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Optimising Power Flow in Transmission Networks: A Comparative Study of Genetic Algorithm and Particle Swarm Optimisation Approaches

Omorodion Idemudia [1]; Ikenna Onyegbadue [2]; & Fred Izilein [2]

[1]Electrical/Electronic Engineering Department, School of Engineering, Edo State Polytechnic, Usen, Nigeria. [2]Electrical and Computer Engineering Department, College of Engineering, Igbinedion University, Okada, Nigeria.

Corresponding Author: william.idemudia-omorodion@iuokada.edu.ng

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Abstract

The efficient operation of power systems is crucial for meeting growing electricity demands, but traditional load flow methods often struggle with complex and large networks. This study aims to investigate the effectiveness of Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) in optimising load flow in the Etete 33 kV transmission network. The objectives are to evaluate the performance of GA and PSO in reducing power losses and improving voltage magnitude, compare their convergence behaviour, and determine the most effective approach. The study uses a base case load flow analysis to establish a benchmark, followed by GA and PSO optimisation. The results show that PSO outperforms GA in reducing power losses (94.27% reduction) and improving voltage stability. PSO's targeted reactive power injection strategy is more effective in minimising losses and maintaining voltage profiles within acceptable limits. The significance of this study lies in its potential to contribute to the development of more efficient power systems. The findings demonstrate the effectiveness of PSO in load flow optimisation, providing insights for power system operators to improve network performance. The study's results have implications for power system planning, operation, and control, enabling utilities to optimise their networks and reduce power losses. This study provides a valuable comparison of GA and PSO for load flow optimisation, highlighting the benefits of using advanced optimisation techniques in power system operation.

Keywords: Optimal Power Flow (OPF), Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Optimisation, Load Flow, Radial Distribution System.

Introduction

Power systems are crucial to the functioning of any society, particularly in countries where the electricity supply is inconsistent. The efficiency and stability of power delivery depend significantly on how well energy is transmitted through networks. Load flow analysis, also known as power flow analysis, is an essential tool that helps engineers understand the movement of electricity within a power system. It assesses voltage levels, power losses, and the flow of real and reactive power under varying load conditions. Traditionally, engineers have relied on methods such as the Newton-Raphson method, the Gauss-Seidel method, and the Backwards-Forward Sweep approach to conduct these calculations. While these methods perform adequately for smaller or less complex networks, they encounter challenges when applied to large, highly interconnected systems (Papazoglou & Biskas, 2023). As electricity demand continues to rise and grids become more sophisticated with the integration of renewable energy sources, existing methods often struggle to meet performance requirements. This shift has prompted researchers to explore new approaches for addressing load flow problems in increasingly complex environments. Initial efforts to enhance traditional methods often involved modifying the structure of the original equations to improve convergence. However, these modifications were insufficient for very large systems, where the number of variables becomes overwhelming (Karimi et al., 2019). It became apparent that novel solutions must efficiently navigate vast numbers of potential outcomes, adapt to nonlinear conditions, and respond well to system changes. To improve the flow of electricity through networks, researchers have turned to advanced techniques, including artificial intelligence and evolutionary algorithms. In particular, Genetic Algorithms and Particle Swarm Optimisation have garnered significant attention in recent years. Unlike traditional methods, these approaches do not rely on strict equations; instead, they mimic natural or social behaviours to solve complex problems. Genetic Algorithms use a population of potential solutions that undergo a process akin to evolution, where weaker solutions are supplanted by better ones through crossover and mutation (Alhijawi & Awajan, 2024). This process enables the algorithm to explore a broad range of possible solutions before identifying the optimal one. Particle Swarm Optimisation operates on a different concept. In this approach, a set of particles navigates through a solution space, learning from their own experiences and the successes of their peers. Each particle seeks to improve its answer by adjusting its movement based on shared knowledge (Nasiri et al., 2023). The effectiveness of this method lies in its balance

between exploration and refinement, as it avoids stagnation in one area and can swiftly adapt when a better solution emerges. Numerous studies have applied this method to large power systems, demonstrating superior performance compared to traditional techniques. Recently, these two methods have been combined into what is known as hybrid optimisation. This approach merges the strengths of both methods into a single system. Genetic Algorithms are adept at comprehensive searching, while Particle Swarm Optimisation tends to find the optimal answer more quickly once close to the solution. Combining both methods enhances both speed and accuracy (Priyadarshi & Kumar, 2025). Some researchers have already tested these hybrid techniques on real transmission networks, finding that they can reduce power losses, improve voltage profiles, and enhance reliability across the network (Ismail et al., 2020). These modern methods extend beyond theoretical research; they have been applied to operational transmission systems worldwide. For instance, a hybrid optimisation approach implemented on the Algerian network successfully lowered reactive power loss and enhanced power distribution quality (Cherki et al., 2024). In another study, a variation of Particle Swarm Optimisation effectively addressed the load flow problem in complex network settings, resulting in improved solution times and quality (Onyegbadue et al., 2022). Such outcomes underscore the necessity of moving beyond traditional load flow methods and embracing innovative tools capable of meeting the challenges of contemporary power systems. Additionally, the increasing use of renewable energy across many grids introduces new challenges. Sources like wind and solar energy are intermittent and do not maintain a fixed output, complicating system stability. Traditional methods are ill-equipped for such dynamic environments. In contrast, Genetic Algorithms and Particle Swarm Optimisation offer the flexibility needed to adapt to these conditions, effectively managing numerous variables and handling uncertainty.

The Newton-Raphson method, Gauss-Seidel method, and Backwards-Forward Sweep (BFS) approach have been widely used over the years in performing load flow analysis in electrical power systems. These techniques are known for their structured computation processes and are often chosen due to their relatively straightforward implementation in small and medium-scale networks. Each of these methods offers unique strengths. Newton-Raphson is recognised for its fast convergence in networks that are not heavily loaded. Gauss-Seidel is known for its simplicity in formulation, while the BFS method has proven effective, particularly in radial distribution systems.

Despite these benefits, their application becomes less suitable when the system grows in size or complexity. These methods often rely on several simplifying assumptions, which can be limiting in more dynamic and realistic grid scenarios. As power networks evolve with an increasing number of buses and non-linearities, these traditional methods begin to lose accuracy and efficiency. They also tend to suffer from higher computation time and reduced convergence speed under complex system conditions, especially when applied to systems with high variability in load or with multiple control constraints (Papazoglou & Biskas, 2023).

While they have played a vital role in the early development and management of power systems, the changing landscape of electricity networks has exposed the need for more robust, flexible, and scalable alternatives. This sets the stage for the advancement and application of modern computational and heuristic-based optimisation methods.

Traditional load flow methods such as Newton-Raphson, Gauss-Seidel, and Backwards-Forward Sweep have shown clear weaknesses in handling the realities of large and complex power systems. As electrical networks expand to cover more nodes and introduce additional variability, these methods become increasingly inefficient. Their limitations are often linked to issues such as slow convergence, poor handling of non-linearities, and reduced accuracy in heavily loaded or unbalanced (Aljarrah et al., 2024).

