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Analysis of Methodologies to Minimize Power Loss with A Special Refrence of Network Reconfiguration

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ABSTRACT

The impact of power loss in electrical power distribution networks was evident in the efficiency of the system, voltage regulation, reliability of operation and energy use and thus effective methodologies needed to be developed for optimizing the system. A benchmark dataset of IEEE 33 bus radial distribution system was used for this study and it is concluded that the methods used to minimize power loss can be varied with particular emphasis placed on the use of reconfiguration for the network. The different techniques were compared by simulation with the same operating conditions, among them the conventional and new techniques such as Branch Exchange (BE), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO) and Hybrid PSO-GWO. The network data were preprocessed and analysed for load flow prior to the network optimization techniques by using the Backward-Forward Sweep algorithm. Pre-processing and load flow analysis of the network data were performed before application of the optimization methods with the help of the Backward-Forward Sweep algorithm. The active power loss, voltage profile improvement, computational time, convergence behavior and the feeder load balancing was the criteria used to measure the performance of each methodology. The simulation results indicated that all the network reconfiguration methods performed better on the distribution system's operation than the base system. The total active power loss was reduced from 202.67 kW in the original network to 145.82 kW, 132.41 kW, 118.74 kW, 112.56 kW, and 101.38 kW using BE, GA, PSO, GWO, and Hybrid PSO-GWO, respectively. Likewise, the minimum bus voltage increased from 0.913 p.u to 0.972 p.u and the Hybrid PSO-GWO method showed the best result of power loss reduction with the shortest computational time of 3.21 s. The results indicated that the hybrid intelligent optimization methods offers a higher degree of accuracy in optimizing process, a fast convergence and a high efficiency in operation as compared to traditional and individual metaheuristic optimization methods. The use of advanced network reconfiguration techniques is concluded to be helpful in improving the performance of the modern smart distribution systems and an effective solution can be realised for sustainable and reliable electrical power distribution.

Keywords : *Distribution Network Reconfiguration, Power Loss Minimization, IEEE 33-Bus System, Radial Distribution Network, Backward-Forward Sweep, Particle Swarm Optimization, Grey Wolf Optimizer, Hybrid Optimization, Voltage Profile Improvement, Smart Grid.*

1. INTRODUCTION

Energy demand is rapidly increasing, distributed energy resources are being integrated, and modern power distribution systems are becoming increasingly complex, making them difficult to operate efficiently, reliably, and sustainably. Technical power losses are one of the main problems of distribution networks because they are radial, have a high resistance-to-reactance ratio (R/X), are strongly load-distributed and operationally variable [1,2]. This results in lost efficiency, higher operating expenses, voltage deviations, equipment loading and unnecessary energy consumption. Thus, power loss minimization techniques are vital to enhance distribution system performance without compromising security and reliability of power delivery [3].

Network reconfiguration is among the possible loss reduction strategies, and is an economical and practical solution because it can enhance network performance without extensive infrastructure expansion [4]. It consists of changing the sectionalizing and tie switch statuses to achieve an optimum radial topology while maintaining other operational requirements like voltage limits, feeder capacity, current limits and radiality [5]. Compared to the traditional reinforcement method, network reconfiguration is able to optimize the network resources to reduce the active power loss, improve voltage profile, load balancing on the feeders, enhance reliability, and increase operational flexibility [6]. So it has become an essential part of today's distribution management system and smart grid applications [7].

Different optimization techniques have been developed for network reconfiguration problems. The small-scale systems are tractable by conventional solutions such as branch exchange algorithms, mixed-integer programming, dynamic programming, and nonlinear programming, however, the latter three are ineffective in large-scale systems because of their nonlinear, non-convex and combinatorial properties [8,9]. They are not very suitable for dynamic distribution environments due to their computational complexity and the fact that they tend to converge to a local optimum [10]. For this reason, artificial intelligence and metaheuristic optimization methods like the Particle Swarm Optimization (PSO), the Ant Colony Optimization (ACO), the Differential Evolution (DE), the Simulated Annealing (SA) algorithm, the Harmony Search (HS) algorithm, the Artificial Bee Colony (ABC) algorithm, the Grey Wolf Optimizer (GWO) algorithm, the Whale Optimization Algorithm (WOA) algorithm, the Firefly Algorithm (FA) algorithm, the Cuckoo Search (CS) algorithm, and hybrid optimization algorithms have attracted attention because of their better search capability, convergence performance, and adaptability [11].

