At an iteration t, where $GX(t) < X(t)$, $GX(t)$ replaces the $X(t)$ solution. Again, the best solution amongst the gorillas of the GTO population at iteration t becomes the silverback. The implementation of the GTO algorithm is shown in Figure 1.

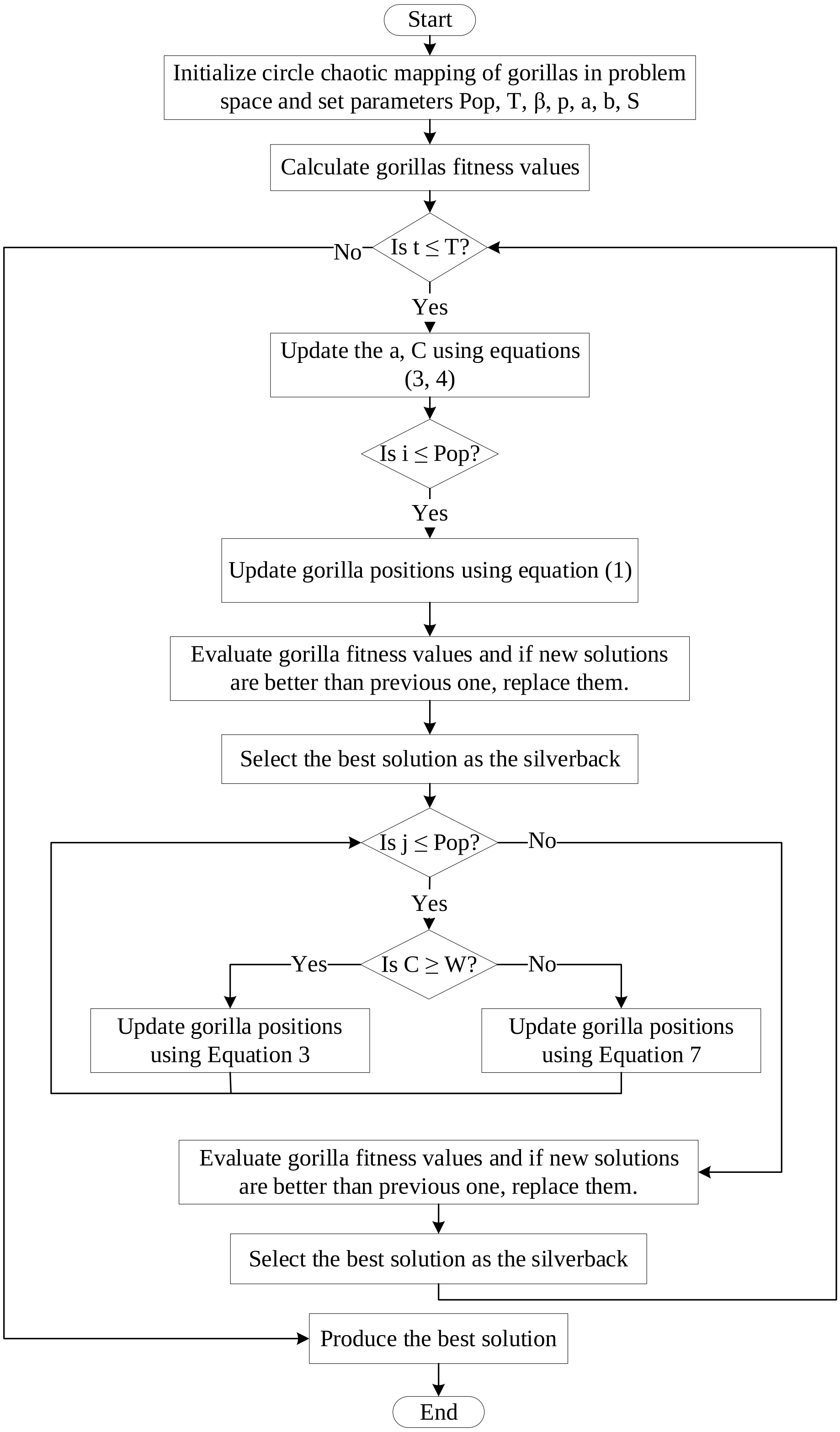

Figure 1. Flow chart of the proposed algorithm.

2.1.2. Proposed modification ASGTO

Circle chaotic mapping initialisation

Inspired by the work done in [27], a circle chaotic mapping technique was deployed to improve the population at the initialization stage of the algorithm to ensure diversity in generating the initial population. Chaotic mapping is a technique used in nonlinear systems that possess properties such as unpredictability, ergodicity, and randomness. Chaotic mapping is preferred over a random distribution since it allows individuals within the population at the initial stage to thoroughly explore the search space with a higher convergence speed and good sensitivity. Compared to the commonly used Tent chaotic mapping strategy and the Logistic chaotic mapping technique, chaotic mapping is widely adopted to improve an optimization algorithms' performance in solving complex optimization problems. The main impact of the chaotic mapping-based technique of generating the initial population is that it gives an initial population with relatively better diversity. All aspects of the search space are thoroughly explored to generate the population.

