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Pelican Optimization Algorithm (POA)-based Method for Solving the Optimal Capacitor Integration (OCI) Problem

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Abstract—This study presents a pelican optimization algorithm (POA) based technique for optimizing the integration of capacitor banks in radial power distribution systems. The proposed approach adopts a hybrid approach that combines the loss sensitivity factors (LSF) and the POA to determine the appropriate placement and sizing of the capacitor banks, respectively, for best system performance. The proposed methodology is tested on the IEEE 33-bus distribution system using MATLAB software. The performance for integrating two capacitor banks is compared to that of the particle swarm optimization (PSO) and the genetic algorithm (GA) methods. The proposed POA method achieved a significant improvement in system performance. Specifically, it reduced active power losses (PLoss) by 68.08%, which surpasses the reductions achieved by PSO (61.79%) and GA (57.73%). In the case of reactive power loss (QLoss), the POA-based approach also proved superior with a 39.035% reduction, while PSO and GA-based methods achieved 28.50% and 22.59% reductions, respectively. These results underscore the effectiveness of the POA-based approach in capacitor bank placement and sizing, making it a promising candidate for enhancing voltage profiles and minimizing power losses in radial distribution systems.

Keywords: Algorithm, Capacitor, Optimization, Power loss, and Pelican optimization.

1. Introduction

Distribution of electrical power is a critical aspect of modern energy systems, serving as the final stage in delivering electricity from generation sources to consumers [1]. Distribution networks are designed to ensure that electrical energy reaches end-users reliably and at acceptable voltage levels, but they often encounter operational inefficiencies. These inefficiencies are primarily caused by technical losses, which arise during power transfer through distribution lines [2]. The losses are inevitable due to the operation of distribution networks at low-voltage levels and higher current levels, which lead to higher energy dissipation in the form of heat losses [3]. Among the key contributors to these losses is the flow of reactive power, a component only essential for maintaining voltage levels and energizing inductive loads. The presence of high reactive power flow elevates current levels throughout the network, further increasing energy losses and stressing system components. Research and practical implementations have consistently shown that addressing reactive power demands locally within the distribution system is one of the most effective strategies for mitigating technical losses, improving operational efficiency, and prolonging equipment life [4].

Shunt capacitor banks are widely deployed within distribution networks to provide localized reactive power compensation to meet the reactive power needed by the system. By injecting the required reactive power into the system, capacitors help reduce the amount of reactive power flowing through the distribution lines, thereby lowering current levels and associated losses [5]. This also leads to improved voltage profiles across the network, enhancing the quality and reliability of power delivered to consumers. The strategic determination of the placement and sizing of capacitors within a

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distribution system is referred to as Optimal Capacitor Integration (OCI). OCI seeks to maximize the technical and economic benefits of capacitor deployment, such as enhanced system capacity, reduced power losses, and better voltage regulation, while minimizing associated costs [6]. Effective OCI is thus not only a matter of technical optimization but also a critical economic consideration in modern power systems. By achieving an optimal balance, OCI ensures that distribution networks operate efficiently, with improved stability and performance.

Despite the widespread adoption of capacitor banks, achieving their optimal placement and sizing remains a complex challenge. The placement and sizing decisions depend on a wide range of factors, including network topology, load distribution, and dynamic variations in power demand. Analytical methods, such as mixed-integer programming and dynamic programming, have traditionally been employed to solve this problem [7]. These techniques aim to identify precise solutions by systematically analyzing all possible configurations. However, these methods often suffer from substantial computational complexity, particularly for large-scale networks with numerous buses and interconnected components [8]. Furthermore, their applicability is limited in scenarios where system parameters and conditions change frequently, as recalculations become computationally expensive and time-consuming. As a result, there is a growing need for alternative approaches that can overcome these limitations and deliver near-optimal solutions efficiently and reliably [9].

Metaheuristic algorithms, especially the swarm intelligence-based types, have been identified as effective tools for solving optimization problems, including those encountered in OCI. These algorithms leverage principles inspired by natural and social phenomena to explore large and intricate search spaces [10]. Unlike traditional methods, metaheuristic approaches are less constrained by the need for mathematical formulations or assumptions, making them versatile and robust for a wide range of applications. Algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Gravitational Search Algorithm (GSA) have demonstrated considerable promise in addressing the OCI problem by effectively balancing exploration (global search) and exploitation (local refinement) [11]. While these techniques have achieved notable success in improving network performance, challenges such as convergence to suboptimal solutions and computational overhead remain, necessitating the need to explore new algorithms for better-performing approaches [12].