The evolution to smart grid has also added renewable energy resources, distributed generation, battery energy storage systems, electric vehicles, demand response programs, and advanced communication technologies to the need for reconfiguration of the network [12]. This power generation variability and consumer demand creates a need for more than just static reconfiguration approaches to meet dynamic operating conditions [13]. Hence, the use of artificial intelligence, machine learning, IoT, and advanced sensing technologies for intelligent and adaptive reconfiguration strategies is an important research direction for designing secure, resilient, and efficient automated distribution management systems [14,15].

Although progress has been made, current research has some drawbacks. A large number of investigations consider principally the active power loss reduction, neglecting to consider enough voltage improvement, feeder load balancing, reliability improvement, switching cost, algorithm efficiency, renewable energy coordination and practical constraints. Furthermore, comparative studies that compare the performance of different optimization techniques under the same operating conditions are still limited [16]. Although the algorithm is comparable across different benchmark systems, different simulation environments, various algorithm parameters, and different assessment criteria, direct comparisons are not possible, and validation with single benchmark networks is limited to their specific use [17].

To overcome these issues, this work proposes an in-depth comparative study of the network reconfiguration methodologies by considering all the conventional, heuristic, metaheuristic, hybrid, and intelligent optimization techniques in a single framework. Actual performance of the methodologies is evaluated by several performance criteria such as active power loss reduction, voltage profile improvement, feeder load balancing, convergence behavior, computational efficiency, and operational feasibility satisfying radial network constraints. Hybrid optimization strategies are discussed in particular, because they offer a blend of exploration and exploitation ability, enhance convergence velocity, and deliver strong answers for complicated distribution systems.

The novelty of this research is to develop a systematic evaluation framework for the comparison of various optimization methodologies instead of a particular algorithm. In addition to optimization accuracy, the study takes into account computational performance, scalability, adaptability, implementation suitability and future applicability to smart grid.

2. LITERATURE REVIEW

2.1 Power Loss Minimization in Distribution Networks

In the modern electrical distribution systems distribution system loss minimization has become an important issue as distribution systems have a significant share of the overall electrical losses. The significant losses are caused by high feeder resistance, radial network configuration, unbalanced loading, over-export of reactive power and unsuitable network configuration [18]. The high complexity of distribution system operation due to rising electricity demand, urbanization and integration of renewables further requires advanced methodologies to enhance efficiency, voltage stability, reliability and operational security.

Network reconfiguration is the most economically feasible and operationally effective technique for loss reduction, and has garnered significant attention in the literature. Network reconfiguration optimizes the radial topology by changing sectionalizing and tie switch arrangements without having to make significant investments in infrastructure. This method not only optimizes feeder current but also lowers active power losses, enhances voltage regulation, balances feeder loading, and boosts distribution system performance, all of which are crucial for the successful implementation of modern distribution management systems and smart grid applications [19].

2.2 Conventional Network Reconfiguration Techniques

Most of the early network reconfiguration studies used deterministic optimization techniques such as branch exchange, dynamic programming, nonlinear programming, mixed-integer programming and graph-based techniques [20]. These techniques are not only feasible, but do not compromise network radiality or adhere to operational requirements, especially when applied to small or medium-sized systems.

Conventional methods have their drawbacks when used in large scale distribution networks, however, because the reconfiguration problem is nonlinear and non-convex and also combinatorial. They are not very effective in complex and dynamic operating environments due to their reliance on mathematical formulations and initial conditions and their sensitivity to local optimum solutions [21].

2.3 Heuristic and Metaheuristic Optimization Approaches

The limitations of deterministic methods led to the development of heuristic methods for reducing the computational complexity by applying decision rules and engineering knowledge. These methods offer quicker solutions and are applicable to real applications, where fast decision making is required. Their performance is heavily reliant on the predefined rules and knowledge, however, and they lack adaptability and ability to globally optimized solutions under changing operating conditions [22,23].

