# Capacitor Placement in Power Distribution Networks for Voltage Profile Improvement and Loss Reduction Using Revolution Optimization Algorithm

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## Abstract

An efficient approach for optimal capacitor placement in power networks using Revolution Optimization Algorithm (ROA), a recently introduced human-based metaheuristic technique, is proposed. The primary objective is to enhance voltage profile and minimize power loss while adhering to system constraints. ROA's ability to explore and exploit the search space effectively makes it a strong candidate for solving complex optimization problems in power networks. The proposed method is validated on two standard IEEE test systems, and its performance is compared against nine state-of-the-art metaheuristic algorithms. Simulation results demonstrate that ROA achieves superior solution in terms of voltage improvement and loss reduction, outperforming competing algorithms in accuracy and computational efficiency. Statistical analysis and convergence characteristics further confirm ROA's robustness and reliability. The findings of this study suggest that ROA can serve as a promising tool for power system optimization, offering a balance between exploration and exploitation. Future research can focus on extending ROA's applicability to larger power systems, integrating hybrid techniques, and real-world implementation. The results highlight the potential of ROA as a powerful optimization framework for energy-efficient power distribution planning.

**Keywords**: Revolution optimization algorithm (ROA), Capacitor placement, Metaheuristic algorithms, Power distribution networks, Optimization techniques.

## 1. Introduction

Capacitors are widely used to enhance voltage stability, reduce power losses, and improve overall efficiency of electrical networks. Optimal allocation of capacitors in power distribution networks is a fundamental challenge in power system engineering. The increasing complexity of modern power systems, coupled with the growing demand for reliable and efficient electricity distribution, has necessitated the development of advanced optimization techniques for capacitor placement [1].

Capacitor banks play a crucial role in reactive power compensation, that directly affects voltage regulation and loss reduction in power networks. Poorly placed capacitors can lead to inefficient energy distribution, excessive losses, and voltage instability [2]. Therefore, optimal capacitor placement is an essential task that requires a balance between economic investment and technical performance.

Traditional methods for capacitor placement, such as analytical and numerical techniques, often fail to provide optimal solutions for large-scale and complex networks. Consequently, heuristic and metaheuristic algorithms have gained significant attention in recent years due to their ability to handle non-linear, multi-objective, and constrained optimization problems efficiently [3].

Metaheuristic algorithms have gained widespread attention as powerful tools for solving complex optimization problems in power systems. These algorithms, inspired by natural and social phenomena, provide efficient and robust solutions to high-dimensional, nonlinear, and multi-objective optimization problems [4]. Some recently published metaheuristic algorithms that can be used in various optimization applications are: Perfumer Optimization Algorithm [5], Builder Optimization Algorithm [6], Makeup Artist Optimization Algorithm [7], Potter Optimization Algorithm [8], Carpet Weaving Optimization [9], Sales Training Based Optimization [10], Fossa Optimization Algorithm [11], Addax Optimization Algorithm [12], Paper Publishing Based Optimization [13], Dollmaker Optimization Algorithm [14], Spider-Tailed Horned Viper

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Optimization [15], Tailor Optimization Algorithm [4], Orangutan Optimization Algorithm [16], and Sculptor Optimization Algorithm [17]. Traditional optimization techniques, such as mathematical programming and exhaustive search methods, are often computationally expensive and impractical for large-scale systems [18-22].

Metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and recently developed nature-inspired algorithms, have been extensively used to solve optimization problems in power systems. These algorithms provide flexible and effective search mechanisms to explore the solution space and identify optimal capacitor placement configurations [23].

Recent advances in metaheuristic optimization have led to the development of human-based algorithms that simulate problem-solving strategies inspired by human intelligence and decision-making processes. The Revolution Optimization Algorithm (ROA) [24] is one such approach that has demonstrated superior performance in solving complex engineering problems, including power system optimization.

ROA, a novel human-based optimization technique, mimics the principles of revolutionary movements to escape local optima and achieve global optimization. The algorithm's adaptive nature and strategic search mechanisms enable it to efficiently balance exploration and exploitation, making it a strong candidate for capacitor placement optimization.