The proposed chaotic mapping-based strategy of generating the initial population is mathematically given as follows:

$$z_{k+1} = z_k + b - \frac{a}{2\pi}.sin(2\pi z_k)\,mod(1), z_k \in (0,1) \tag{14}$$

where $a = 0.5$, and $b = 0.2$.

Self-adaptive and dynamic step-size

In the original GTO updating formula, the random step typically involves a random number vector (Z) drawn from a uniform, Gaussian, or other distribution. However, this approach can lead to individual gorillas becoming trapped in local optima during the updating process, particularly for high-dimensional test functions where random turbulence can occur and slow down convergence. Consequently, the algorithm may fail to converge to an optimal value. To tackle this problem, a step modification factor ω is introduced to address any decrease in optimization accuracy in the standard GTO when the search dimension of an individual gorilla increases. This modification aims to enhance the algorithm's ability to effectively handle higher-dimensional optimization problems:

$$\omega = \beta^D * T * e^{(-t/T)} \tag{15}$$

where t represents the current iteration, T represents the largest iteration, D denotes the dimension of individual gorillas, and $\omega \in [0,1]$. In this research, β = 0.1. In the operation of the algorithm, as the search dimension of an individual gorilla or the iteration number increases, the random step size undergoes a reduction. By diminishing the step size, the algorithm promotes a more focused exploration of the solution space, which enables the gorilla to navigate with greater precision and efficiency in higher-dimensional spaces or as the optimization process advances. This adaptive step size modulation optimizes the balance between exploration and exploitation for improved convergence towards optimal solutions.

Adaptive simulation

In GTO, a global solution is achieved by both exploitation and exploration of the search space. This is achieved by randomly simulating the mechanisms that define the behaviors of the gorillas. The numerous mechanisms in the algorithm help it to achieve a better performance compared to other algorithms. Regardless of the performance of the GTO, it still suffers from slower convergence and local optima entrapment in solving optimization problems. These deficiencies must be addressed and requires improvement. In this work, a novel ASGTO is introduced, which modifies the exploitation phase of the GTO. In the exploitation search process, the GTO exploits two important mechanisms: following the silverback gorilla or having male gorillas compete amongst themselves for females. These predominantly depend on the behavior of silverback gorillas and are randomly simulated with variables C and W in the implementation of the GTO. In this work, a new adaptive simulation is introduced to simulate the two mechanisms based on the state and behavior of the silverback in the troop, which is done using (16) and (17). The proposed simulation leverages the state of the silverback gorilla and the search space in the exploitation phase to decide which of the two mechanisms gets to operate, rather than a random simulation. In the proposed adaptive simulation, gorillas follow the silverback if $C \geq S$, and adult male gorillas compete for females when $C < S$. Hence, the two mechanisms are adaptively simulated based on the value of C and S.

$$S(t) = S\frac{cos(\,K(t) - 1)}{cos(\,K(t) + 1)}minmax_{max} \tag{16}$$

$$K(t) = \frac{fitness(silverback) - 1}{fitness(silverback) + 1} \tag{17}$$

In (16), S_{max} and S_{min} are the maximum and minimum weights, respectively, that determine the extent of Silverback's behavior at every iteration t. In this modification, S_{max} and S_{min} are chosen as 0.9 and 0.1, respectively. cos is the cosine function, which reduces the effect of sudden changes in the gorilla's behavior throughout iterations. The implementation procedure (steps) of the newly proposed algorithm (ASGTO) is presented in Figure 1.

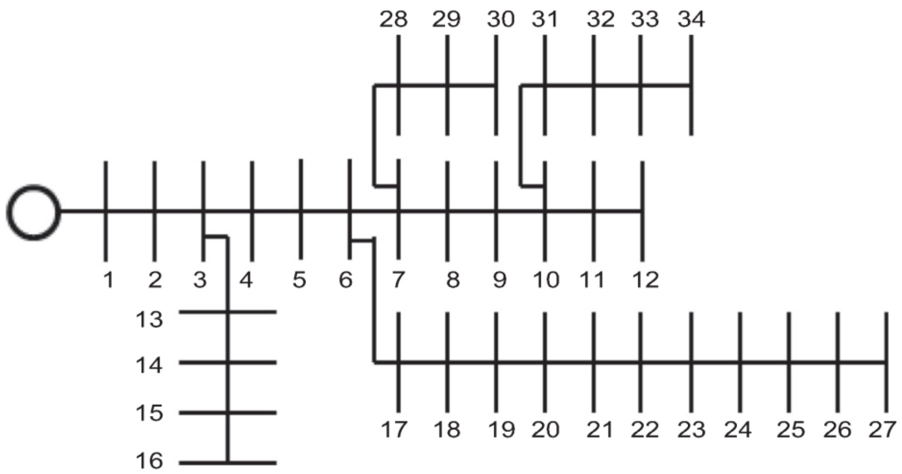

Figure 2. The standard IEEE 34-bus radial distribution network.