These drawbacks become more apparent when used in dynamic conditions where multiple constraints must be met. Conventional techniques struggle with modelling voltage instability or predicting the system response under stressed or faulted scenarios. Some methods require an initial guess that is very close to the actual solution to converge properly, which becomes impractical when dealing with unpredictable load behaviours. In cases where systems include renewable sources, reactive compensation equipment or advanced controllers, the limitations are even more pronounced due to the non-linear and interdependent nature of the variables (Basit et al., 2020).

As a result, these methods are less adaptable to the increasing demand for speed, reliability and computational efficiency in modern networks. They are often unable to provide fast enough responses needed for real-time system monitoring and optimisation. Studies have shown that when applied to real power networks, particularly in regions like Nigeria, where instability is frequent, the results from these traditional techniques are not sufficient to support optimal decision-making (Alimi et al., 2020). This reinforces the importance of exploring alternative, intelligent techniques that offer better adaptability and performance.

As power systems grew in size and complexity, the limitations of traditional methods created the need for more advanced approaches (Ukagu et al., 2025). The growing electricity demand, coupled with the integration of renewable sources and the need for grid flexibility, made it necessary to develop optimisation techniques that could handle non-linear, multi-variable conditions more efficiently (Pedram et al., 2023). These new approaches focused on improving accuracy, reducing power losses, and adapting to variable load patterns that older methods could not manage effectively.

Early improvements involved modifying existing techniques, but this was not enough for larger networks. The focus then shifted to intelligent algorithms that could search wider solution spaces and adapt to changing network behaviours. This marked a major shift in power system analysis, opening the door to methods that could solve complex problems with higher speed and reliability (Bessa et al., 2019; Yekini S. M. et al., 2024). These optimisation approaches have since become essential for meeting modern energy challenges.

Genetic Algorithm (GA), based on the principles of natural selection, uses population-based search to find optimal solutions in complex power systems (Vargas et al., 2024). Each

potential solution undergoes fitness evaluation, and through selection, crossover and mutation, better-performing solutions evolve over successive generations (Chiriac et al., 2023). This approach enables GA to explore a wide solution space, making it suitable for non-linear and multi-objective problems common in load flow optimisation.

GA has been successfully applied in power loss reduction, voltage control, and economic generation dispatch (Wu et al., 2019). In reactive power optimisation, it improves voltage stability by adjusting transformer taps, capacitor placements and generator settings (Korpikiewicz & Mohamed-Seghir, 2022). It also reduces transmission losses by optimising generation dispatch and load balance (Hanif & Mohammad, 2021), while generation scheduling with GA minimises fuel costs under varying demand (Sharifi et al., 2022)

Studies show that GA enhances performance in both standard test systems and practical networks like those in India and Europe (Bajaj & Sangwan, 2019). Although GA may require more computation time and risk local convergence, hybrid models have emerged to overcome these limitations (Jaafari et al., 2019).

Particle Swarm Optimisation (PSO) is inspired by the social behaviour of birds flocking or fish schooling. In PSO, particles represent potential solutions that move through the search space, influenced by their own experience and that of neighbouring particles (Salomon et al., 2013). This method is well-suited for solving optimisation problems in large, complex and dynamic power systems (Yekini S. M. et al., 2024)

PSO has been used in optimal power flow, reactive power control, voltage profile improvement and transmission loss minimisation (Madueme & Onyegbadue, 2019). Its ability to adjust dynamically makes it effective in smart grids and systems integrating renewable energy, where load and generation fluctuate frequently (Ourahou et al., 2020). Compared to Newton-Raphson or Gauss-Seidel methods, PSO achieves better results in handling non-linearities and constraints (Khaled et al., 2017)

In benchmark tests like the IEEE 30-bus system, PSO has achieved loss reductions and improved voltage levels more efficiently than traditional solvers. It is also favoured due to its simplicity, lower dependence on system equations and robustness under stressed conditions (Mohamed et al., 2025). However, parameter tuning remains critical to avoid early convergence and improve global search efficiency.

A distributed method of solving power flow problems was introduced using mathematical formulations supported by simulation. The approach relied on privacy-aware tools like ADMM and ALADIN, which were effective in ensuring fast convergence and scalability on systems with up to 4662 buses (Yang et al., 2023). However, the model did not apply its technique to real-world networks like those found in Nigerian distribution systems, leaving a practical gap for local implementation.

Another research focused on off-grid electrification using hybrid renewable energy systems. A multi-objective optimisation approach was employed to reduce energy costs and load loss while improving energy reliability in rural areas. Over ten years, the solution delivered lower carbon emissions and a more efficient energy supply (Min et al., 2022). The limitation here is

that the study was centred on off-grid systems, without addressing how such optimisation could improve existing grid infrastructure, especially at the 33 kV feeder level.

An investigation into Nigeria's transmission grid used an Artificial Neural Network to place power flow controllers optimally. This helped to correct voltage issues in weak buses and brought total power losses to almost half their original value (Okechukwu & Onoh, 2022; Suberu et al., 2024). While this study improved power quality, it did not explore how multiple computational approaches could work together to enhance performance.

Voltage instability and high losses across Nigeria's transmission network were addressed using Particle Swarm Optimisation. The study reported a significant reduction in voltage errors using simulation tools like MATLAB and ETAP (Kabeyi & Olanrewaju, 2022). Despite this achievement, there was no specific application of the model to targeted locations such as feeders in Benin City.

Other researchers modelled a smaller seven-bus system and used FACTS devices like STATCOM and IPFC to manage losses and voltage conditions (Alimi et al., 2020). The results showed strong performance in minimising losses and enhancing voltage profiles (Haider et al., 2021). However, the study limited its scope to FACTS-based solutions without assessing the potential of other optimisation algorithms like Genetic Algorithm or Particle Swarm Optimisation.

One research made use of a Genetic Algorithm in solving power flow issues in a 33-bus system and showed how DG placement could be optimised using various classical techniques. The solution improved voltage levels and reduced losses (Aljarrah et al., 2024)). Still, the method did not consider combining the Genetic Algorithm with other tools, such as PSO, for wider application in system optimisation.

The Artificial Bee Colony Algorithm was applied to both IEEE and Nigerian test networks to control voltage and reactive power. Results showed improvements in power quality across different loading levels (Bakare et al., 2020). Yet, the study remained focused on a single algorithm and did not compare its effectiveness with other popular tools used in load flow optimisation.

This study aims to investigate the effectiveness of Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) in optimising load flow in the Etete 33 kV transmission network. The specific objectives are to; evaluate the performance of GA and PSO in reducing power losses and improving voltage stability in the network, compare the convergence behaviour and optimisation results of GA and PSO in solving load flow problems and determine the most effective approach for optimising load flow in the Etete 33 kV transmission network.

The significance of this study lies in its potential to contribute to the development of more efficient power systems, reducing power losses and improving voltage stability. By exploring the application of GA and PSO in load flow optimisation, this study aims to provide insights into the most effective approaches for addressing the challenges of modern power systems. The findings of this study will have implications for power system planning, operation, and control, enabling utilities to optimise their networks and improve overall performance.