Among the various metaheuristic algorithms, the Pelican Optimization Algorithm (POA) stands out due to its unique inspiration derived from the cooperative and competitive hunting behaviors of pelicans. This algorithm emulates the semicircular formations and organized diving strategies exhibited by pelicans during hunting. By simulating these natural behaviors, POA achieves a remarkable balance between exploration and exploitation, which is critical for solving high-dimensional and multimodal optimization problems. This characteristic makes POA particularly well-suited for applications such as capacitor placement and sizing in radial distribution systems, where the solution space is complex [13].

Despite the theoretical advantages and performances demonstrated on other optimization problems by the POA, its application to solve the OCI problem has not been extensively investigated. This creates room to evaluate its potential in solving the OCI problem. Researchers have explored different optimization methods for the said capacitor placement and sizing in distribution networks. Methods such as the Dragonfly Algorithm [14], Constriction-Factor-Based Optimization [15], Hybrid Grey Wolf Optimizer [16], Whale Optimization Algorithm [17], Harmony Search Algorithm [18], and Fuzzy and Shuffled Frog Leaping Algorithm (SLFA) [19] have been utilized. However, these methods have shown limitations in achieving results that are deemed globally optimal.

This study seeks to leverage the potential of the POA to solve the OCI problem in the radial distribution system. A two-step methodology is proposed, combining loss sensitivity analysis with POA to optimize both the placement and sizing of capacitors in the IEEE 33-bus system [19][20]. Loss sensitivity analysis is employed as a preliminary step to identify candidate buses that are most likely to benefit from capacitor placement, thereby narrowing the search space and improving computational efficiency [21]. The identification of sensitive buses for capacitor placement aligns with voltage stability principles, where weak buses (buses with low active power margins) are prioritized for reactive power compensation to mitigate losses and enhance voltage profiles [22][23]. The POA is then applied to determine the optimal configuration of capacitors, aiming to minimize active and reactive power losses, improve voltage profiles, and enhance system reliability [24][25][26].

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2. Method

2.1 Determination of sensitive bus (optimal capacitor placement)

The well-established loss sensitivity technique in determining the most sensitive buses in a distribution system is adopted for selecting the most sensitive bus as the optimal location for the capacitor placement. This technique utilizes the Loss Sensitivity Factors (LSF), which use derivatives to calculate how sensitive system losses vary with respect to changes in reactive power injection at the bus [5]. The active power loss is presented in Equation (1):

$$P_{ij(Loss)} = \frac{P_j^2+Q_j^2}{V_j^2} \times R_{ij} \tag{1}$$

Differentiating equation (1) in terms of Q yields the LSF as shown in Equation (2).

$$LSF = \frac{2Q_j}{V_j^2} \times R_{ij} \tag{2}$$

Where the variable P represents active power, the variable V is bus voltage, and the variable R represents the line resistance. The LSF values at all the buses are calculated using equation (2) and ranked from the most sensitive bus to the least sensitive bus in the system. Capacitor banks are connected to the buses with the highest sensitivity to optimize system performance.

2.2 Problem formulation

Nature-inspired algorithms like the Pelican Optimization Algorithm (POA) are designed to work with optimization problems that have been translated into mathematical objective functions [27]. In this research, the optimization task involves minimizing the total losses in the system, which include both active and reactive power losses. To achieve this, a weighted multi-objective function is formulated, allowing the algorithm to consider both types of losses simultaneously in the optimization process. This objective function serves as the basis for evaluating potential solutions and guiding the search toward optimal capacitor placement and sizing. The specific formulation is detailed in Equation (3) of the study.

$$F_{objective} = \omega_1 \sum_{i=1}^{Nb} P_{iL} + \omega_2 \sum_{i=1}^{Nb} Q_{iL} \tag{3}$$

Where P_L and Q_L represent active power loss and reactive loss, respectively, and ω_1 and ω_2 weight factors satisfying:

$$\omega_1 + \omega_2 = 1 \tag{4}$$

2.3 The pelican optimization algorithm (POA)

The POA, inspired by pelican hunting strategies, is utilized to determine the optimal capacitor sizes [12]. By effectively balancing exploration and exploitation phases, the POA identifies capacitor bank sizes that minimize power losses and improve system voltage profiles.