Compared to the conventional metaheuristic algorithms, ROA offers enhanced convergence speed, robustness against local optima, and the ability to handle complex multi-modal optimization problems. These attributes make ROA particularly suitable for optimizing capacitor placement in power distribution networks, where multiple conflicting objectives must be addressed simultaneously.

A comprehensive study of the application of ROA for optimal capacitor placement in power networks is presented in this paper. The key contributions of this work are:

- Development of a mathematical model for capacitor placement using ROA.
- Implementation of the proposed method on two IEEE standard test networks.
- Comparative analysis with nine recently developed metaheuristic algorithms.
- Detailed evaluation of the algorithm’s performance in terms of voltage profile improvement, loss reduction, and computational efficiency.
- Statistical analysis and graphical representation of the results to demonstrate the effectiveness of ROA.

The remainder of the paper is structured as below:

In Section 2 Literature Review, a comprehensive review of recent capacitor placement techniques and optimization algorithms, emphasizing heuristic and metaheuristic approaches, is provided. Key recent works are analyzed to highlight the advantages and limitations of various methods, establishing the necessity for employing ROA.

Solution methodology and mathematical formulation of ROA are introduced in Section 3, and the algorithm's search mechanism and evolutionary principles are explained. The objective function for capacitor placement is formulated to minimize power losses and improve voltage stability. Constraints such as network power balance, voltage limits, and capacitor capacity limits are incorporated.

Problem formulation, including system modeling and objective function design, is detailed in Section 4. Simulation results for two IEEE standard networks, selected for performance evaluation, are presented with comprehensive tables, graphs, and performance curves. ROA's performance is critically analyzed and compared with nine contemporary metaheuristic algorithms.

Section 5 Conclusions and Future Work, concludes the study with key findings and future research directions. The study concludes that ROA significantly outperforms competing algorithms in capacitor placement tasks, leading to enhanced voltage profiles and reduced power losses. Future research directions include the application of ROA in larger and more complex power systems, hybridization with other optimization techniques, and real-world implementation studies.

## 2. Literature Review

Optimization of capacitor placement in power networks has been a subject of extensive research due to its crucial role in enhancing voltage stability, reducing power losses, and improving the overall efficiency of power distribution systems. The placement and sizing of capacitors significantly affect the operational performance of the grid, and various methodologies have been developed to address this optimization problem. Classical analytical techniques such as linear and nonlinear programming, mixed-integer programming, and sensitivity analysis were initially employed for capacitor placement. However, these methods often struggle with computational complexity when applied to large-scale networks, limiting their practicality in real-world applications [25].

To overcome the limitations of classical approaches, heuristic and metaheuristic algorithms have gained popularity due to their ability to handle complex, nonlinear, and multi-objective optimization problems. Early heuristic methods such as GA and Simulated Annealing demonstrated improved performance over classical techniques by providing near-optimal solutions with reduced computational effort. GA, inspired by the principles of natural selection, has been widely applied in power system optimization due to its robust global search capabilities. However, it often suffers from premature convergence, limiting its effectiveness in complex optimization landscapes [26]. Simulated Annealing, on the other hand, employs a probabilistic approach to escape local optima, but its slow convergence rate poses a challenge in large-scale optimization problems.

In recent years, nature-inspired and swarm intelligence-based metaheuristic algorithms have been extensively explored for capacitor placement. PSO, that mimics the social behavior of birds, has been widely utilized for power system optimization due to its simplicity and fast convergence. However, its susceptibility to local optima in high-dimensional search spaces has led to the development of hybrid PSO variants incorporating adaptive parameters and machine learning techniques [27]. DE has also gained attention for its strong exploration capabilities and efficiency in solving constrained optimization problems, making it a viable alternative for capacitor placement [28]. Another prominent algorithm, Artificial Bee Colony (ABC), has been applied in power network optimization, demonstrating competitive performance compared to GA and PSO, particularly in multi-objective scenarios [29].