Problem Statement

The Etete 33 kV feeder in the Benin Electricity Distribution Company's network faces significant operational challenges, including undervoltage, high power losses, and stability issues. These problems are symptomatic of deeper systemic weaknesses, such as inadequate reactive power compensation, inefficient load flow management, and insufficient infrastructure capacity. To address these challenges, advanced computational methods, such as the Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO), are employed in the load flow management operations.

Methodology

Research Approach/Framework

This research was carried out using a simulation-based approach in MATLAB. The method involved modelling the Etete 33kV distribution feeder, where the bus data, line data, load demand and system parameters were clearly defined to capture the behaviour of the network. The load flow equations were solved using the Backwards-Forward Sweep Method, with Newton-Raphson and Gauss-Seidel techniques serving as benchmarks. The performance of these traditional methods was then compared to that of advanced optimisation techniques, specifically Genetic Algorithm and Particle Swarm Optimisation, to evaluate improvements in computation and solution accuracy. The framework was structured to begin with a base case load flow using the backwards-forward sweep method, which is suitable for radial distribution systems. The results from this base case provided initial values of voltage profiles and total power losses. These were then compared with the outcomes obtained after optimisation. The Genetic Algorithm explored possible solutions through selection, crossover and mutation, while the Particle Swarm Optimisation updated possible solutions based on the best positions reached by the swarm.

Study Area and System Description

The study was carried out on the Etete Injection Substation located in Benin City under the network of the Benin Electricity Distribution Company. The substation is an important supply point within the distribution network as it receives high voltage supply from the 132/33kV transmission system and steps it down for onward delivery to consumers. It is equipped with two 7.5MVA, 33/11kV transformers that supply power to four outgoing 11kV feeders serving Country Home, Akai, Arugba and Stella Obasanjo service zones. The substation also connects to the GRA sector of Benin City through three monitored 11kV feeders, namely GRA Etete, Ihama and Oko.

The Etete substation operates with two incoming 33kV feeders, one linking it directly to the transmission system and the other connecting it with the Stella Obasanjo Injection Substation. This configuration makes the substation a central pivot in the distribution chain, as it ensures a reliable flow of power into several key parts of Benin City.

The major components of the substation are summarised in Table 1, which presents the feeders, transformers and their operational roles.

Table 1: Etete Substation Components

Component Type	Quantity	Notes
33 kV feeder lines	1	Primary sub-transmission link from the transmission grid
7.5 MVA transformers	2	33/11 kV units feeding the Etete 11 kV network
11 kV outgoing feeders	4	Country Home, Akai, Arugba, Stella Obasanjo zones
Monitored 11 kV SES	3	G.R.A. Etete, Ihama and Oko feeders within the local BU

Source: Researcher, 2025

The physical arrangement and interconnection of the feeders and transformers are illustrated through a single-line diagram as seen in Figure 1. This diagram provides a clear visual representation of the system layout, showing how power flows from the transmission source into the distribution feeders.

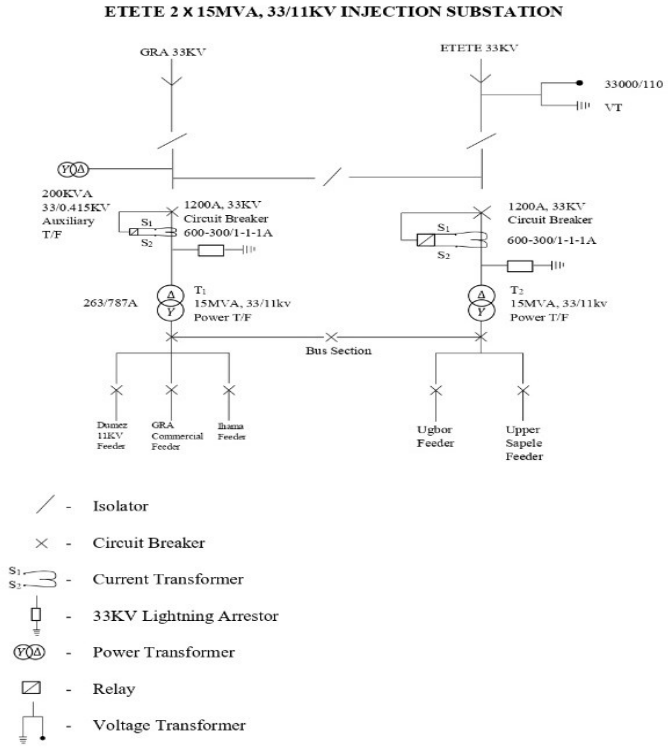


Figure 1: Line Network Diagram of Etete 33 kV transmission network

Data Collection

The data for this study were obtained from the operational records of the Etete 33 kV transmission network. Key inputs included bus load data, initial voltage magnitudes, line impedance parameters, and network configuration details. These datasets were necessary for

modelling the system and performing load flow analysis. The information was structured into bus and line data tables, which served as the foundation for both the base case simulation and the optimisation processes using Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO).

Load Flow Optimisation Approach

The proposed method follows a hybrid optimisation strategy where the Backwards-Forward Sweep Approach (BFS) load flow analysis serves as the base algorithm, and optimisation is achieved using GA and PSO. The process begins with a conventional load flow analysis to establish baseline values of voltage profiles, active and reactive power losses, and power flow in transmission lines. These initial results form the basis for comparison against optimised results obtained after applying GA and PSO.

The data is read from an Excel file named loadflow_data.xlsx, which contains two sheets: BusData and LineData. The BusData sheet contains information about each bus (node) in the network, including the bus number, type (e.g., slack, PQ), and the real and reactive power demands at that bus. The LineData sheet contains data about the distribution lines connecting the buses, specifically their impedance values and the sending and receiving bus numbers.

After reading the data into MATLAB tables, the code converts them into numerical arrays for further computation. The number of buses (n-bus) and the number of lines (n-line) are determined using the dimensions of the respective arrays. The base power (used for per-unit normalisation) is set to 30 MVA. The real power demands P and reactive power demands Q from the bus data are normalised to per-unit (pu) values by dividing each by the base MVA. The bus types are stored for later use in the load flow algorithm, as they determine which variables are known or unknown at each bus. The line impedances Z are calculated as complex numbers by combining the resistance and reactance values from the line data. Lastly, the code extracts the "from" and "to" bus indices for each line, which define the topology of the network and are essential for computing power flow along the branches.