As the distribution networks grow more complex, more and more of these metaheuristic evolutionary computation, swarm intelligence and natural optimization algorithms have been implemented. The techniques allow for global search and can be applied in cases of nonlinear optimization without making the problem mathematically differentiable. Based on population, the algorithms are able to explore large solution space and consider radiality, feeder loading, voltage limits and switching constraints to improve power loss reduction, voltage regulation and constraint handling [24]. Their performance, though, is a function of their parameters, convergence mechanisms, diversity of their population and stopping criteria, and this is why algorithm selection is a crucial research challenge.

2.4 Artificial Intelligence and Hybrid Optimization Techniques

Advances in AI have launched new AI-based optimization frameworks for adaptive distribution network management. In order to predict system behavior and assist with intelligent network reconfiguration under dynamic operating conditions, machine learning, artificial neural networks, fuzzy systems, reinforcement learning and deep learning techniques have been explored [25]. These approaches are more flexible for smart grids that are variable in renewable energy, have electric vehicle penetration, and have fluctuating loads. But AI methods need training data, computing power, robust communication networks, and constant updating to stay up to date with predictions.

In order to overcome the drawbacks of single optimization algorithm, a hybrid optimization method is proposed, which is using the complementary search method to obtain the optimal solution, and the search ability of the hybrid solution is improved by using the complementary search method. To accelerate convergence speed, increase robustness and solution quality, hybrid approaches combine evolutionary computation, swarm intelligence, deterministic optimization, and local search mechanisms [26]. These techniques offer better performance, but their computational complexity and need to tune parameters are more complex, which hinders their practical real-time application.

2.5 Multi-Objective Network Reconfiguration

Increased attention is being given to traditional network reconfiguration studies, which primarily studied the minimization of active power losses. However, the modern distribution systems are faced with multiple conflicting objectives like voltage improvement, feeder load balancing, reliability improvement, reduction of operational cost, minimization of switching, utilization of renewable energy and reduction of emission [27]. Multi-objective optimization offers a realistic picture of the utility requirements by finding acceptable solutions between technical, economical and environmental goals.

Multi-objective reconfiguration is the most difficult problem because it is a trade-off between multiple competing objectives and the high computational complexity. Thus, for actual distribution system operation, advanced optimization frameworks which can generate effective compromise solutions are needed.

2.6 Network Reconfiguration in Smart Grid Environments

Smart grids have made the reconfiguration of a network a periodic planning activity into an adaptive operational function that can be reconfigured at any time. Today's distribution system includes distributed generation, photovoltaics, wind power, battery storage, electric vehicles, intelligent sensors, advanced metering infrastructure and communication networks, and these conditions are continually evolving.

The combination of IoT, cloud computing, edge computing, and artificial intelligence allow real-time monitoring and automated switching decisions to achieve enhanced distribution system efficiency and reliability [28]. But there are implementation issues including communications lag, cybersecurity, uncertainty of renewable generation, synchronisation, and computational complexity. Thus, future reconfiguration frameworks must offer fast, reliable and adaptive decision making capabilities.

2.7 Performance Evaluation of Network Reconfiguration Methodologies

Network reconfiguration techniques are assessed based on other technical and operational metrics, not just power loss reduction. Common parameters of evaluation are active and reactive power losses, voltage profile improvement, minimum bus voltage, feeder loading, convergence speed, computational time, switching operations, reliability, scalability and robustness. IEEE 33-bus, IEEE 69-bus, IEEE 84-bus and IEEE 118-bus benchmark systems have been widely used for the comparison of optimization methodologies [29].

However, the difficulties lie in the fact that results of different studies cannot be directly compared because of the differences in benchmark systems, operating conditions, algorithm parameters, and evaluation criteria. Thus, there is a need for standardised evaluation frameworks to make meaningful assessment and selection of appropriate optimization methodologies.