2.2. Problem formulation

The optimal capacitor placement problem is one of the well-known optimization problems in electrical engineering, which seeks to determine the locations for optimal capacitor placements in radial distribution networks, as well as the corresponding sizes to inject the optimal amount of reactive power into the systems for the best performance. Inaccurate placements and sizing can lead to financial losses and system instability. This makes it a very sensitive optimization problem that needs to be tackled with a very effective technique. The problem can be mathematically formulated by taking the total cost involved into consideration to ensure it is as minimal as possible to be cost effective and the voltage deviations of the system are minimal as possible to ensure system security.

The problem is mathematically presented in Equation (18).

$$Min(S) = \omega_1 \left(K_p \sum_{i=1}^{N_b - 1} P_{Lossi} + K_C \sum_{j=1}^{N_C} Q_{Cj} \right) + \omega_2 \left(\sum\nolimits_{i=1}^{N_b} |V_i - V_{nominal}\ | \right) \tag{18}$$

The term S (objective function) denotes the sum of the total costs ($/year) and the sum of the system voltage deviations, K_p represents the yearly expense associated with each unit of power loss in the system ($/kilowatt (kW)-year), and K_c represents the capacitor banks' total cost ($/kilovolt-amperes reactive (kVAr)). P_{Lossi} signifies the active power loss in line i, while Q_{Cj} symbolizes the cumulative reactive power introduced at the designated location within the system j. N_b represents the total number of system buses, and N_C indicates the number of capacitors to be installed. The term V_i denotes a voltage at bus i, and $V_{nominal}$ represents the system nominal voltage given as 1 per unit (p.u). The weights $\omega_1$and ω_2 are selected as 0.5 for each.

$$Total\ capacitor\ cost = \frac{K_C * Q_C^{Total}}{Life\ exp\ e\ c\ tan\ c\ y} \$/year \tag{19}$$

The objective function is constrained according to the conditions that are outlined below.

Bus voltage limit:

Every bus's voltage V_p must adhere to predefined and acceptable thresholds or boundaries. In this study, the voltage limit for each bus is defined within in the range of 0.95 p.u to 1.05 p.u.

$$V_{min} \le V_p \le V_{max} \tag{20}$$

The number of capacitor placement constraints:

In the study, the maximum possible count of plausible sites or positions that could be considered is denoted as N_{Cmax} and the ideal number of potential allocations or positionings to be examined is denoted as N_C, which should be equal to or less than this specified maximum.

$$N_C \le N_{Cmax} \tag{21}$$

Maximum power flow constraints:

The upper limit for power flow in any given line is established at 5 megawatts (MW).

$$Pf_k < Pf_{kmax} \tag{22}$$

Capacitor size constraints:

The total reactive power introduced into the system at a given bus must be within the confines of a specified range, that is, the reactive power injected should not exceed the appropriate maximum and must be greater than the minimum limits. In the scope of this research, the capacitor sizes range from 150 to 1200 kVAr.

$$Q_{cjmin} \le Q_{cj} \le Q_{cjmax} \tag{23}$$

Reactive power compensation constraint:

The cumulative reactive power (KVar) injected, denoted as Q_{pC}, must not exceed the overall total reactive power of the system load, which is represented as $\sum_{p=1}^{n} Q_{Lp}$. The mathematical representation of this constraint is expressed in Equation (24).

$$Q_{pC} \leq \sum_{p=1}^{n} Q_{Lp} \tag{24}$$

$$\omega_1 + \omega_2 = 1 \tag{25}$$

Loss sensitivity factor:

The LSF is a numerical value that indicates how sensitive the total system power losses are to changes in reactive power injections at different buses. It is commonly used in optimization problems such as capacitor placement to determine which buses most effectively reduce losses when reactive power is injected.

The procedure for ranking load buses involved utilizing two Loss Sensitivity Indices ($LSIs$) to identify the most suitable buses that are under consideration as potential options for the installation of capacitor banks. These indices serve to significantly narrow down the search range within which the exploration for an optimal solution is conducted. Equations (27) and (29) represent LSI_1 and LSI_2, respectively.

The concept for LSI_1 utilized the derivation of the active power with respect to the bus voltage; alternatively, the concept for LSI_2 utilized the derivation of the active power with respect to reactive power at the given bus.

$$LSI_1 = \frac{\partial P_{loss}}{\partial V_q} \tag{26}$$

$$LSI_1 = -2R * \left(\frac{P_{eff_q}^2 + Q_{eff_q}^2}{V_q^3} \right) \tag{27}$$

$$LSI_2 = \frac{\partial P_{loss}}{\partial Q_q} \tag{28}$$

$$LSI_2 = \left(\frac{2 * P_{eff_q}^2 * R_k}{V_q^2} \right) \tag{29}$$

The parameters P_{eff_q} and Q_{eff_q} correspond to the total effective active and the total reactive powers at node q of the branch. Consequently, in the case of LSI_1, the buses displaying the most negative values are identified as the optimal positions for capacitor installation. Conversely, in the case of LSI_2, the buses exhibiting the highest degree of positivity are considered prime candidates for capacitor placement. Notably, it is assumed that the count of buses considered is equivalent to fifty percent of the overall system's total bus count. The final selection of optimal buses for capacitor deployment involves a combination of both LSI_1 and LSI_2 buses, which act as control variables within the optimization process.