Parameter Setting for GA and PSO

The parameter setting for GA is thus;
Population Size: 50
Mutation Rate: 0.05 (5%)
Crossover Probability: 0.8 (80%)

The parameter setting for PSO is thus;
Inertia Weight (w): 0.8
Cognitive Coefficient (c1): 2.5
Social Coefficient (c2): 2.0

Mathematical Equations

Let:

- $S_{base} = 30MVA$ (the base apparent power).
- $P_i^{MW} and\ Q_i^{MVAR}$ (the real and reactive power demands at the bus i.)
- $R_{ij}\ and\ X_{ij}$ (the resistance and reactance of the line between buses i and j)
- Z_{ij} (the complex impedance of the line between buses i and j)
- T (the total number of lines.)
- N (the total number of buses)

Then the equations implemented are:

1. **Per-unit Conversion of Power Demands:**

$$P_i = \frac{P_i^{MW}}{S_{base}} \quad (1)$$

$$Q_i = \frac{Q_i^{MVAR}}{S_{base}} \quad (2)$$

2. **Complex Line Impedance Calculation:**

$$Z_{ij} = R_{ij} + jX_{ij}\ for\ each\ line\ ij \in [1, T] \quad (3)$$

3. **Network Topology Definition:**

- The from and to arrays specify the sending and receiving nodes:

From $k = i$, to $k =$ j for each line $k \in [1, T]$

4. **Objective Function**

Equation of the Objective Function.

Step 1: Reactive power update with capacitor placement

Mathematically:

$$Q_i' = \begin{cases} Q_i + x_i, & if\ bus\ i \in PQ\ set \\ Q_i, + x_i, & otherwise\ huppp \end{cases} \quad (4)$$

Where:

Q_i= Original reactive power load at bus iii

x_i = Reactive power injected by the capacitor at bus iii

Step 2: Load Flow Solution

The load flow solves for bus voltages V_i and line currents I_{ij} from:

$$S_i = P_i + jQ_i' = V_i \sum_{j=1}^{n_{bus}} Y_{ij}^* V_j^* \quad (5)$$

where:

S_i = complex power at bus i

Y_{ij} = admittance matrix element

V_i = complex voltage at bus i

From this, line currents between the buses i and j are:

$$I_{ij} = \frac{V_i - V_j}{Z_{ij}} \quad (6)$$

Where: $Z_{ij} = R_{ij} + jX_{ij}$ is the branch impedance.

Step 3: Real Power Loss

The real power loss in the line (i, j) is:

$$P_{loss,ij} = |I_{ij}|^2 . R_{ij} \quad (7)$$

Summing over all lines:

$$P_{loss,total}(x) = \sum_{(i,j)\in lines} |I_{ij}|^2 . R_{ij} \quad (8)$$

5. **Final Objective Function**

Putting it all together:

$$\min_x f(x) = \sum_{(i,j)\in lines} \left|\frac{V_i(x) - V_j(x)}{Z_{ij}}\right|^2 . R_{ij} \quad (9)$$

subject to:

$Q_i' = Q_i + x_i$ for PQ buses

$V(x)$ obtained from load flow equations

Capacitor limits: $x_{min} \leq x_i \leq x_{max}$

Load Flow Execution Section (Base Case)

This section performs the base load flow analysis for a radial distribution system using the backwards/forward sweep method and computes the total real power loss in per unit (pu). It involves calling a custom function, runLoadFlow, which returns the voltage and current distribution across the system for the given base load.

The function runLoadFlow is invoked to calculate the voltage profile (V_{base}) and branch currents (I_base) across the network under normal (uncompensated) operating conditions. It uses:

- P: vector of real power loads (in pu)
- Q: vector of reactive power loads (in pu)
- Z: vector of complex line impedances
- from and to: vectors representing the sending and receiving bus numbers of each line
- n_bus: total number of buses
- n_line: total number of lines

This function internally applies the backwards/forward sweep method, commonly used for load flow analysis in radial distribution networks due to its simplicity and convergence efficiency.

This line calculates the total real power loss in the system using the formula:

$$P_{loss} = \sum_{k=1}^{n_{line}} |I_k|^2 . R_k \quad (10)$$

Where:

- $|I_k|$is the magnitude of the current in line k
- R_k is the resistance (real part of impedance) of the line k

In MATLAB syntax:

- abs(I_base).^2 computes the squared magnitude of the current in each line
- real(Z) extracts the resistive (real) part of the line impedance vector
- .* performs element-wise multiplication
- sum(...) adds up the real power loss from each line
- real(...) ensures any negligible imaginary part due to floating-point errors is discarded

Backwards-Forward Sweep (BFS)

The Backwards-Forward Sweep (BFS) method is a widely accepted and computationally efficient technique for performing load flow analysis in radial and weakly meshed distribution networks. Unlike transmission systems, distribution systems have unique characteristics such as high R/X ratios, radial topology, and unbalanced loading. These attributes make conventional methods like Newton-Raphson or Gauss-Seidel unsuitable or inefficient for distribution systems. The BFS method overcomes these limitations by capitalising on the tree-like structure of radial networks and simplifying the power flow equations accordingly.

Performance Metrics for Evaluation

The effectiveness of the optimisation algorithms was measured to understand how well they improved system performance in terms of power loss reduction and voltage stability. The study emphasised two main aspects, which were the accuracy of optimisation and comparative effectiveness.

Accuracy was assessed through the ability of the algorithms to reduce technical losses and maintain voltages within the required operational limits. Before optimisation, the network recorded high real power losses as a result of uneven distribution of reactive power and noticeable voltage drops across the feeders. Once optimisation was introduced, both the Genetic Algorithm and Particle Swarm Optimisation reduced these losses by identifying the best points for capacitor placement. This reduction in losses improved the overall efficiency of the network and led to a more stable delivery of power. Accuracy was also measured through voltage profiles across the buses. Some buses initially recorded values outside the acceptable band of 0.95 to 1.05 per unit, particularly towards the end of the feeder. After optimisation, the capacitor placements corrected these deviations, and all voltages remained within the required range. The Particle Swarm Optimisation produced slightly better results than the Genetic Algorithm, though both methods provided reliable improvement.

Comparative effectiveness focused on how the two optimisation methods performed when placed side by side. The comparison was not centred on computational speed but rather on how each method improved technical outcomes. Both approaches achieved significant loss

reduction and voltage stabilisation, though Particle Swarm Optimisation showed stronger consistency in convergence and in delivering improved bus voltage levels.
Figure 2 illustrates the flowchart for the methodology.