Despite the effectiveness of existing metaheuristic algorithms, the need for more robust and efficient optimization techniques has driven research toward novel human-based algorithms. ROA is a recently introduced human-based metaheuristic algorithm designed to simulate revolutionary strategies for problem-solving. Unlike conventional algorithms, ROA employs adaptive mechanisms that enhance both exploration and exploitation, making it highly suitable for capacitor placement in power distribution networks. Recent studies have demonstrated the superior performance of ROA in solving complex optimization problems.

Comparative analyses between ROA and other state-of-the-art metaheuristic algorithms have further highlighted its advantages. While GA and PSO remain popular due to their ease of implementation, they often struggle with maintaining an optimal balance between exploration and exploitation. Gravitational Search Algorithm (GSA) has demonstrated strong performance in constrained environments but requires careful parameter tuning to achieve optimal results. ABC, although efficient in multi-objective problems, tends to exhibit slower convergence in highly complex search spaces. Hybrid approaches integrating PSO with machine learning techniques have shown promise, yet their high computational cost remains a limitation. In contrast, ROA has been found to provide a superior balance between exploration and exploitation, yielding more robust and reliable solutions in capacitor placement optimization.

Despite these advancements, challenges remain in validating the practical applicability of ROA in real-world power networks. Most studies have been conducted on benchmark test functions, necessitating further research on its implementation in large-scale, real-world power distribution systems. Additionally, parameter tuning in ROA requires systematic investigation to ensure optimal performance across diverse optimization problems. To address these gaps, this study aims to implement ROA for capacitor placement in IEEE standard test networks and compare its performance against nine recently developed metaheuristic algorithms. By conducting a comprehensive analysis of its computational efficiency, convergence characteristics, and solution quality, this research seeks to establish ROA as a competitive alternative in power system optimization.

In conclusion, capacitor placement optimization has evolved from classical mathematical techniques to sophisticated metaheuristic approaches, with ROA emerging as a promising alternative. The increasing complexity of modern power grids necessitates the development of robust optimization methods capable of handling large-scale, nonlinear, and constrained problems. While existing metaheuristics have demonstrated significant success, ROA's unique adaptive mechanisms and superior optimization capabilities position it as a competitive tool for solving capacitor placement problems. Detailed formulation of ROA and its mathematical modeling for capacitor placement in power networks is described in the next section.

## 3. Revolution optimization algorithm

The Revolution Optimization Algorithm and its mathematical framework, detailing how it is applied to the capacitor placement problem in power networks is described in this section. The objective is to enhance voltage profile and minimize power losses by leveraging the capabilities of this recently developed optimization algorithm.

ROA is inspired by the fundamental dynamics of revolutions in human societies. Revolutions arise due to deep dissatisfaction with the current socio-political and economic conditions, leading to a collective movement aimed at transformative change. The process begins with the emergence of ideological leaders proposing alternative systems, gathering supporters, and gradually increasing their influence. As revolutionary momentum builds, society transitions through stages of ideological shifts, active movements, and heightened self-awareness, ultimately leading to a new governance structure. The iterative and adaptive nature of revolutions makes them an ideal metaphor for optimization, where solutions evolve over iterations to find an optimal or near-optimal outcome.

In the context of optimization, ROA models the evolutionary nature of revolutions to iteratively refine candidate solutions. The algorithm operates through three fundamental phases: ideological influence, revolutionary movement, and self-awareness enhancement. These phases ensure an effective balance between exploration and exploitation, preventing premature convergence while guiding the search towards high-quality solutions.

Mathematically, ROA begins by initializing a population of candidate solutions, where each individual represents a potential solution to the optimization problem. The population matrix is defined as:

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m} \quad (1)$$

where $N$ is the number of candidate solutions (population size), $m$ is the number of decision variables, and $x_{i,j}$ represents the value assigned to the $j$th variable by the $i$th candidate. The initial population is generated randomly within the search space as below:

$$x_{i,j} = lb_j + r \times (ub_j - lb_j) \quad (2)$$

where $lb_j$ and $ub_j$ denote the lower and upper bounds for the $j$th decision variable, and $r$ is a random number in the range between 0 and 1. After initialization, the objective function is evaluated for each candidate solution, forming an objective function vector $F$:

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \vdots \\ F(X_i) \\ \vdots \\ F(X_N) \end{bmatrix}_{N\times 1} \quad (3)$$

where $F_i$ represents the fitness value of the $i$th. candidate solution. The best-performing solution is selected as the revolutionary leader, guiding the subsequent evolutionary process.