2.3. The backward-forward sweep load flow

To obtain the load flow results, this study employs the well-established backward-forward sweep (BFS) algorithm for the load flow analysis. This algorithm is widely adopted because of its straightforward and uncomplicated nature, reliability, precision, and efficient computational demands. The BFS method is comprised of three primary iterative phases: a computation of nodal currents, a subsequent backward sweep, and finally a forward sweep. The following steps outline the implementation of the BFS algorithm.

Step 1: Initial data input

The input data related to distribution network lines and load information, as well as the base voltage levels and base apparent power, are entered. Subsequently, the per-unit values for the system loads and lines are computed, thus establishing all the initial voltages for all the buses at 1 p.u..

Step 2: Numbering of sections within the radial distribution network

During this stage, the process of numbering each section that connects two buses in the RDN takes place. Each line section that connects two buses in the RDN is assigned a unique identifier based on the topological structure of the network—typically from the root (source) node outward—to aid in the traversal during the sweep processes.

Step 3: computation of the nodal current

Nodal currents are computed at each bus using the specified complex power loads and the current bus voltages using the following formula:

$$I_i = \frac{S_i^*}{V_i^*} \tag{30}$$

where S_i is the complex load, and S_i is the bus voltage.

Step 4: The backward sweep

Using Kirchhoff's Current Law (KCL), branch currents are calculated from the leaf nodes back toward the source by summing the nodal currents and downstream branch currents.

Step 5: The forward sweep

Voltages are updated from the source (slack) node toward the leaves using Kirchhoff's Voltage Law (KVL). For a branch between bus i and j,

$$V_j = V_i - Z_{ij} . I_{ij} \tag{31}$$

Step 6: Evaluation of the stoppage condition

The condition to stop the iteration cycle is when either the iteration count reaches the maximum allowed number of iterations or when the convergence of voltage mismatches is established ($\Delta V_{max} \leq \varepsilon$).

Step 7: Determination of power losses

During this phase, the total apparent power losses within the distribution system, which encompass both the active and reactive power loss components, are computed. This involves the assessment of power dissipation across the network.

2.4. Implementation of ASGTO

Step 1.

Input the system data: the line reactance (X), the line resistance (R), the active power (P), the reactive power (Q), the error limit, the initial bus voltages, the base power (S_{base}), and the base voltage (V_{base}).

Step 2.

Initialize the ASGTO parameters such as the population size (number of gorillas), maximum number of iterations (MaxIter), β, p, S_{max}, and S_{min}, initialize the upper band (*ub*) and lower band (*lb*) of the gorilla's position, initialize positions of gorilla in the population using sensitivity factors from (25) and (26), initialize the total number of capacitors to be placed,. and initialize the maximum and minimum size of the capacitors.

Step 3.

Generate the initial positions for the gorillas using circular chaotic mapping. These positions need to fulfill all constraints, with each gorilla's position represented as a variable vector. Each gorilla in the group serves as a potential solution to address the objective function. The positioning of the i^{th} gorilla is determined using the following equation:

$$GX^i = [l_1^i, \ldots, l_j^i, \ldots, l_{N_c}^i, s_1^i, \ldots, s_{N_c}^i] \tag{32}$$

$$i = 1,2, \ldots, GX, \ldots, s \tag{33}$$

where l_j and s_j stand for the location and size of the capacitors, respectively.

Step 4.

Conduct a load flow analysis for individual gorillas using the BFS method. Assess the objective function's value using (18). Subsequently, verify the constraints (20)-(24) by factoring in the load flow analysis outcomes. Should the constraints prove unsatisfactory, introduce a penalty to the objective function.

Step 5.

Using the value of the objective function, potential solutions are discerned and selected. This process involves evaluating the outcomes of different solution candidates according to the objective function's numerical assessment. The candidates which demonstrate favorable results as per the objective function's criteria are identified for further consideration.

Step 6.

The solution variable is updated according to p by applying the exploration migration movements using (1).

Step 7.

Apply the exploitation search phase updating rules using (3) and (7) to compute the new positions and objective function value.

Step 8.

Repeat step 4 to step 7 until the stoppage condition is met. This iteration can be concluded after a predetermined count of cycles is accomplished. The implementation of the ASGTO procedure is alternatively presented in Figure 3.