2.3.1 Background of the POA

The POA is a metaheuristic optimizer inspired by pelican behavior. It is based on swarm intelligence, where the algorithm mimics pelicans' collaborative and competitive foraging behaviors [28]. In this system, each agent within the swarm shares communal knowledge to enhance their search efficiency and effectiveness [12]. POA optimizes the search process by emulating pelicans' natural hunting strategies to solve optimization problems effectively [29]. The POA approach leverages the strength of collective intelligence and adaptive behavior to achieve superior performance in various optimization tasks.

Similar to Particle Swarm Optimization (PSO) [30], which simulates birds flying in unison in search of food, POA utilizes the group dynamics of pelicans foraging for prey to efficiently solve complicated optimization problems [31]. The Pelican Optimization Algorithm (POA) utilizes pelicans as primary elements in its population, with each pelican representing a potential solution to the optimization problem. These pelicans propose values for the optimization variables based on their positions within the search space. Initially, the pelicans are assigned random values within the problem's defined lower and upper bounds [32]. This random assignment ensures a diverse set of solutions from the start, allowing the algorithm to effectively explore the search space. As the algorithm progresses, the pelicans continuously adjust their values in pursuit of the optimal solution. They do this by evaluating their current positions and updating them according to the optimization criteria. This iterative process enables the pelicans to gradually converge toward the best possible solution by refining their positions based on the feedback from the optimization process. Through this method, POA balances exploration and exploitation, leveraging the pelicans' movements to efficiently navigate the search space and identify optimal solutions.

2.3.2 Mathematical Concept of the POA

The algorithm is designed to tackle complex optimization problems by drawing inspiration from the distinctive hunting strategies of pelicans, which exhibit a fascinating blend of cooperative behavior and competitive interaction while capturing their prey. In nature, pelicans hunt in groups, coordinating their movements to herd fish toward shallower waters, where individual members then compete to secure their catch. This natural phenomenon forms the conceptual foundation of the Pelican Optimization Algorithm (POA), where the collective intelligence and adaptive dynamics of pelicans are mathematically modeled to enhance search efficiency and convergence.

Within the POA framework, each pelican represents a candidate solution within the overall population, functioning as an essential element of the algorithm’s search mechanism. The position of every pelican in the search space corresponds to a specific set of decision variable values for the optimization problem under consideration. Through iterative interactions and emulating both cooperation and rivalry, the pelicans explore and exploit the search space to identify the most promising regions that lead toward the global optimum. This biologically inspired modeling approach allows the algorithm to effectively balance exploration and exploitation, improving its capability to solve a wide range of optimization tasks with accuracy and efficiency [12].

Initially, the members of the population are given random values that fall within the established lower and upper limits of the problem. As the algorithm advances, these members modify their positions to enhance their solutions, akin to how pelicans refine their hunting methods. The POA capitalizes on the collaborative and competitive aspects of pelican behavior, where individuals cooperate while also vying against one another to maximize their chances of capturing prey. This interactive process enables the POA to thoroughly explore and utilize the search space, ultimately identifying optimal or near-optimal solutions for intricate optimization issues [12]. At the beginning, the population members are introduced with random values within the problem's defined lower and upper bounds, as outlined in Equation (5).

$$x_{ij} = l_j + (u_j - l_j).rand\ ,\ \ i = 1,2,\dots,N \quad\ j = 1,2,\dots,m \tag{5}$$

In this context, x_{ij} denotes the value assigned to the jth decision variable in the ith candidate solution. The parameters N and m refer to the total number of candidate solutions in the population and the number of decision variables in the optimization problem, respectively. Each variable x_j is constrained within a defined range, where l_j and u_j represent its lower and upper bounds. To ensure diversity in the initial population or during the search process, a random value denoted as rand is generated within the interval [0, 1] and used to scale or position variable values within their defined limits.

The POA emulates the behavior and tactics of pelicans when hunting prey to enhance potential solutions. This hunting method is divided into two distinct phases: the exploration phase (this phase focuses on approaching the prey) and the exploitation phase (this phase involves gliding across the water's surface). In the exploration phase, the pelican monitors the movements of the prey. In this phase, the pelican executes swift, precise maneuvers on the water to catch its prey. By imitating these two phases, the POA successfully refines and improves potential solutions.