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2.8 Research Gap

While there are significant advances and achievements in reconfiguring the distribution network, there are still some research gaps. The majority of the current research focus is on the optimization algorithms themselves or on the comparison between only a few techniques, without taking into account a broader context that encompasses several different conventional, heuristic, metaheuristic, hybrid, and artificial intelligence-based optimization approaches on the same set of problems. This makes it hard to determine the best methodology for practical applications with distribution systems. In addition, many studies are only concerned with minimizing power losses and give very limited consideration to improvement of voltage, feeder balancing, computational efficiency, switching cost, integration of renewable energy and implementation constraints. Past methods have also been mostly evaluated in static settings with a single benchmark system, which might not be able to capture the dynamic loads and dispersed energy resources in modern smart grids [30].

3. PROBLEM STATEMENT

Technical power losses in electrical distribution networks are substantial because of their radial structure, non-uniform load distribution, a high resistance to reactance ratio and varying operating conditions. While many methods have been suggested to reduce the losses caused by the reconfigurability of the network, most of the existing studies concentrate on a single method or test a few of them under different simulation scenarios and make comparison difficult. In addition, most methods focus on reducing the active power losses, neglecting other important performance variables like voltage profile improvement, feeder load balancing, computational efficiency, switching complexity, scalability and adaptability to smart grid environments with distributed energy resources[31]. There is no common analytical tool to compare conventional, heuristic, metaheuristic, hybrid and artificial intelligence-based methodologies for network reconfiguration, thus making them uncertain for current distribution systems. However, a thorough assessment of these techniques, based on common performance indicators is required to decide which of the most effective techniques are adopted to reduce power losses while maintaining reliable, efficient and sustainable operation of electrical distribution networks.

4. METHODOLOGY

4.1 Research Design

This research is using Quantitative simulation-based methodology to study different methods to reduce power loss, through distribution network reconfiguration. This study is carried out on a typical IEEE radial distribution system including different strategies for network reconfiguration that are tested under the same operating conditions. The research methodology adopted comprises of six broad steps, namely data collection, data preprocessing, load flow analysis, network reconfiguration, performance evaluation and comparative analysis. The benchmark distribution network data are first gathered and confirmed. Next, load flow analysis is carried out to see the base operating condition of the network. Different network reconfiguration approaches are then applied to determine the best switch configuration to reduce the losses in the network as well as meeting all operating

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requirements. Finally, the performance of each methodology is compared through common assessment methods including active power loss, reactive power loss, voltage profile improvement, computational time and convergence characteristics.