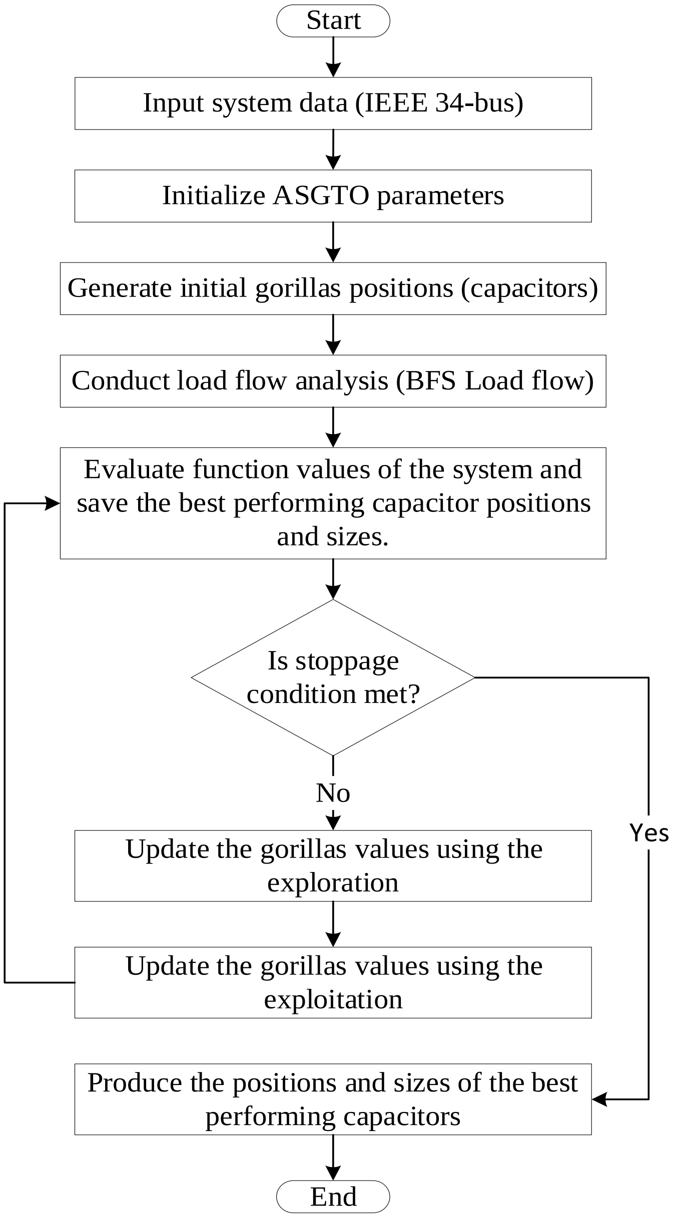

Figure 3. Implementation of ASGTO.

The proposed approach of optimizing the capacitor integration into distribution systems was implemented in MATLAB (MATLAB R2018). The implementation was performed following the aforementioned procedure using an HP Pavilion laptop computer. The simulation parameters are presented in Table 1. It is worth noting that though any reasonable number of capacitors can be integrated using the proposed technique in a radial distribution system, four (4) capacitors were considered for this simulation test in the IEEE 3-bus test system.

Table 1. Parameters settings.

No	Parameter	Value
1	Population size	50
2	Maximum number of iterations	1000
3	Number capacitors	4

3. Results and discussion

To effectively assess the performance of the proposed algorithm, it was tested on a standard IEEE 34 bus radial distribution network shown in Figure 2 using MATLAB. To compare the performance of the suggested algorithm with other works in the literature, the system was configured with the same parameters in the literature [28] as follows: S_b = 100 MVA, V_b = 11 KV, and an overall power factor of 0.85. The maximum permissible power flow in each line was 5 MW.

This study mainly focused on evaluating flexible or switched capacitors with a fixed step size of 150 KVAR. The combined active and reactive power loads amounted to 4.7735 MW and 2.8735 MVAR, respectively. Additionally, the equivalent cost parameters were adopted. In this context, K_p was established at 168 $/(KW) and K_c was set at 5 $/kVAR. It is essential to emphasize that K_p represents the cost associated with annual power losses, which is calculated on an annual basis, with the calculation based on the magnitude of power losses per hour. The anticipated lifespan of the capacitors was set at 10 years. To establish a maximum cap on the number of buses eligible for capacitor placement, a value of 4 was assumed; this value can also be taken as the number of capacitors intended to be connected to the distribution system.

At the end of the simulation, the results achieved through the utilization of the ASGTO for the switched-type capacitors are outlined in Table 2. These results were compared with those obtained by highly competitive algorithm-based methods reported in existing literature. It is worth noting that the proposed ASGTO algorithm demonstrated remarkable performance in curtailing the active power loss from **221.7199kW** to **159.831kW;** the overall yearly energy cost was impressively minimized to a mere **26,851.628**$/year, thus signifying a whopping **27.9%** reduction from the base case of **37248.944$/year**. In the case of the reactive power, the ASGTO equally reduced the reactive power from 65.1 to 46.81, thus representing a 28.09% reduction. The minimum and maximum voltages were 0.9505 and 0.9952, respectively, which confirms that the introduction of flexible capacitors led to a substantial enhancement in system voltage, as shown in Figure 4.