2.3.2.1 The exploration phase:

The pelican movement towards the location of prey is mimicked to develop an exploration update operator presented in Equation (6) as follows.

$$x_{ij}^{P1} = \begin{cases} x_{ij} + rand.\left(p_j - I.x_{ij}\right), & F_p < F_i \\ x_{ij} + rand.\left(x_{ij} - p_j\right), & else \end{cases} \tag{6}$$

In Equation (6), x_{ij}^{P1} denotes the revised position of the *i*th pelican in the *j*th dimension during the exploration phase of the algorithm. The variable I is a randomly selected integer, either 1 or 2, used to introduce stochastic behavior in the position update process. The term p_j represents the position of the prey in the *jth* dimension, serving as a guiding reference for the pelican's movement, while F_p stands for the prey's corresponding objective function value, which reflects its fitness [12]. Throughout the exploration phase, the algorithm continuously tracks and updates the best-performing pelican using Equation (7), ensuring that promising solutions are retained and leveraged to guide the search process effectively.

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \tag{7}$$

Here, X_i^{P1} represents the updated position of the pelican in the *i*th dimension as determined during the exploration phase, with F_i^{P1} denoting the corresponding objective function value at that new position. In contrast, X_i indicates the pelican's current or previous position in the same dimension, and F_i is the associated objective function value. These variables are used to compare the performance of the pelican's new and existing positions to guide further movement within the search space.

2.3.2.2 The exploitation phase:

The update mechanism in the exploitation phase, expressed in Equation (8), simulates pelicans spreading their wings over the water's surface, effectively modeling their strategy of capturing and pulling prey out of the water.

$$x_{ij}^{P2} = x_{ij} + R.\left(1 - \frac{t}{T}\right).(2.rand - 1).x_{ij} \tag{8}$$

In this context, x_{ij}^{P2} indicates the revised status of the *i*th pelican in the *j*th dimension. The constant R is established at 0.2. The variables *t* and *T* represent the current iteration number and the total iterations, respectively. Importantly, the exploitation phase utilizes a similar updating method as the exploration phase, as demonstrated in equation (9).

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \tag{9}$$

In this context, X_i^{P2} represents the updated position of the pelican in the ith dimension during the exploitation phase, while F_i^{P2} denoting the corresponding value of the objective function, reflecting the pelican's performance at that specific stage of the optimization process.

2.4 Capacitor sizing using the POA

The POA is applied to determine the most suitable sizes of the capacitor banks to be installed at the optimal bus locations to improve system performance. This optimal sizing refers to the precise amount of reactive power the capacitor needs to supply to the system to minimize power losses and improve the voltage profile. The approach ensures that the selected capacitor sizes closely match commercially available units, making it practical for real-world implementation. The procedure for determining these optimal capacitor sizes involves a series of steps, which are outlined to guide the accurate and effective execution of the algorithm for the desired results.

1. **Initialization**: The algorithm begins by setting initial parameters, including the current iteration number (t), the maximum number of iterations (T), and the population size (N). Once these parameters are defined, the algorithm proceeds to generate the initial set of capacitor sizes randomly, following the formulation provided in Equation (5).
2. **Objective function evaluation**: This step involves evaluating the function values that represent the performance of the initial pelican population. The objective function is based on the optimization problem. The top-performing pelican in the population is identified and saved as the current optimal solution (Capacitor size).
3. **Exploration:** During the exploration phase, the population of pelicans - each representing a potential capacitor size - is updated using Equation (6). After this update, the new set of solutions is re-evaluated, and the best-performing candidate is identified. The optimal solution is then refined and updated accordingly, following the criteria outlined in Equation (7).
4. **Exploitation**: In this phase, the pelican population, representing various capacitor size options, is updated using Equation (8). These newly adjusted solutions are then evaluated to identify any performance improvements. If a better solution is found, the best result is updated accordingly, following the process defined by Equation (9).
5. **Iteration and Termination**: The exploration and exploitation processes are carried out repeatedly in an iterative manner until the stopping criterion - defined as the maximum number of iterations - is met. Throughout these iterations, candidate solutions are continuously refined. Once the final iteration is reached, the pelican with the highest performance is selected as the optimal solution, representing the most suitable capacitor size for effective system performance.