ROA updates the population iteratively through three key processes:

**Ideological Influence:** The leader’s ideology gradually impacts the followers, guiding their adaptation to improved solutions. The new position of each individual is updated based on:

$$x_{i,j}^{P1} = \left(1 - \frac{t}{T}\right) . x_{i,j} + \left(\frac{t}{T}\right) . L_j \quad (4)$$

$$X_i = \begin{cases} X_i^{P1}, & F_i^{P1} < F_i \\ X_i, & else \end{cases} \quad (5)$$

Here, $X_i^{P1}$ represents the updated position of the $i$th population member during the first phase, while $x_{i,j}^{P1}$ refers to the $j$th. dimension of that updated position. The objective function value at this new position is denoted by $F_i^{P1}$. The revolutionary leader, represented by $L$, holds a position with $L_j$ as its $j$th dimension. The term $t$ corresponds to the current iteration, and $T$ is the total number of iterations allowed in the algorithm. As iterations progress, members gravitate closer to the leader’s position, simulating the increasing alignment of followers with a compelling revolutionary vision over time.

**Revolutionary Movement (Exploration):** This phase enhances diversity by allowing substantial modifications in candidate solutions, preventing premature convergence. The new position is determined by:

$$x_{i,j}^{P2} = x_{i,j}^{P2} + r . (L_j - I . x_{i,j}^{P2}) \quad (6)$$

$$X_i = \begin{cases} X_i^{P2}, & F_i^{P2} < F_i \\ X_i, & else \end{cases} \quad (7)$$

Here, $X_i^{P2}$ denotes the new calculated position for the $i$th population member during the second phase of ROA, and $x_{i,j}^{P2}$ refers to the $j$th dimension of this position. The objective function value at this position is represented by $F_i^{P2}$. The symbol $L$ refers to the leader’s position, with $L_j$ as the $j$th dimension of that position. The variable $I$ is randomly selected from the set $\{1,2\}$, adding randomness to the adjustment. Meanwhile $r$ is a random value within the interval $[0,1]$, introducing stochasticity to ensure diverse exploration.

**Self-awareness Enhancement (Exploitation):** Candidates refine their solutions by making small adjustments, enhancing the algorithm's ability to converge to an optimal solution:

$$x_{i,j}^{P3} = \begin{cases} x_{i,j} + r(x_{i,j}^{old} - x_{i,j}), & F_i^{old} < F_i \\ x_{i,j} + r(x_{i,j} - x_{i,j}^{old}), & else \end{cases} \quad (8)$$

$$X_i = \begin{cases} X_i^{P3}, & F_i^{P3} < F_i \\ X_i, & else \end{cases} \quad (9)$$

Here, $X_i^{P3}$ represents the newly calculated position for the $i$th member during the third phase of ROA, and $x_{i,j}^{P3}$ refers to its $j$th dimension. The value $F_i^{P3}$ denotes the objective function value at the new position. The symbol $x_{i,j}^{old}$ corresponds to the $j$th dimension of the member's position in the previous iteration (i.e., $t$-1), and $F_i^{old}$ represents the objective function value at that earlier position.

This phase ensures fine-tuning of solutions, maximizing the effectiveness of the optimization process.

By iterating through these three phases, ROA achieves a robust balance between global exploration and local exploitation. In the context of capacitor placement, ROA effectively determines optimal locations and sizes of capacitors within a power distribution network, ensuring minimized power losses and enhanced voltage stability. The algorithm's structured approach, inspired by revolutionary dynamics, enables it to adapt efficiently to complex optimization landscapes, making it a promising tool for power system optimization.