The optimal buses selected by the algorithm for capacitor placement were {9, 22, 18, 27} with optimal sizes {750, 600, 750, 450}, respectively. It is worth nothing that a savings of 9122.324($/year) was achieved. These results are compared to those of other algorithms in Table 2. From the comparison, it can be observed that the proposed method outperformed the other methods from the literature that similarly integrated 4 capacitors in the IEEE 34 bus system. In the case of the Hybrid Grey Wolf Optimizer (HGWO)-based method, the proposed method in this work outperformed it in terms of power losses, with a lower loss value of 159.831 kW as compared to 160.592 kW. However, due to the smaller number of capacitors (3) placed in the HGWO, it produced a slightly better overall cost saving, and the difference comes from the capacitor unit cost.

Figure 4 shows the voltage profile for the base case scenario without any capacitor compensation and the voltage profile for the compensated scenario using capacitor banks. The voltage profile of the compensated system, which is represented by the green line, shows a relatively better performance with minimal voltage deviation relative to the system voltage profile without any compensation, which is represented by the red line. This indicates that the integration of the capacitors using the proposed ASGTO-based optimization technique improved the system voltage performance of the standard IEEE 34-bus radial distribution system.

Table 2. Results comparison.

Item	**Base system**	**With compensation**					
		GA [29]	ACO [30]	HGWO [19]	WOA [28]	GTO	Proposed ASGTO
Total PLoss (kW)	221.7199	168.955	164.508	160.47	160.5942	161.00	159.831
%Ploss reduction	-	23.78	-	-	27.57	27.38	27.89
Total QLoss (kVar)	65.1	-	-	-	-	47.054	46.81
%QLoss	-	-	-	-	-	27.38	28.09
V-minimum (p.u)	0.9417	0.949	0.9501	0.9505	0.95	0.95	0.9505
V-maximum (p.u)	1.02	0.994	-	-	0.995	0.9503	0.9952
Optimal size (bus)	-	7 buses (1629)	9(450) 19(450) 25(1050)	8(750) 18(900) 23(750)	23(600) 17(600) 8(600) 27(600)	19(600) 25(750) 8(750) 27(600)	22(600) 18(750) 9(750) 27(450)
Total capacitor compensation (KVAR)	-	1629	1950	2400	2550	2700	2550
Total power loss cost ($/year)	37248.944	28384.00	27637.344	26,958.96	26,979.82	27,047.866	26,851.628
Total capacitor cost	-	814.5	467.1	578.7	1275	1370	1275
Total cost ($/year)	-	29198.5	28104.44	27359.11	28254.82	28417.866	28126.62
Net savings ($/year)	-	8042.5	9146.20	9890.43	8986.18	8831.078	9122.324

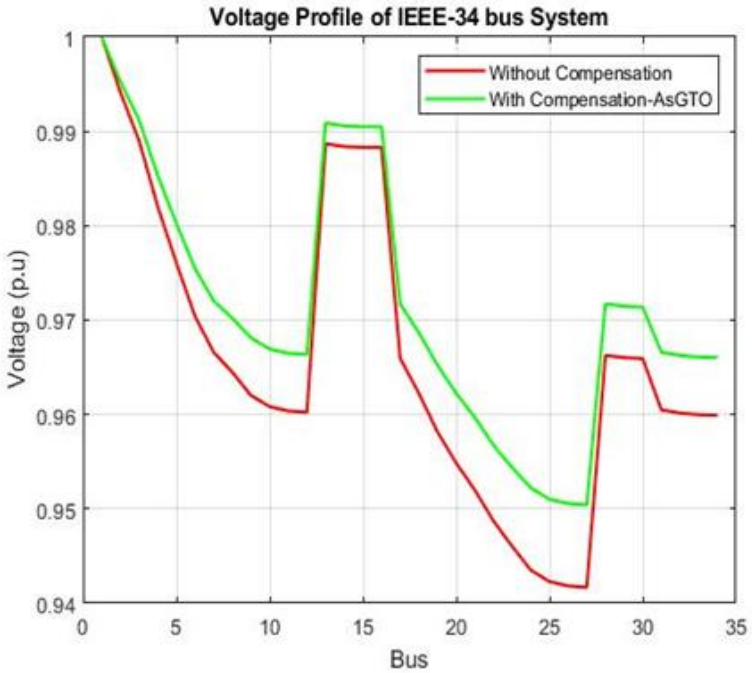

Figure 4. Voltage profiles of the IEEE-34 bus system.

4. Conclusions

This study proposed the ASGTO to address the optimal capacitor placement problem in radial distribution systems. The algorithm incorporated adaptive strategies to improve the exploration-exploitation balance and enhance the solution quality. To streamline the search process, the LSI was employed to identify high-impact buses, thereby reducing the solution space and improving the computational efficiency. Simulation results demonstrated that the ASGTO effectively minimized power losses, improved voltage profiles, and reduced the total cost of capacitor installation. Comparative evaluations confirmed its superiority over conventional optimization techniques, particularly in avoiding local optima and handling high-dimensional problem spaces. The findings highlight the ASGTO's potential as a robust and efficient tool for reactive power compensation planning in distribution networks. Future research may focus on parameter tuning, scalability to large-scale systems, adaptation to dynamic loading conditions, and the integration of modern reactive power devices such as static var compensators (SVCs) and static synchronous compensators (STATCOMs). The outcomes of this work meaningfully contribute to the advancement of intelligent optimization methods in power system planning. Their fast response and adaptability to real-time grid conditions offer significant potential to enhance the system stability and reactive power control in modern power distribution networks.