2.5 Implementation on the IEEE 33-bus system

The proposed methodology has been developed and implemented using MATLAB software, providing a flexible and powerful computational environment for modeling, simulation, and optimization. To assess its effectiveness, the method is tested on the standard IEEE 33-bus radial distribution system, which is a widely recognized benchmark network established by the Institute of Electrical and Electronics Engineers (IEEE) for power system research and performance evaluation. This test system accurately reflects the operational characteristics of a practical radial distribution network, comprising 33 buses and 32 interconnected distribution lines, thereby replicating the complexities and challenges associated with real-world power distribution environments.

Specifically designed for academic, experimental, and research applications, the IEEE 33-bus system has become a reference framework for analyzing, comparing, and validating various algorithms and methodologies aimed at improving distribution system efficiency and reliability. Figure 1 presents the single-line diagram of this network, offering a clear visual depiction of its structure, bus arrangement, and line connectivity, which together define its operational layout. The careful implementation and evaluation of the proposed method on this well-established benchmark network ensure that the developed approach is both technically robust and practically applicable, reinforcing its potential for real-life deployment in modern electrical distribution systems.

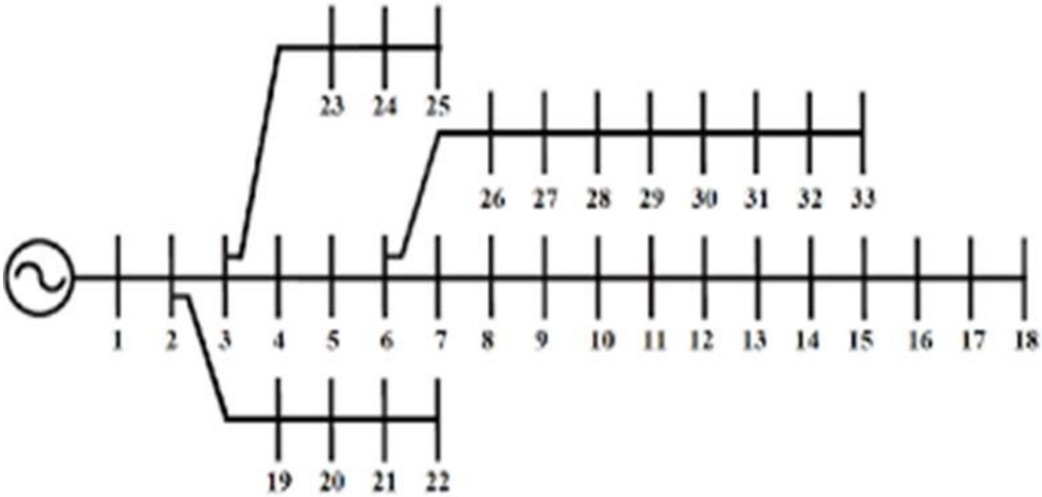

Figure 1. Single-line diagram of the IEEE 33-bus system

The proposed methodology is evaluated using the standard IEEE 33-bus distribution network, where the optimization focuses on determining the most effective locations for installing two capacitor banks. A comprehensive description of the implementation procedure is illustrated in Figure 2, which presents a detailed, sequential outline of each stage involved in the process. This systematic framework facilitates a structured testing and validation of the proposed technique, ensuring that its capability to improve the overall performance of the distribution network through the optimal placement and sizing of capacitors is thoroughly examined and demonstrated.