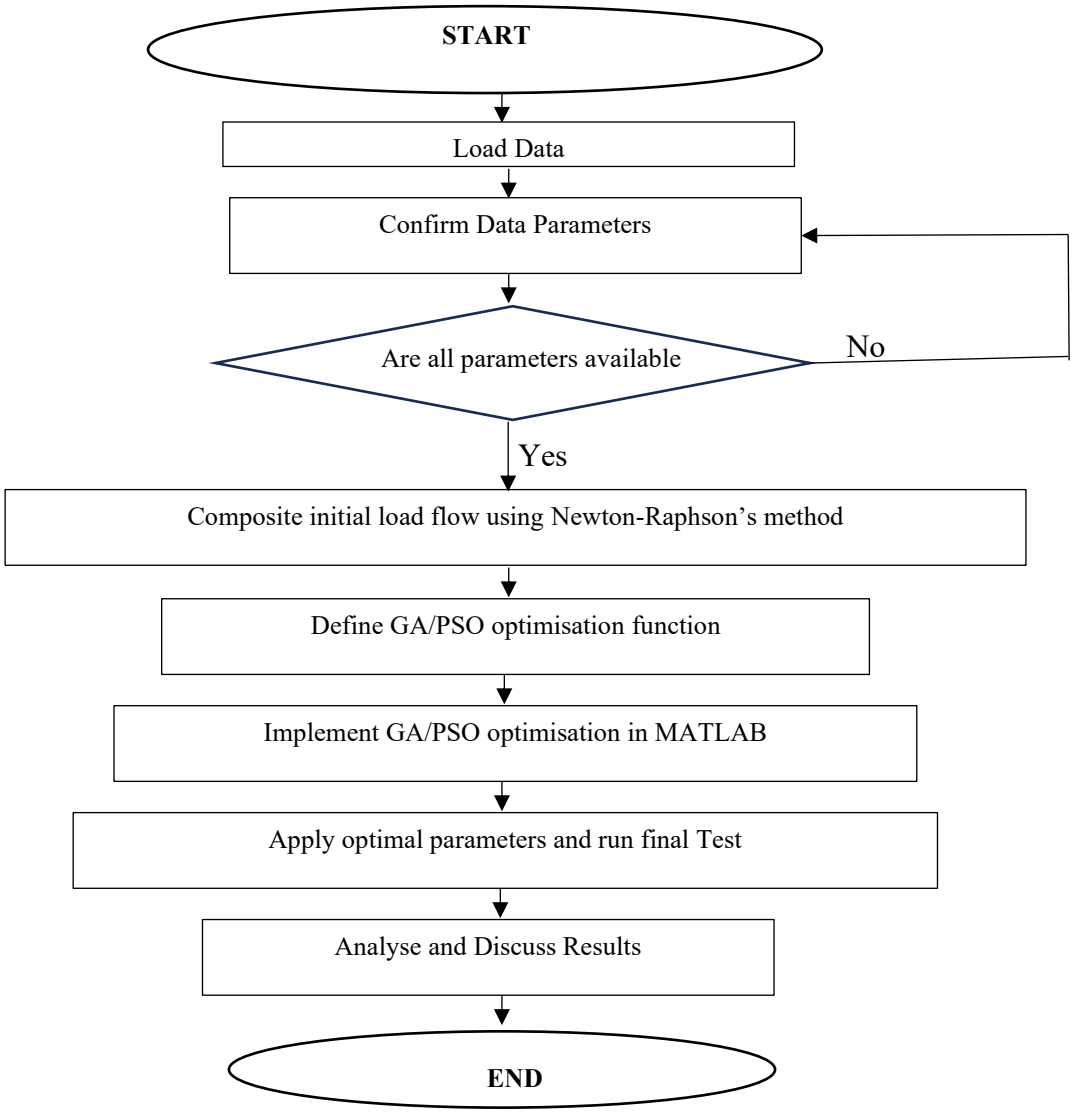


Figure 2: Flowchart Explaining the Implementation Approach

Results and Discussions

Base Case Load Flow Analysis

The base case load flow analysis provides the benchmark performance of the Etete 33 kV transmission network before any optimisation is introduced. This scenario reflects the actual condition of the network under normal operating parameters, using the given load and line data without the inclusion of any reactive power compensation devices. The results from this

stage form the standard against which the improvements from the Genetic Algorithm and Particle Swarm Optimisation are evaluated.
The complex voltage outputs for the five buses in the base case are shown in Table 2.

Table 2: Complex Bus Voltages for Base Case

Bus No.	Voltage (Real)	Voltage (Imag)
1	0.7872	-0.2083
2	0.9816	-0.0136
3	0.9577	-0.0624
4	0.8780	-0.1101
5	0.8226	-0.1549

The results show a significant voltage deviation at Bus 1, with a magnitude of 0.7872 pu, far below the acceptable tolerance band of ±5% of nominal voltage. Bus 2 records the highest voltage magnitude of 0.9816 pu, which falls within acceptable operational limits. The remaining buses record values lower than 0.96 pu, highlighting a progressive drop in voltage along the feeder.
This reduction is mainly due to the cumulative effect of line resistance, reactance, and the active and reactive power demands at each bus. Buses located further from the source are more affected due to longer line segments and the loads they supply.
The voltage drops for each bus are presented in Table 3.

Table 3: Voltage Drops for Base Case

Bus No.	Voltage Drop (pu)
1	0.2083
2	0.0136
3	0.0624
4	0.1101
5	0.1549

The highest voltage drop occurs at Bus 1 as seen in Figure 3, indicating that it is the most affected point in the network under base case conditions. This reflects the need for compensation measures to improve the voltage profile.

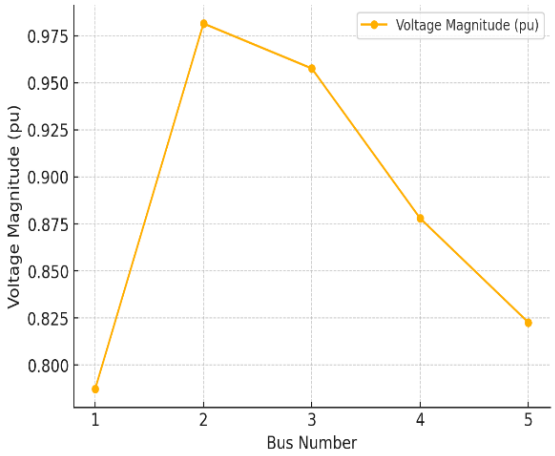


Figure 3: Voltage Magnitude Profile – Base Case

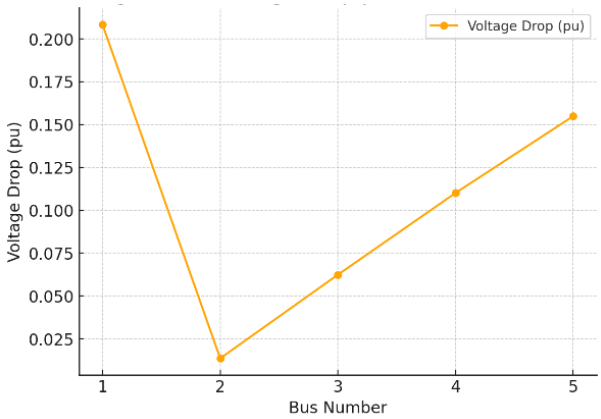


Figure 4: Voltage Drop per Bus – Base Case

The total system power loss in the base case is calculated at 0.044776 pu. Figure 4 reflects the inherent inefficiencies in the network, caused by the combined effects of load demand, line impedance, and absence of reactive power support. The magnitude of this loss forms a clear basis for evaluating the benefits of applying computational optimisation.

Genetic Algorithm (GA) Optimisation Results

The Genetic Algorithm was applied to the Etete 33 kV transmission network to improve the voltage profile and reduce system losses through optimal placement and sizing of reactive power support. The GA operates by simulating the process of natural selection, where a population of candidate solutions evolves over successive generations to achieve the desired objective. In this study, the algorithm worked to minimise total real power losses while keeping bus voltages within acceptable limits.

The convergence trend of the GA is presented in Table 4.