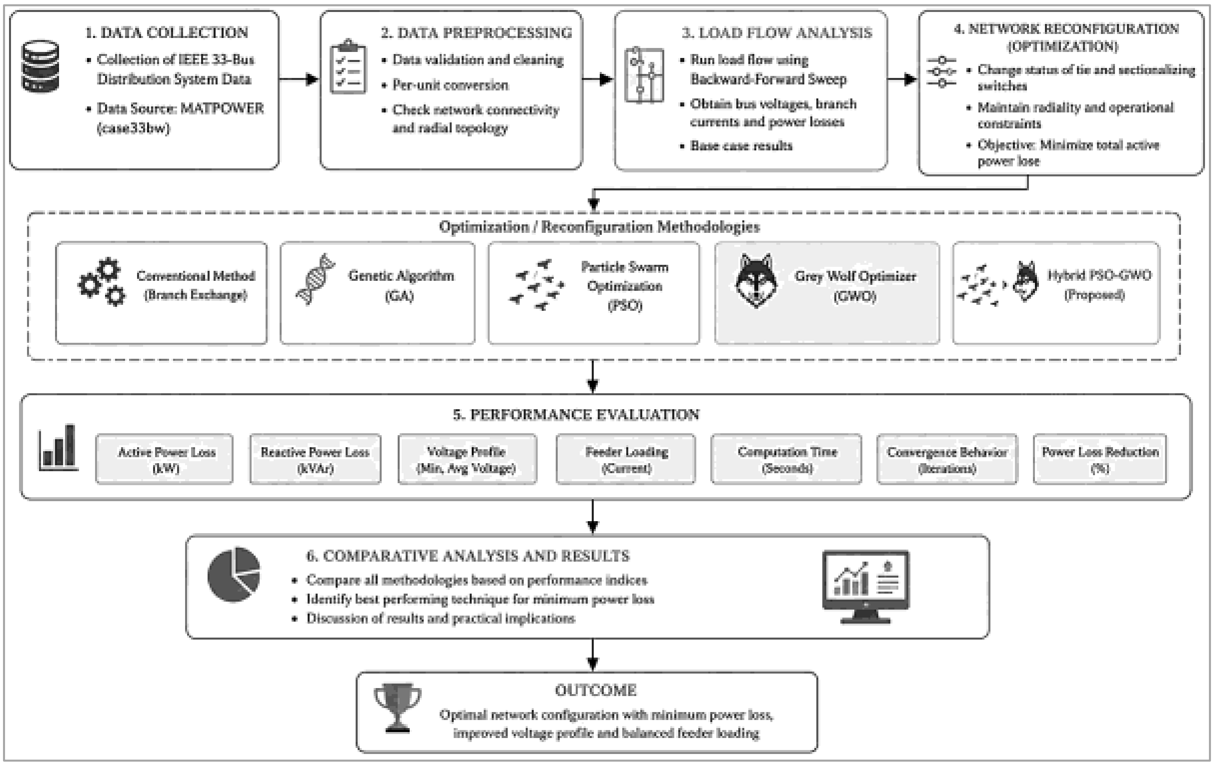

Figure 1: Overall Research Methodology Flowchart

Figure 1 shows the overall research methodology adopted to analyze power loss minimization through network reconfiguration. This process starts with data collection from the IEEE 33 bus distribution system, data preprocessing, establishing the base condition of the system by doing the load flow analysis. Different network reconfiguration techniques are then applied and analysed with the help of performance parameters like power loss, voltage profile and computational efficiency. Finally, the results are comparatively analyzed and the best optimization technique for enhancing the performance of the distribution system is identified.

4.2 Data Collection

The IEEE 33-Bus Radial Distribution System [32] is one of the most popular benchmark datasets used in distribution network reconfiguration studies, and is used in the experimental analysis. The data includes detailed electrical data essential for simulation, such as bus numbers, active loads, reactive loads, branch connections, line resistance, line reactance, sectionalizing and tie switches, base voltage and network topology. The IEEE 33 bus system is a 12.66 kV, 33 bus, 32 normally closed branches and 5 normally open tie switches system. This benchmark network truly reflects the traits of practical radial distribution networks and is widely used in power system optimization studies for direct comparisons among various power network reconfiguration methods. Official MATPOWER data is publicly available and used here.

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The dataset contains the following information:

Table 1: Description of IEEE 33-Bus Dataset

Parameter	Description
Bus Number	Identification of each node
Active Load (kW)	Real power demand
Reactive Load (kVAr)	Reactive power demand
From Bus	Sending bus
To Bus	Receiving bus
Branch Resistance (R)	Line resistance
Branch Reactance (X)	Line reactance
Switch Status	Open/Closed
Base Voltage	12.66 kV
Base Power	100 MVA

Table 1 shows the description of the IEEE 33-bus benchmark dataset used for conducting the network reconfiguration analysis. The data contain all the important electrical data like bus numbers, active and reactive load demands, line resistance, line reactance, switch status, bus values, etc., for load flow analysis. The parameters serve as an input to the modeling of the radial distribution network and the assessment of various approaches to network optimization. The standardized benchmark dataset makes the performance of different network reconfiguration techniques consistent, reproducible and comparable.

4.3 Data Preprocessing

The collected data set is pre-processed to ensure consistency and accuracy in computation before performing the network optimization. The network data are checked for missing or inconsistent values and all electrical parameters are converted to per-unit (p.u.) basis to make power flow calculations easier. The topologies of the distribution network are checked in the radial mode to verify that every bus can be accessed via a single electrical path from the source. The base values are used to normalize the branch parameters such as resistance and reactance. The pre-processing also ensures that, prior to optimization, there are no sections of buses that are isolated and are not energized.