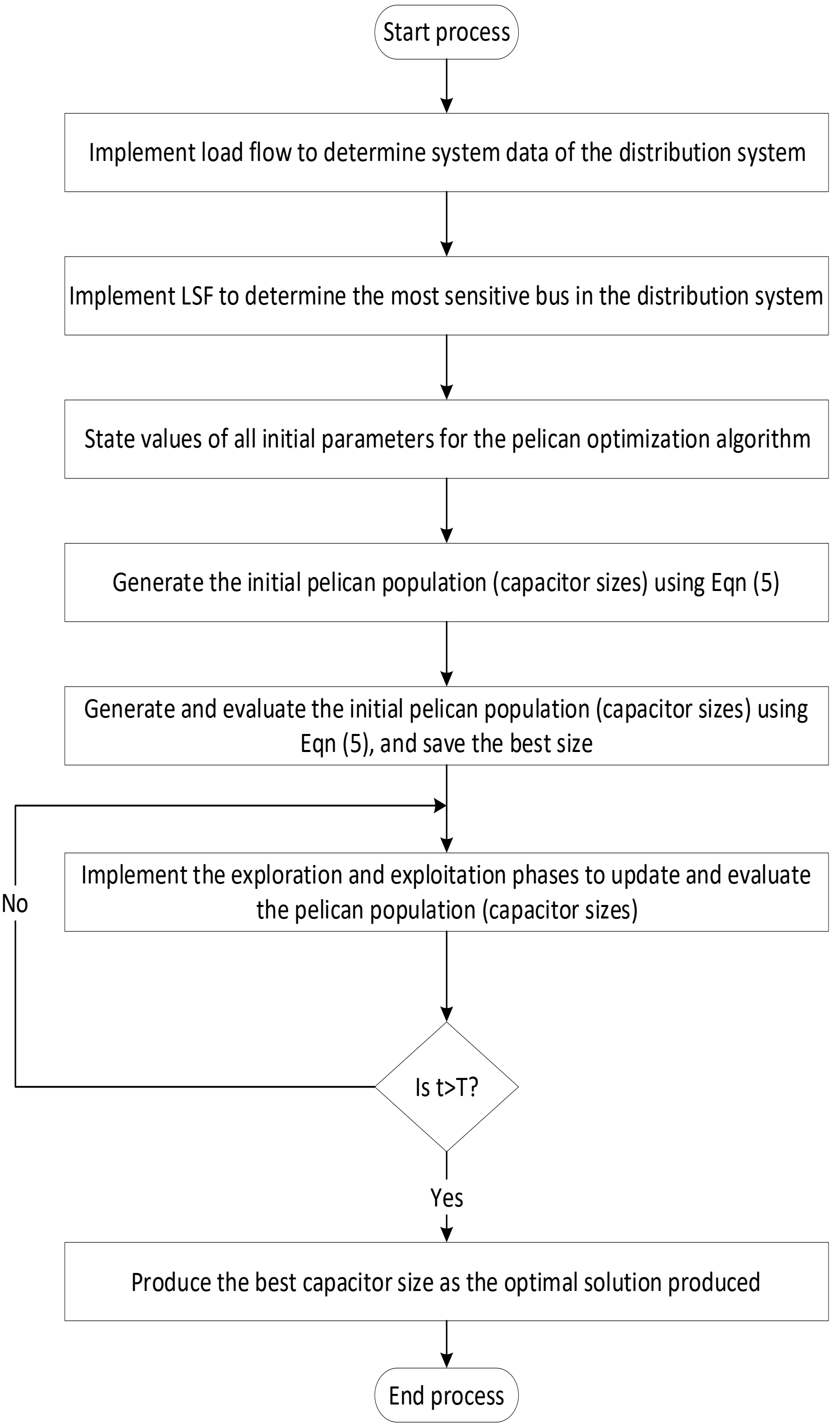

Figure 2. Implementation flowchart

The simulation was conducted using MATLAB software to apply the proposed method, following the steps outlined in Figure 2. The process relied on the parameter configurations provided in Table 1, which include the numerical values assigned to different parameters essential for the POA algorithm to operate effectively on the radial distribution system. These settings ensured the accurate execution of the algorithm, enabling the simulation to proceed as intended while adhering to the specified computational requirements. The parameters were carefully selected to align with the system's needs, facilitating the successful implementation of the proposed approach.

Table 1. Parameters for simulation

No	Parameter/ Term	Value
1	Number of capacitors	2
2	Population size / Search agents	30
3	Maximum number of iterations	50
4	Search range (KVar)	0 to 3000
5	ω_1	0.55
6	ω_2	0.45

3. Result and Discussion

This section presents the findings derived from this research work. The findings encompass the performance of the POA-based method in solving the OCI problem. It demonstrates its practicality in placing and sizing two (2) capacitor banks in the standard IEEE 33-bus test system. The simulation result is then benchmarked against the well-established and popularly known particle swarm optimization algorithm and the genetic algorithm to justify the effectiveness of the POA-based method in solving the capacitor integration optimization problem. The results are categorized under specific headings, providing a comprehensive presentation of the outcomes. They include the performance of the proposed POA-based method in integrating two (2) capacitors into the IEEE 33-bus system and the performance comparison of the proposed POA-based method to that of PSO and GA-based methods on the IEEE 33-bus network, respectively.