Table 4: GA Convergence Data

Generation	Best Loss (pu)
1	0.040009
2–11	0.040009
12–50	0.039938

Source: Researcher, 2025

The results indicate that the algorithm achieved a reduction in total system losses from the base case value of 0.044776 pu to 0.039938 pu. Significant improvements were made by the twelfth generation, after which the best loss value remained constant, indicating convergence to an optimal solution. This pattern shows that the GA quickly identified a near-optimal range of solutions early in the search process, but minor refinements in later generations contributed little to further loss reduction. The convergence curve is seen in Figure 5.

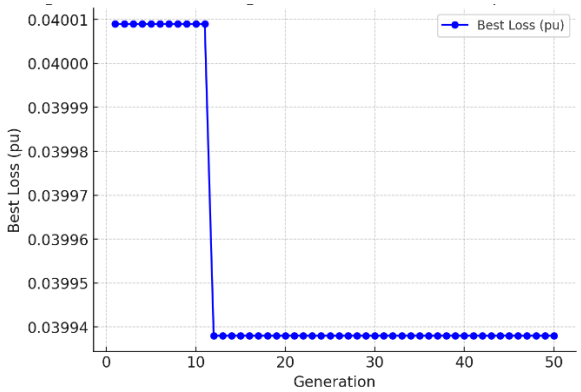


Figure 5: GA Convergence Curve – Best Loss per Generation

The complex bus voltages obtained from the GA-optimised case are presented in Table 5.

Table 5: Complex Bus Voltages for GA Optimisation

Bus No.	Voltage (Real)	Voltage (Imag)
1	0.8145	-0.2136
2	0.9846	-0.0146
3	0.9636	-0.0640
4	0.8916	-0.1139
5	0.8410	-0.1604

The magnitude of the voltage at Bus 1 improved from 0.7872 pu in the base case to 0.8145 pu under GA optimisation. Buses 2 to 5 also recorded slight improvements, with Bus 5 increasing from 0.8226 pu to 0.8410 pu. These changes indicate that the GA successfully redistributed reactive power support to boost voltage levels, though the improvements are moderate

compared to those observed later in the PSO case. Figure 6 shows the voltage magnitude profile of buses with GA optimisation.

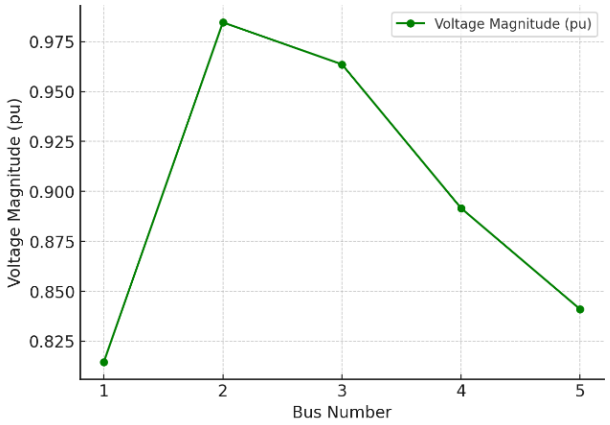


Figure 6: Voltage Magnitude Profile – GA Optimisation)

The voltage drop for each bus after GA optimisation is presented in Table 6.

Table 6: Voltage Drop Values for GA Optimisation

Bus No.	Voltage Drop (pu)
1	0.2136
2	0.0146
3	0.0640
4	0.1139
5	0.1604

The drops remained noticeable but were slightly reduced compared to the base case. The most significant drop occurred at Bus 1, where improved voltage support lowered the deficit from the substation reference.

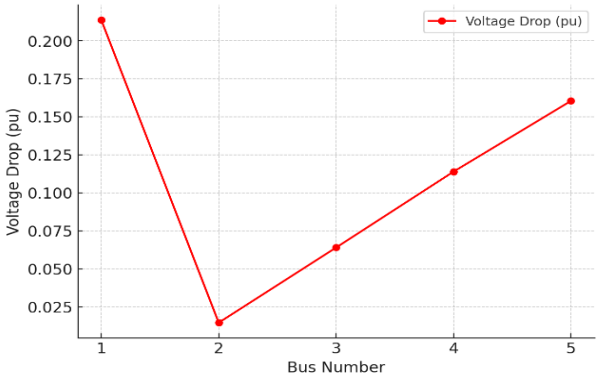


Figure 7: Voltage Drop per Bus – GA Optimisation)

Capacitor Placement Strategy from GA

The GA determined optimal reactive power injections as follows:

- Bus 2: 0.0499 pu
- Bus 3: 0.0138 pu
- Bus 4: 0.0356 pu
- Bus 5: 0.0137 pu

The pattern as seen in Figure 8 shows a strategy of distributing reactive power across several buses, ensuring no single location bears the entire burden of voltage support. This distribution helps in balancing reactive power flows and reducing the chances of localised overvoltage.

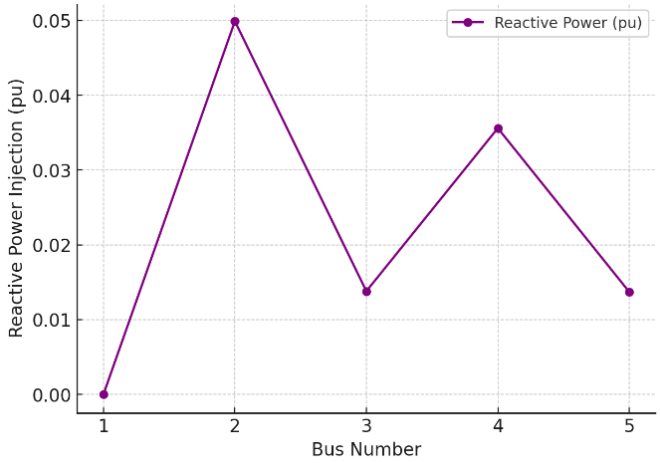


Figure 8: GA Capacitor Placement Chart

The GA's moderate improvements in voltage profile and loss reduction are partly due to its approach of gradual evolution over generations. By allocating smaller amounts of reactive power across multiple buses, the algorithm achieved a balanced but less aggressive enhancement of the voltage profile. The convergence pattern shows that most improvements were captured early, with diminishing returns thereafter.

This behaviour reflects the nature of GA, where early exploration quickly identifies promising solutions, followed by slower exploitation of those solutions to fine-tune results. While effective, this approach may not fully exploit potential improvements in cases where larger and more targeted reactive injections could yield better performance.

Particle Swarm Optimisation (PSO) Results

The Particle Swarm Optimisation technique was applied to the Etete 33 kV network to achieve optimal reactive power placement and voltage profile enhancement. PSO works by mimicking the social behaviour of bird flocks or fish schools, where each particle adjusts its position in the search space based on its own best experience and that of the group. The goal in this case was to minimise real power losses while keeping bus voltages within statutory limits.

The iteration results for PSO are presented in Table 7.