Author contributions

Bright Ayasu: Conceptualization, writing original draft, writing review, and editing; Abdul-Fatawu Seini Yussif: Simulations, results analysis, review, and editing; Emmanuel Agyepong Nyantakyi: reviews and formal analysis. All authors have read and agreed to the published version of the manuscript.

Use of Generative-AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare that they have no competing interests.

References

1. Twumasi E, Abdul-Fatawu YS, Frimpong EA (2023) Optimal Sizing and Placement of Series Capacitors in Distribution Networks Using Modified Elephant Herding Optimization Algorithm. *J Appl Res Electr Eng* 2: 173–181. https://doi.org/10.22055/jaree.2023.44430.1076
2. Bilal M, Shahzad M, Arif M, Ullah B, Hisham SB, Ali SSA (2021) Annual cost and loss minimization in a radial distribution network by capacitor allocation using pso. *Appl Sci* 11: 11840. https://doi.org/10.3390/app112411840
3. Yussif AFS, Seini T, Ayasu B, Nyantakyi EA (2024) Enhancing Reactive Power Compensation in Distribution Systems through Optimal Integration of D-STATCOM using the Pelican Optimization Algorithm. *International Journal of Electrical Engineering and Applied Sciences (IJEEAS)* 7: 2600–9633. https://doi.org/10.54554/ijeeas.2024.7.01.006
4. Amiel I, Rajput S, Averbukh M (2021) Capacitive reactive power compensation to prevent voltage instabilities in distribution lines. *Int J Electr Power Energy Syst* 131: 107043. https://doi.org/10.1016/j.ijepes.2021.107043
5. Stanelyte D, Radziukynas V (2019) Review of Voltage and Reactive Power Control Algorithms in Electrical Distribution Networks. *Energies* 13: 58. https://doi.org/10.3390/en13010058
6. Díaz P, Pérez-Cisneros M, Cuevas E, Camarena O, Martinez FAF, González A (2018) A swarm approach for improving voltage profiles and reduce power loss on electrical distribution networks. *IEEE Access* 6: 49498–49512. https://doi.org/10.1109/ACCESS.2018.2868814
7. Biswal SR, Shankar G (2018) Optimal Sizing and Allocation of Capacitors in Radial Distribution System using Sine Cosine Algorithm. *Proc. 2018 IEEE Int. Conf. Power Electron. Drives Energy Syst. (PEDES),* 1–4. https://doi.org/10.1109/PEDES.2018.8707739
8. Addisu M, Salau AO, Takele H (2021) Fuzzy logic based optimal placement of voltage regulators and capacitors for distribution systems efficiency improvement. *Heliyon* 7: e07848. https://doi.org/10.1016/j.heliyon.2021.e07848
9. Ortiz L (2020) Ubicación y dimensionamiento óptimo de bancos de capacitores usando compensación VOLT-VAR en Microredes. *IEEE Latin America Transactions*. Available from: https://www.researchgate.net/profile/Leony-Ortiz/publication/356998075_Ubicacion_y_dimensionamiento_optimo_de_bancos_de_capacitores_usando_compensacion_VOLT-VAR_en_Microredes/links/61c472338bb20101842f9df3/Ubicacion-y-dimensionamiento-optimo-de-bancos-de-
10. Rama ST, Rajini V (2023) Optimization of Switching Control and Microgrid Energy Management System with Alternate Arm Converter Based on Bacterial Foraging Algorithm. *Int Trans Electr Energy Syst* 2023: 5585420. https://doi.org/10.1155/2023/5585420
11. Roy A, Verma V, Gampa SR, Bansal RC (2023) Planning of distribution system considering

residential roof top photovoltaic systems, distributed generations and shunt capacitors using gravitational search algorithm. *Comput Electr Eng* 111: 108960. https://doi.org/10.1016/j.compeleceng.2023.108960