3.1 Performance of the POA-based method on the IEEE 33-bus system

Table 2 below presents the performance of the POA-based method in determining the optimal placement and sizing of the two (2) capacitor banks within the distribution system. The evaluation of POA's performance is based on three key indicators: total active power losses (P_{Loss}), total reactive power losses (Q_{Loss}), and the minimum voltage level across the system (V_{min}). These parameters serve as crucial benchmarks for assessing the overall efficiency and voltage profile enhancement resulting from the capacitor integration. The results provide insight into how well POA minimizes power losses while maintaining acceptable voltage levels within the network.

Table 2. Comparison of POA with the base case

Indicator	Base case	POA
Cap Size (KVar) (Location)	-	1259.53 (30), 986.73 (24)
P_{Loss} (KW)	202.68	64.68
% P_{Loss} Reduction	-	68.08
Q_{Loss} (KVar)	135.24	82.45
% Q_{Loss} Reduction	-	39.035
V_{Min} (p.u.)	0.913	0.93558

In Table 2, the proposed POA-based method showed very good performance in placing and sizing the two capacitors. The active power losses of the 33-bus system reduced from 202.68kW to about 64.68kW, representing about 68.08% active power loss reduction in the system. Also, the total reactive power losses significantly reduced from 135.24kvar to 82.45kvar, representing a 39.035% reduction in reactive power losses. The overall voltage profile improved with the minimum voltage being 0.93558p.u. The enhanced voltage profile is shown in Figure 3 below, where the green line correctly represents the voltage profile under the POA-based compensation with the capacitors, while the red line represents the voltage profile of the base system without any reactive compensation.

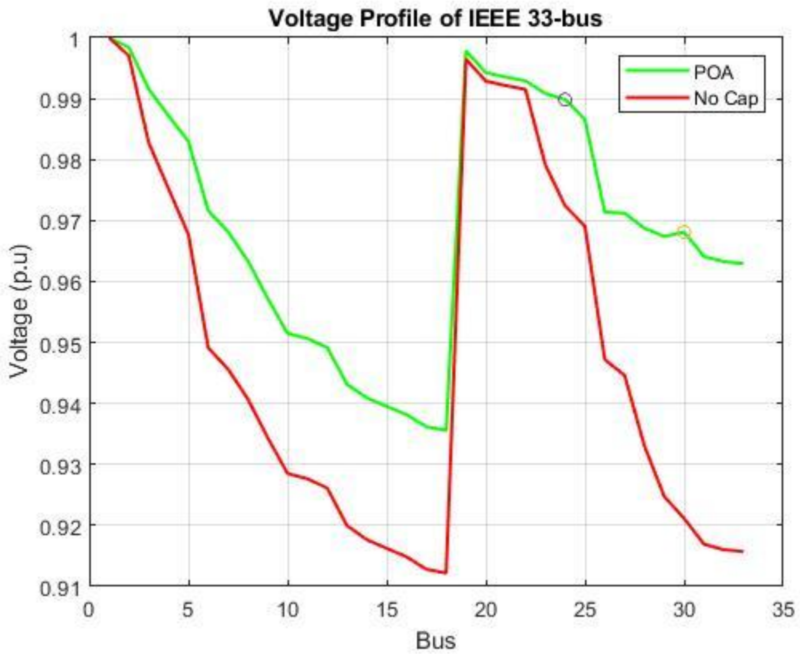

Figure 3. Performance comparison of POA with the base case

3.2 Performance comparison of the POA-based method with PSO and GA methods

To justify the effectiveness of the POA-based approach, its performance is compared with that of the PSO and the GA. This comparison aims to highlight the relative efficiency of POA in solving the capacitor integration (OCI) problem. Both PSO and GA were implemented using MATLAB software under identical operating conditions to ensure a fair and consistent evaluation. The key performance indicators used in the comparison include system power losses and voltage levels. The detailed results of this comparative analysis are presented in Table 3, offering a clear view of how POA performs relative to the other methods.