Table 7: PSO Convergence Data

Iteration	Best Loss (pu)
1	0.0272
2	0.0034
3–50	0.0026

The results show a dramatic reduction in losses, from 0.044776 pu in the base case to 0.002566 pu under PSO optimisation. Convergence occurred very early, at the third iteration, with no further improvement thereafter. This rapid convergence demonstrates PSO's strength in quickly identifying optimal or near-optimal solutions in fewer iterations compared to GA. This speed advantage is particularly useful for online or real-time applications where optimisation needs to be performed within strict time constraints. The convergence curve is as seen in Figure 9.

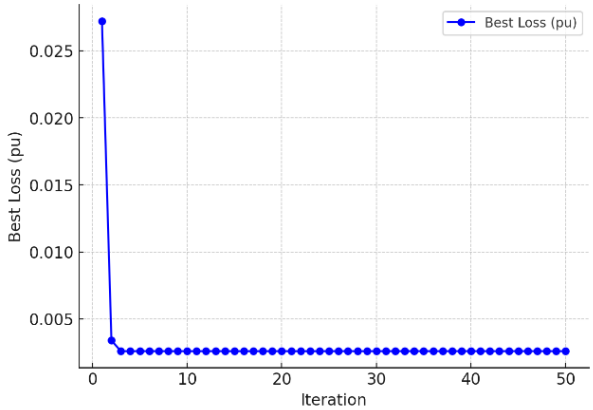


Figure 9: PSO Convergence Curve – Best Loss per Iteration

The voltage profile can be seen in Table 8.

Table 8: Complex Bus Voltages for PSO Optimisation

Bus No.	Voltage (Real)	Voltage (Imag)
1	0.9820	-0.0744
2	0.9975	-0.0051
3	0.9950	-0.0205
4	0.9834	-0.0384
5	0.9834	-0.0585

The voltage magnitudes as seen in Figure 10 show significant improvement compared to both the base case and GA results. Bus 1, which recorded the lowest voltage in the base case (0.7872 pu), improved to 0.9820 pu. All buses achieved values close to 1.0 pu, indicating that the network operates near the nominal voltage level after optimisation.

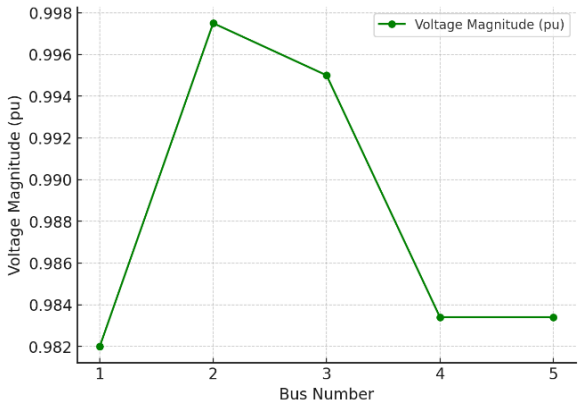


Figure 10: Voltage Magnitude Profile – PSO Optimisation

The Voltage Drop can be seen in Table 9.

Table 9: Voltage Drop Values for PSO Optimisation

Bus No.	Voltage Drop (pu)
1	0.0744
2	0.0051
3	0.0205
4	0.0384
5	0.0585

The voltage drops as seen in Figure 11 were reduced substantially across all buses, with Bus 1's drop reduced from 0.2083 pu in the base case to 0.0744 pu. This improvement reflects better voltage stability and more balanced voltage distribution along the feeder.

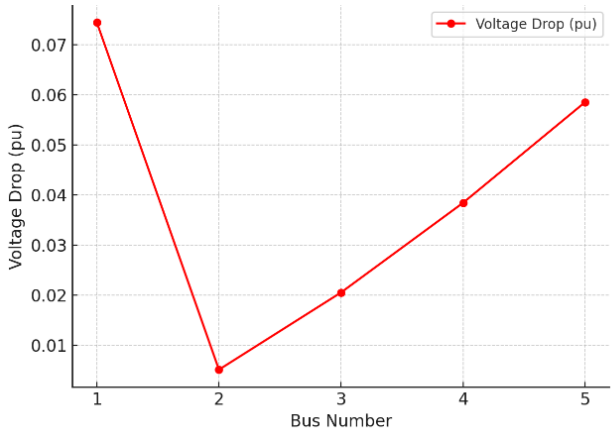


Figure 11: Voltage Drop per Bus – PSO Optimisation

Capacitor Placement Strategy from PSO

The PSO's optimal reactive power allocation was:

- Bus 2: 0.0500 pu
- Bus 3: 0.0191 pu
- Bus 4: 0.0500 pu
- Bus 5: 0.0500 pu

Compared to GA, PSO allocated higher reactive power levels as seen in Figure 12 to the weakest buses, ensuring stronger voltage support and minimised losses.

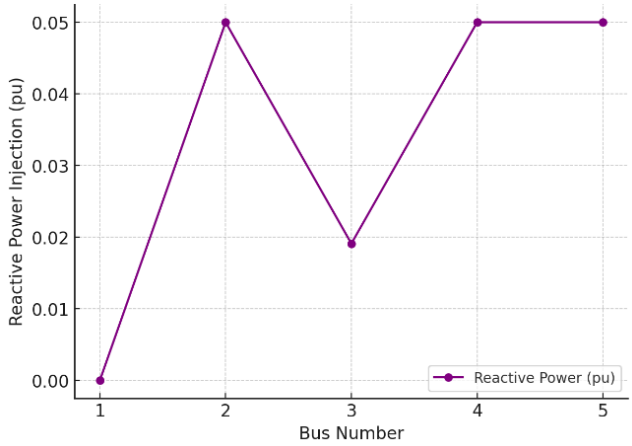


Figure 12: PSO Capacitor Placement Chart

PSO achieved a much greater loss reduction and faster convergence compared to GA. The rapid convergence pattern suggests that PSO's swarm intelligence and ability to exploit both individual and group experiences makes it more effective for this optimisation problem. The larger and more targeted reactive injections in PSO's solution directly improved bus voltages and reduced line losses.

In practical terms, applying PSO in the Etete 33 kV network would mean a much more efficient voltage control strategy, capable of sustaining nominal voltage conditions even under varying load demands. This translates to improved power quality, reduced technical losses, and extended equipment life due to reduced thermal stress on network components.

Comparative Performance Analysis

The comparative analysis evaluates the performance of the Etete 33 kV network under three operating conditions: the base case without optimisation, optimisation using the Genetic Algorithm (GA), and optimisation using Particle Swarm Optimisation (PSO). This section focuses on voltage magnitude improvements, voltage drop reductions, loss minimisation, and the capacitor placement strategies adopted by the two algorithms.

A. Voltage Magnitude Comparison

In the base case, the voltage magnitudes ranged between 0.7872 pu and 0.9816 pu, with Bus 1 recording the lowest value. Under GA optimisation, this range improved to between 0.8145

pu and 0.9846 pu. With PSO, the range increased significantly, from 0.9820 pu to 0.9975 pu, bringing all buses closer to nominal voltage.