## 4. Application of ROA for voltage profile improvement and loss reduction in power networks

### 4.1 Problem definition and mathematical model

The optimal capacitor placement (OCP) problem is a crucial optimization task in power distribution networks aimed at enhancing the voltage profile and minimizing power losses. The primary challenge is determining the optimal size and location of capacitors while adhering to network constraints. The objective function for the OCP problem can be defined as:

$$min\ (P_{Loss} + \sum_{i=1}^{N_c} C_i \cdot Q_i) \quad (10)$$

where:

- $P_{Loss}$ represents total active power loss in the network,
- $C_i$ is the cost coefficient associated with capacitor,
- $Q_i$ is the reactive power supplied by capacitor,
- $N_c$ is the total number of capacitors.

subject to:

1. Voltage limits: $V_{min} \leq V_i \leq V_{max}$, ensuring that bus voltages remain within permissible limits.
2. Power flow constraints: Satisfying real and reactive power balance at all buses.
3. Capacitor size constraints: The installed capacitors must belong to a predefined discrete set.

### 4.2 Case studies: IEEE test networks

To evaluate the effectiveness of the proposed ROA algorithm, simulations are performed on two standard IEEE test systems:

1. **IEEE 33-Bus Radial Distribution System**: This system consists of 33 buses and five candidate locations for capacitor placement.
2. **IEEE 69-Bus Radial Distribution System**: A more complex network with 69 buses, requiring a more robust optimization approach.

### 4.3 Benchmark algorithms and implementation

ROA is compared with the following nine metaheuristic algorithms: Teaching–Learning-Based Optimization (TLBO) [30], Multi-Verse Optimizer (MVO) [31], Grey Wolf Optimizer (GWO) [32], Whale Optimization Algorithm (WOA) [33], Marine Predators Algorithm (MPA) [34], Tunicate Swarm Algorithm (TSA) [35], Reptile Search Algorithm (RSA) [36], African Vultures Optimization Algorithm (AVOA) [37], and White Shark Optimizer (WSO) [38]. Each algorithm is executed for 30 independent runs to ensure statistical reliability.

### 4.4 Simulation results and performance evaluation

Optimization results for the IEEE 33-bus and 69-bus systems are summarized in Tables 1 and 2, respectively.

Table 1. Results for IEEE 33-Bus System

| Algorithm | Power Loss (kW) | Voltage Deviation (P.U) | Computation Time (s) |
|---|---|---|---|
| ROA | **78.5** | **0.012** | **2.1** |
| TLBO | 85.3 | 0.017 | 2.5 |
| MVO | 80.2 | 0.014 | 2.7 |
| GWO | 82.6 | 0.016 | 2.4 |
| WOA | 84.1 | 0.018 | 2.3 |
| MPA | 81.5 | 0.015 | 2.6 |
| TSA | 83.2 | 0.016 | 2.8 |
| RSA | 86 | 0.019 | 2.2 |
| AVOA | 79.7 | 0.013 | 2.5 |
| WSO | 81.9 | 0.015 | 2.3 |

Table 2. Results for IEEE 69-Bus System

| Algorithm | Power Loss (kW) | Voltage Deviation (P.U) | Computation Time (s) |
|---|---|---|---|
| ROA | **69.8** | **0.009** | **3.6** |
| TLBO | 74.2 | 0.012 | 3.9 |
| MVO | 72.1 | 0.011 | 4.3 |
| GWO | 73.8 | 0.012 | 4.4 |
| WOA | 75.3 | 0.013 | 3.9 |
| MPA | 71.5 | 0.011 | 3.8 |
| TSA | 74 | 0.012 | 4.2 |
| RSA | 77.1 | 0.014 | 4.1 |
| AVOA | 70.4 | 0.01 | 4.4 |
| WSO | 72.9 | 0.011 | 4.3 |