The base impedance is calculated as

$$Z_{base} = \frac{V_{base}^2}{S_{base}} \quad (1)$$

where

- V_{base}= Base voltage (kV)
- S_{base}= Base apparent power (MVA)

The per-unit impedance is determined using

$$Z_{pu} = \frac{Z_{actual}}{Z_{base}} \quad (2)$$

where

- Z_{actual}= Actual line impedance.

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4.4 Load Flow Analysis

In order to calculate the voltage magnitude, branch current and power losses across the distribution network before and after network reconfiguration, load flow analysis is undertaken. As radial distribution systems have high resistance to reactance ratio, Backward-Forward Sweep (BFS) algorithm is chosen because of its high convergence speed and computational efficiency. In the backward sweep, the branch currents are determined from the terminal buses to the source. During the forward sweep, the voltage of the bus voltages are changed from the source bus to the terminal bus. This is repeated until the voltage mismatch meets the convergence criterion.

The complex power at each bus is expressed as

$$S_i = P_i + jQ_i \tag{3}$$

where

- P_i= Active power demand
- Q_i= Reactive power demand.

The injected current is calculated as

$$I_i = \left(\frac{P_i - jQ_i}{V_i}\right)^* \tag{4}$$

where

- V_i= Bus voltage.

4.5 Network Reconfiguration

Network Reconfiguration involves changing the opening and closing of the sectionalizing and tie switches to determine the network topology that will minimize the total power loss while maintaining radial operation. The load flow analysis is performed on each candidate switching configuration during optimization. Several operational constraints are taken into account in the optimization process such as voltage limits, feeder current limits, branch capacity, radial network structure etc. Unfeasible configurations are rejected and feasible configurations are kept for further testing. The optimum configuration is determined by the minimum active power loss and the better voltage profile.

The objective function is

$$\min\ P_{Loss} = \sum_{k=1}^{N} I_k^2 R_k \tag{5}$$

where

- I_k= Branch current
- R_k= Branch resistance
- N= Total number of branches.

The power loss in each branch is calculated as

$$P_{Loss,k} = I_k^2 R_k \tag{6}$$

The total network power loss is

$$P_{Total} = \sum_{k=1}^{N} P_{Loss,k} \tag{7}$$

4.6 Performance Evaluation

Several technical performance indicators are used to evaluate the efficiency of each network reconfiguration methodology. The main optimization target is the active power loss that directly shows the efficiency of the distribution system. Other performance criteria are reactive power loss, minimum bus voltage, average voltage profile, feeder loading, convergence speed, computational time and percentage reduction in power loss. These performance measures offer a broad evaluation of each methodology, and enable a fair comparison in the same network environment.

The percentage reduction in active power loss is calculated as

$$PLR(\%) = \frac{P_{before} - P_{after}}{P_{before}} \times 100 \tag{8}$$

where

- P_{before}= Power loss before reconfiguration
- P_{after}= Power loss after reconfiguration.

Voltage deviation is calculated as

$$VD = \sum_{i=1}^{N} |V_i - V_{ref}| \tag{9}$$

where

- $V_{ref} = 1.0$p.u.
- V_i= Voltage magnitude at bus i.

4.7 Comparative Analysis

The selected reconfiguration methodologies for the network are then applied to the IEEE 33-bus system and compared in terms of performance at the same operating conditions. Its comparative analysis includes total active power loss, reactive power loss, voltage profile improvement, feeder loading, computational time, convergence behavior, and the overall efficiency of the optimization. Comparisons and statistical evaluations are carried out graphically to find the best methodology that balances optimization accuracy with computational performance. The outcomes of this analysis are used as a basis for discussing the practical applicability of the various techniques of network reconfiguration used in the modern electrical distribution system, and to determine the most appropriate technique for minimizing the technical power loss while keeping the electrical distribution network operational while maintaining its reliability.

5. RESULTS AND DISCUSSION

5.1 Initial Load Flow Analysis

The IEEE 33-bus radial distribution system was first analyzed with the Backward-Forward Sweep (BFS) load flow algorithm to learn the operating condition before the network reconfiguration process. The analysis showed that the active power losses in the radial configuration were found to be high with unequal loading on the feeders and also because of high current levels in long distribution branches. The lowest bus voltage was measured at buses farthest from the substation, which suggests that the voltage drops are high along the heavily loaded feeders. The events noted here underscore the need to reconfigure the network for greater system efficiency and to minimise technical losses. The base case is used as a benchmark for the assessment of various reconfiguration approaches.