The improvement achieved by PSO at Bus 1 is particularly notable, with the value increasing from 0.7872 pu in the base case to 0.9820 pu, eliminating the undervoltage condition. GA provided moderate improvements, but not enough to bring all buses within the preferred ±5% range from nominal voltage. Figure 13 shows the combined Voltage Magnitude profile for the base, GA and PSO cases.

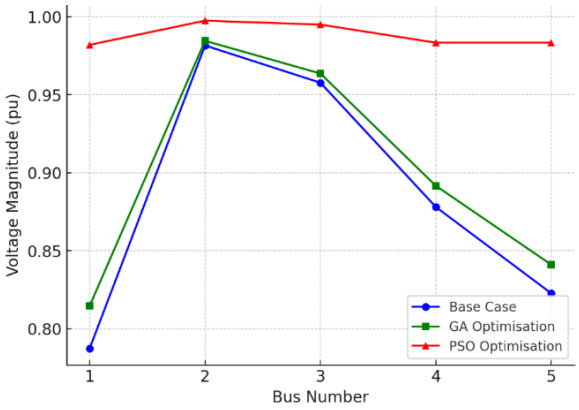


Figure 13: Combined Voltage Magnitude Profile – Base Case, GA, and PSO

B. Voltage Drop Comparison

The voltage drop profiles also show clear differences. In the base case, Bus 1 experienced the largest drop at 0.2083 pu, while Bus 2 had the smallest drop at 0.0136 pu. GA reduced the drop at Bus 1 to 0.2136 pu, a modest improvement. PSO, however, reduced this drop dramatically to 0.0744 pu, improving voltage stability across the network.

The consistent drop reduction in the PSO case as seen in Figure 14 reflects its targeted reactive power placement at the weakest buses, particularly Buses 4 and 5, which experienced marked improvements in voltage levels.

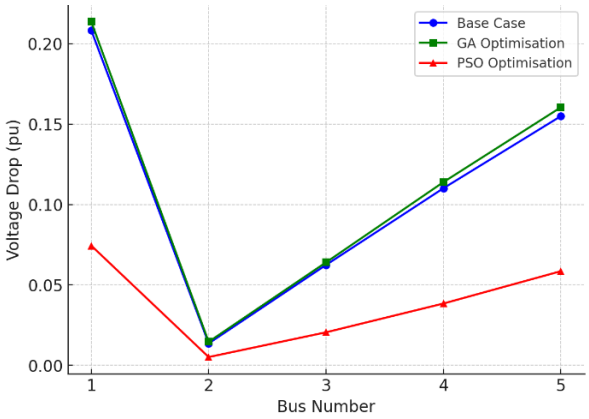


Figure 14: Combined Voltage Drop Profile – Base Case, GA, and PSO

C. Power Loss Comparison

The total real power losses recorded for each case were:

- Base Case: 0.044776 pu
- GA Optimisation: 0.039938 pu
- PSO Optimisation: 0.002566 pu

These results show that PSO achieved a 94.27% loss reduction compared to the base case, and an over 93% improvement compared to GA. This large difference stems from PSO's more aggressive allocation of reactive power to specific buses that have the highest influence on system losses. Figure 15 illustrates the power loss comparison for the three cases.

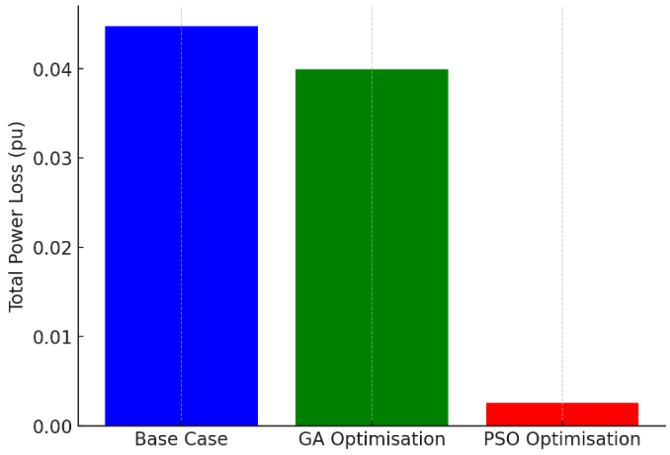


Figure 15: Power Loss Comparison Bar Chart

D. Capacitor Placement Strategy

GA's reactive power allocation was distributed across several buses, with smaller injection levels, aiming to balance voltage support evenly across the network. PSO, on the other hand, concentrated higher levels of reactive power at the most critical buses, leading to greater overall system improvement. This targeted approach was more effective in both improving the voltage profile and reducing losses.

The comparative results as seen in Figure 16 demonstrate that while both GA and PSO improved the network performance over the base case, PSO consistently outperformed GA in every parameter assessed.

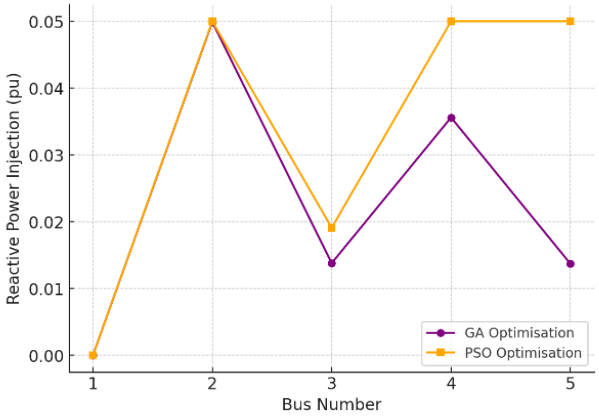


Figure 16: Combined Capacitor Placement Chart – GA vs PSO

. The key factors behind PSO's superior performance are:

1. **Rapid Convergence:** PSO achieved optimal results by the third iteration, compared to GA's convergence after twelve generations.
2. **Targeted Reactive Power Injection:** By focusing reactive support at the weakest points, PSO maximised voltage improvements and loss reduction.
3. **Reduced Computational Effort:** Faster convergence and fewer adjustments in later iterations make PSO more suitable for real-time optimisation scenarios.

GA's distributed approach is advantageous in networks where load conditions are highly variable and uniform voltage support is desirable, but for the given case, PSO's targeted method provided far better results in terms of operational efficiency and network stability.

Conclusion

This study examined the optimisation of load flow in the Etete 33 kV transmission network using Genetic Algorithm and Particle Swarm Optimisation. The base case revealed high voltage drops, undervoltage at critical buses, and significant real power losses. The application of GA improved overall voltage levels and reduced losses modestly, but its distributed allocation of reactive power limited its impact on weak points. In contrast, PSO delivered substantial improvements, achieving near-nominal voltage across all buses, sharply reducing losses by more than 90%, and converging within very few iterations. These results demonstrate that PSO is more effective for both technical and practical purposes, offering faster convergence, better accuracy, and targeted voltage support. Implementing PSO in the Etete network would improve stability, reduce energy losses, enhance supply quality, and extend equipment lifespan through reduced operational stress. Hence, in cases of variable loads requiring distributed Solutions, GA can be implemented, while PSO should be recommended for fast convergence and targeted voltage support.

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