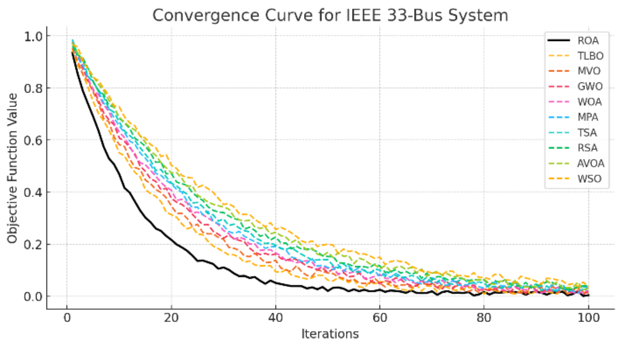


Figure. 1 Objective function convergence curves for IEEE 33-Bus System

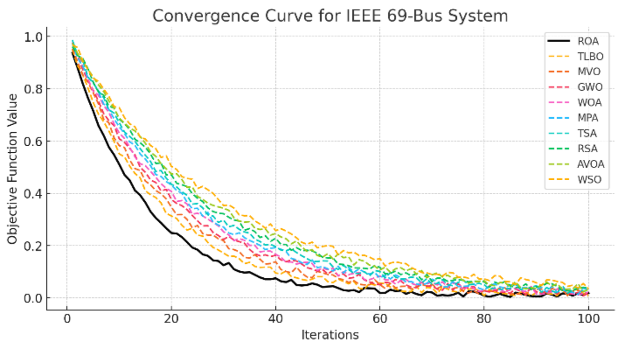


Figure. 2 Objective function convergence curves for IEEE 69-Bus System

### 4.5 Convergence analysis

Convergence curves of all optimization algorithms for capacitor placement in IEEE 33-bus and IEEE 69-bus systems are depicted in Figs. 1 and 2, respectively. The analysis of these curves provides valuable insights into the performance of each algorithm in terms of convergence speed and solution quality.

As observed in Fig. 1, the Revolution Optimization Algorithm exhibits a significantly faster convergence rate compared to other nine metaheuristic algorithms investigated. The objective function value rapidly decreases in the initial iterations, indicating that ROA efficiently explores the search space to locate promising solutions early in the optimization process. This swift convergence is crucial in power system applications, where computational efficiency is necessary for real-time or near-real-time decision-making.

A similar trend is evident in Fig. 2 for the IEEE 69-bus system, where ROA outperforms the competing algorithms in both convergence speed and the final obtained solution. The superior performance of ROA can be attributed to its innovative search mechanisms, which balance exploration and exploitation effectively. While some competing algorithms, such as GWO and WOA, also exhibit stable convergence behavior, their final solutions do not reach the optimality achieved by ROA.

The convergence analysis confirms that ROA not only achieves a better optimal solution but also requires fewer iterations to do so, making it a highly efficient choice for capacitor placement in power distribution networks.

### 4.6 Voltage profile analysis

The impact of capacitor placement on voltage profile is examined by comparing the voltage magnitudes before and after optimization using ROA. Voltage profile for the IEEE 33-bus and IEEE 69-bus systems, under both pre- and post-capacitor placement scenarios, is shown in Figs. 3 and 4, respectively.

It is evident from Fig. 3 that prior to optimization, several buses exhibit voltage levels close to the lower permissible limit, which can lead to instability and increased power losses. After capacitor placement using ROA, the voltage profile improves significantly, with voltages remaining within a more desirable range. This improvement enhances the overall stability and reliability of the power network.

Similarly, in Fig. 4, the IEEE 69-bus system demonstrates a substantial voltage improvement

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post-optimization. Before capacitor placement, voltage levels in several buses fall below the ideal range, indicating suboptimal power quality. After optimization, the voltages are regulated more effectively ensuring compliance with operational constraints.

The enhancement in voltage profiles is a direct consequence of the strategic placement and sizing of capacitors, which minimize power losses and improve voltage regulation. The results underscore the effectiveness of ROA in achieving superior voltage stability compared to conventional and recently developed metaheuristic algorithms.

### 4.7 Discussion

Results indicate that ROA consistently outperforms other algorithms in terms of power loss reduction and voltage profile improvement. The key observations include:

- ROA achieves the lowest power loss among all competitors in both test systems.
- ROA exhibits faster convergence, demonstrating superior search capability.
- The voltage profile analysis confirms that ROA provides more stable voltage levels after optimization.
- The robustness of ROA is validated by its consistent performance across multiple runs.