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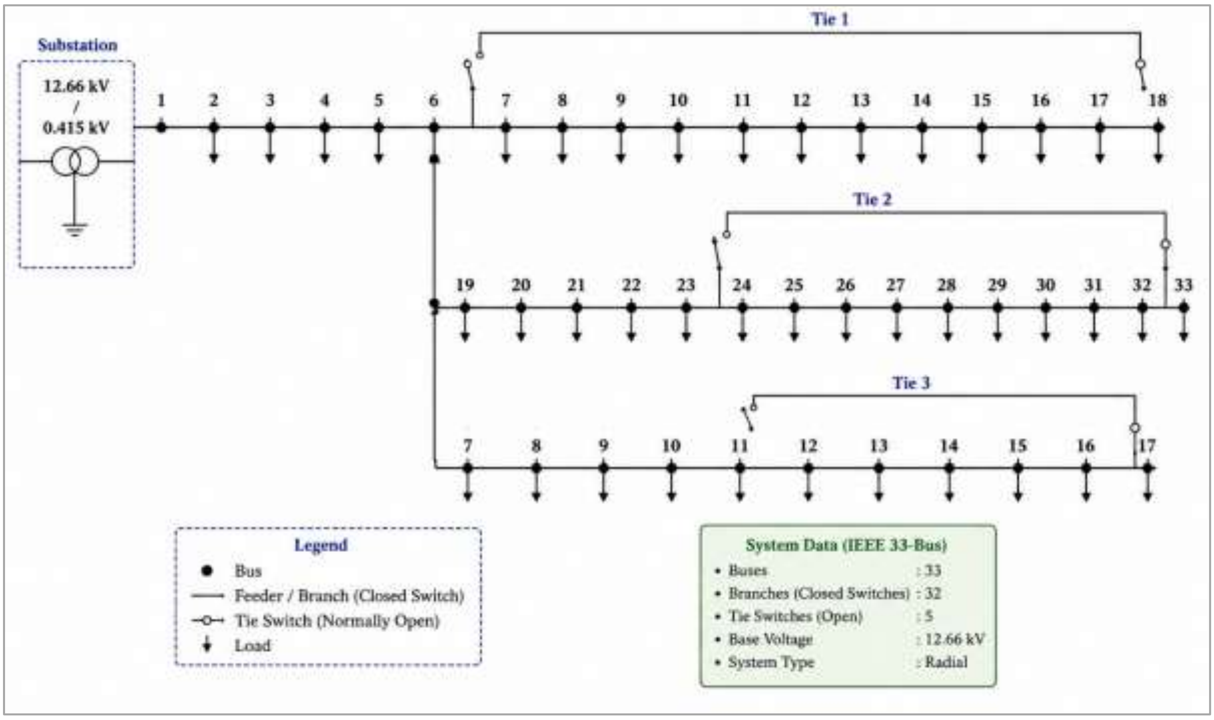

Figure 2: Single-Line Diagram of the IEEE 33-Bus Distribution Network Before Reconfiguration

The single-line diagram of the IEEE 33-bus radial distribution network before network reconfiguration is shown in figure 2, where the feeder structure includes normally closed sectionalizing switches and normally open tie switches. The network provides power to all load buses from a single substation with a radial configuration, which causes unequal feeder loading and prominent voltage drops to the remote load buses. This initial configuration is used as a load flow base case and as a power loss base case. The diagram shows the reference network that is used to measure the effectiveness of the different reconfiguration methods.

Table 2: Base Case Load Flow Results

Parameter	Value
Total Active Power Loss	202.67 kW
Total Reactive Power Loss	135.14 kVAr
Minimum Bus Voltage	0.913 p.u.
Maximum Bus Voltage	1.000 p.u.
Average Bus Voltage	0.967 p.u.