12. Eo O, To A, Ik O, Oo AI (2023) Optimal sitting and sizing of shunt capacitor for real power loss reduction on radial distribution system using firefly algorithm: A case study of Nigerian system. *Energy Source Part A* 45: 5776–5788. https://doi.org/10.1080/15567036.2019.1673507
13. Alghamdi AS (2022) A New Self-Adaptive Teaching–Learning-Based Optimization with Different Distributions for Optimal Reactive Power Control in Power Networks. *Energies* 15: 2759. https://doi.org/10.3390/en15082759
14. Nagpal M, Kaushal M, Sharma A (2022) A feature reduced intrusion detection system with Optimized SVM Using Big Bang Big Crunch Optimization. *Wireless Pers Commun* 122: 1939–1965. https://doi.org/10.1007/s11277-021-08975-2
15. Ibrahim AH, Ashigwuike EC, Oluyombo W, Sadiq AA (2023) Optimal Capacitor Planning for Power Factor Improvement Using Hybrid Particle Swarm and Harmony Search Optimization. *Niger J Technol Dev* 20: 210–226. https://doi.org/10.4314/njtd.v20i3.1825
16. Ding Z, Zhang H, Li H, Chen J, Lu P, Hua C (2023) Improved Harmony Search Algorithm for Enhancing Efficiency and Quality in Optimization of the Distillation Process. *ACS Omega* 8: 28487–28498. https://doi.org/10.1021/acsomega.3c02785
17. Katoch S, Chauhan SS, Kumar V (2021) *A review on genetic algorithm: past, present, and future*. *Multimed Tools Appl* 80: 8091–8126. https://doi.org/10.1007/s11042-020-10139-6
18. Reddy NM, Kiran TV, Kumar IK, Reddy KR, Srinivas C, Divya K (2024) Optimizing Capacitor Placement in Distribution Systems Under Variable Loading Conditions with Golden Jack Optimization (GJO). *Int J Electr Electron Res* 12: 338–344. https://doi.org/10.37391/IJEER.120202
19. Jayabarathi T, Raghunathan T, Sanjay R, Jha A, Mirjalili S, Cherukuri SHC (2022) Hybrid Grey Wolf Optimizer Based Optimal Capacitor Placement in Radial Distribution Systems. *Electr Power Components Syst* 50: 413–425. https://doi.org/10.1080/15325008.2022.2132556
20. Mathenge SW, Mharakurwa ET, Mogaka L (2024) Voltage enhancement and loss minimization in a radial network through optimal capacitor sizing and placement based on Crow Search Algorithm. *Energy Reports* 12: 4953–4965. https://doi.org/10.1016/j.egyr.2024.10.062
21. Ali ES (2025) Efficient Capacitor Location in Radial Distribution Networks via Reptile Search Approach. *WSEAS Trans Circuits Syst* 24: 66–77. https://doi.org/10.37394/23201.2025.24.8
22. Mahato JP, Poudel YK, Chapagain MR, Mandal RK (2024) Power Loss Minimization and Voltage Profile Improvement of Radial Distribution Network Through the Installation of Capacitor and Distributed Generation (DG). *Arch Adv Eng Sci*, 1–9. https://doi.org/10.47852/bonviewAAES42022031
23. Tahir MJ, Rasheed MB, Rahmat MK (2022) Optimal Placement of Capacitors in Radial Distribution Grids via Enhanced Modified Particle Swarm Optimization. *Energies* 15: 2452. https://doi.org/10.3390/en15072452
24. Kavya L, Ramakrishna K (2020) Optimal Placement of capacitor in the Radial Distribution System using Multi Objective BA/CS Algorithm. *Gedrag and Organisatie* 33. https://doi.org/10.37896/GOR33.02/146
25. Hussien AG, Bouaouda A, Alzaqebah A, Kumar S, Hu G, Jia H (2024) An in-depth survey of the artificial gorilla troops optimizer: Outcomes, variations, and applications. *Artif Intell Rev* 57:

246. https://doi.org/10.1007/s10462-024-10838-8

26. Bright A, Emmanuel AK, Elvis T, Emmanuel FA (2023) Enhanced Adaptive Simulated Based Artificial Gorilla Troop Optimizer for Global Optimisation. *International Journal of Electrical Engineering and Applied Sciences (IJEEAS)* 6: 63–76. https://doi.org/10.54554/ijeeas.2023.6.02.008
27. Suryadi MT, Satria Y, Prawadika LN (2020) An improvement on the chaotic behavior of the Gauss Map for cryptography purposes using the Circle Map combination. *J Phys Conf Ser* 1490: 012045. IOP Publishing. https://doi.org/10.1088/1742-6596/1490/1/012045
28. Osama A, Zeineldin HH, Tarek HM EF, El-Saadany EF (2023) Optimal Placement and Sizing of Capacitor Banks in Radial Distribution Systems Using the Whale Optimization Algorithm. *2023 IEEE PES Conf. Innov. Smart Grid Technol. - Middle East, ISGT Middle East 2023 - Proc.*, 1–5. https://doi.org/10.1109/ISGTMiddleEast56437.2023.10078650
29. El-Fergany AA, Abdelaziz AY (2014) Efficient heuristic-based approach for multi-objective capacitor allocation in radial distribution networks. *IET Gener Transm Distrib* 8: 70–80. https://doi.org/10.1049/iet-gtd.2013.0213
30. Abou El-Ela AA, El-Sehiemy RA, Kinawy AM, Mouwafi MT (2016) Optimal capacitor placement in distribution systems for power loss reduction and voltage profile improvement. *IET Gener Transm Distrib* 10: 1209–1221. https://doi.org/10.1049/iet-gtd.2015.0799