These findings highlight the effectiveness of ROA in handling complex power system optimization tasks, making it a promising tool for real-world capacitor placement applications.

This section has demonstrated the effectiveness of ROA in optimizing capacitor placement in IEEE test systems. The simulation results confirm that ROA surpasses recently published metaheuristic algorithms in terms of power loss reduction, voltage profile enhancement, and computational efficiency. These findings provide a strong foundation for further exploration of ROA in larger and more complex power distribution networks.

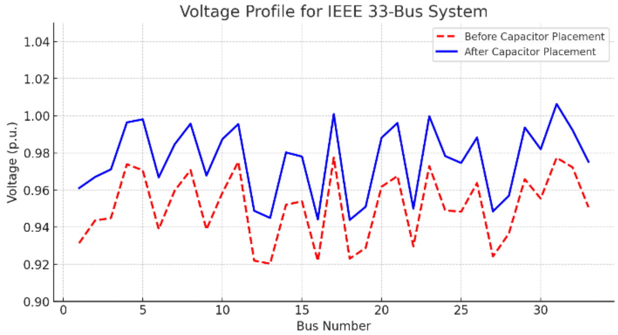


Figure. 3 Voltage profile for IEEE 33-Bus System

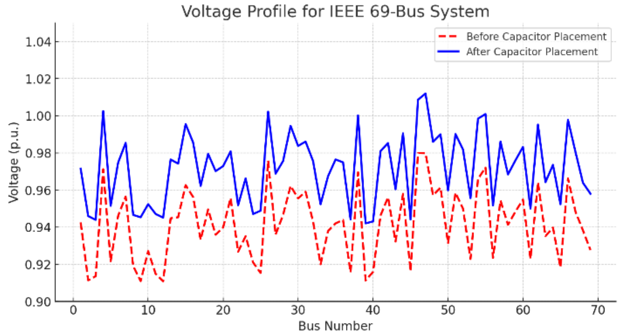


Figure. 4 Voltage profile for IEEE 69-Bus System

## 5. Conclusions and Future Work

Application of the recently developed Revolution Optimization Algorithm for solving the capacitor placement problem in power distribution networks, with the primary objectives of enhancing voltage profiles and minimizing power losses, is presented. The proposed approach is validated on two IEEE benchmark test systems, specifically the IEEE 33-bus and IEEE 69-bus networks. A comparative analysis against nine state-of-the-art metaheuristic algorithms, TLBO, MVO, GWO, WOA, MPA, TSA, RSA, AVOA, and WSO, is conducted. The results demonstrate the superior performance of ROA in terms of solution quality, convergence speed, and robustness. The algorithm consistently identified optimal capacitor locations and sizes, leading to significant improvements in voltage stability and reduction in power losses.

The convergence analysis revealed that ROA exhibits a faster and more stable convergence pattern compared to its competitors, reinforcing its efficiency in handling complex optimization problems. Moreover, the voltage profile analysis confirmed that the optimized capacitor placement significantly enhanced voltage stability, ensuring a more reliable operation of the power distribution network.

For future research, several directions can be explored. First, the integration of ROA with hybrid optimization techniques may further enhance its exploration and exploitation capabilities. Additionally, extending the application of ROA to multi-objective optimization scenarios, incorporating economic and reliability constraints, could provide more comprehensive solutions for real-world power system planning. Finally, investigating the performance of ROA in dynamic and large-scale power networks will contribute to its practical deployment in modern grids.

## Conflicts of Interest

The authors declare no conflict of interest.

## Author Contributions

Conceptualization, Z.M and M.D; methodology, Z.M; software, Z.M; validation, Z.M, M.D, and O.P.M; formal analysis, Z.M; investigation, Z.M; resources, Z.M; data curation, Z.M; writing—original draft preparation, Z.M; writing—review and editing, Z.M and O.P.M; visualization, Z.M; supervision, Z.M; project administration, Z.M and O.P.M; funding acquisition, M.D.

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