Table 3. Performance comparison of POA with PSO, GA, and the base case

Indicator	Base case	POA	PSO	GA
Cap Size (KVar) (Location)	-	1259.53 (30), 986.73 (24)	944.65 (30) 740.04 (24)	818.6950 (30) 641.3723 (24)
P_{Loss} (KW)	202.68	**64.68**	77.44	85.67
% P_{Loss} Reduction	-	**68.08**	61.79	57.73
Q_{Loss} (KVar)	135.24	**82.45**	96.68	104.69
% Q_{Loss} Reduction	-	**39.035**	28.50	22.59
Minimum Voltage (p.u.)	0.913	**0.93558**	0.92999	0.9277

From the simulation results clearly shown in Table 3, the proposed POA-based method exceptionally outperformed the PSO and the GA base methods with significant differences. In specifics, the POA-based method produced the highest percentage reduction in active power losses, represented as "% Ploss Reduction" in the table, with a value of 68.08%. The PSO produced the next best percentage with a value of 61.79% while the GA produced the lowest value of 57.73% among the three methods. For the situation of the reactive power loss reduction, the POA again outperformed the other two algorithms with the highest percentage reduction value of 39.035% as compared to 28.50% and 22.59% for the PSO and GA methods, respectively. The GA produced the least percentage reduction again. Finally, in terms of the system voltage profile, the POA showed relatively better voltage enhancement with a minimum voltage value of 0.93558 p. u. The general voltage profiles under the four (4) conditions of the system, that is, the POA-based, PSO-based, GA-based, and the base case scenario without compensation, are presented in Figure 4 below.

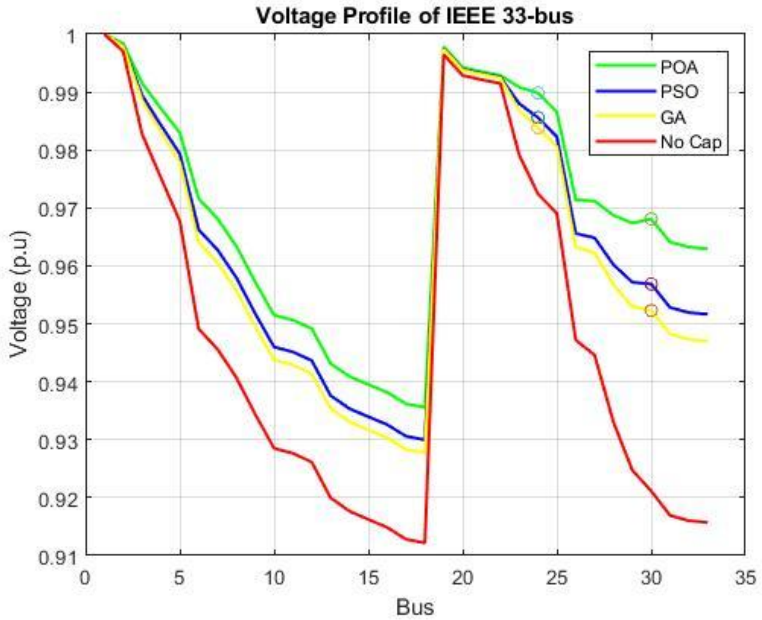

Figure 4. Comparison of the POA, PSO, GA, and the base case

The proposed POA-based method produced the best voltage profile, as indicated in Figure 4 by the green line. It is followed by the PSO-based method illustrated by the blue line, and finally by the GA-based method represented by the yellow line. It is worth acknowledging that all the methods produced voltage profiles significantly better than the base case scenario of the IEEE 33-bus system without any compensation. However, the POA-based method stood out by producing the best profile among the three (3) approaches.

4. Conclusion

A novel hybrid optimization method combining Loss Sensitivity Factor (LSF) analysis and the Pelican Optimization Algorithm (POA) has been developed to address the Optimal Capacitor Integration (OCI) problem in power distribution systems. This two-step approach first uses LSF to identify optimal bus locations for capacitor placement by analyzing their sensitivity to reactive power changes, effectively reducing the search space. Then, POA is employed to determine the optimal sizing of capacitors at these locations. Applied to the IEEE 33-bus radial distribution system, the method demonstrated significant improvements in reducing total active power losses and enhancing voltage profiles. When benchmarked against Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) under identical conditions using MATLAB, the POA-based approach consistently outperformed both, thanks to its superior exploration and exploitation capabilities. The results affirm the method's effectiveness in reactive power compensation and voltage regulation, indicating strong potential for real-world application. This robust and adaptable hybrid technique offers a practical, high-performing solution for improving the efficiency and reliability of power distribution networks.

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