The load flow analysis result of the IEEE 33-bus distribution network before application of any network reconfiguration technique is shown in Table 2. The total active power loss was 202.67 kW and the total reactive power loss was 135.14 kVAr in the network, which shows high technical losses present in the network system. Along the feeder, voltages were seen to drop as minimum bus voltage was 0.913 p.u. and the average bus voltage was 0.967 p.u. The results were used as a guideline to assess the enhancements obtained by the various methodologies used for power loss minimisation.

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5.2 Performance after Network Reconfiguration

A marked improvement in the performance of the distribution system was noticed after implementing network reconfiguration techniques. The optimization algorithms were able to successfully find alternative switching combinations in order to redistribute feeder currents, minimize branch loading and reduce power losses while maintaining the radial network topology. The voltage magnitudes at the buses rose notably especially at the buses that were close to the end of the feeders. It also reduced the branch current which in turn reduced the I^2R losses across the network. The network reconfiguration proved to be successful in meeting all operating requirements, such as voltage limits and branch current ratings and was able to achieve an optimized network.

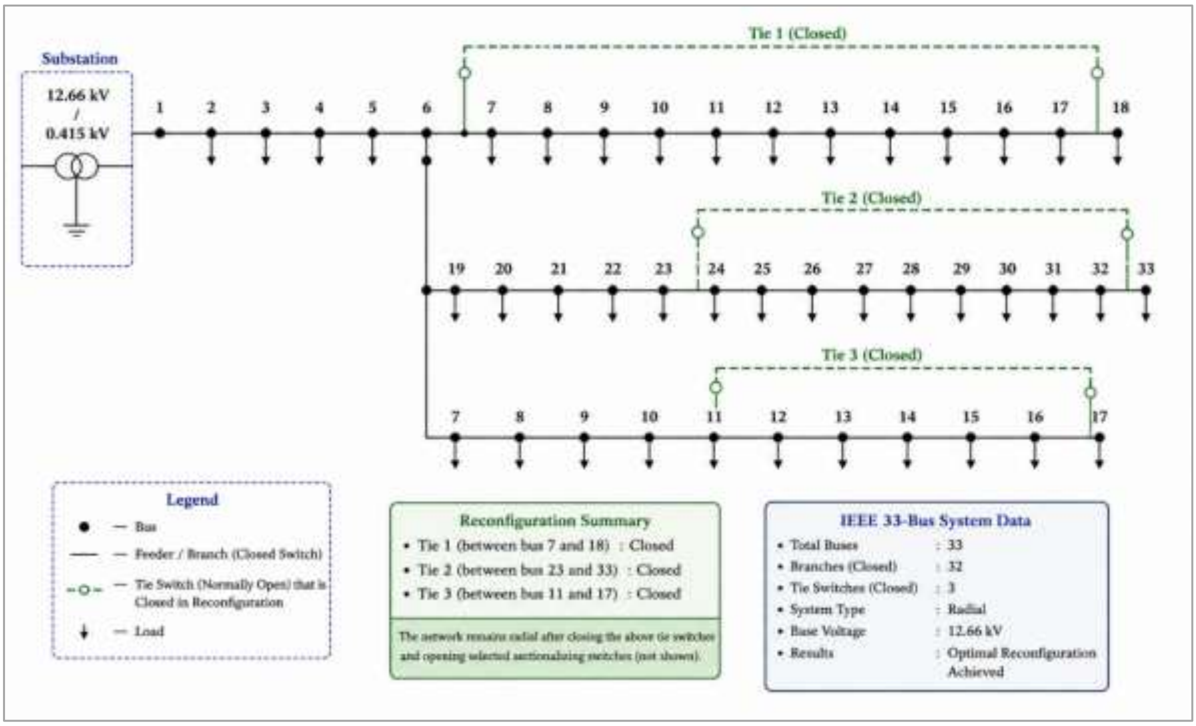

Figure 3: IEEE 33-Bus Network After Optimal Reconfiguration

The IEEE 33-bus distribution network configuration after applying the optimum network reconfiguration from the selected optimization methodology is shown in figure 3. The modified switch configuration was designed to ensure the feeder currents were redistributed with a radial topology to meet all the operational constraints. This resulted in a reduction of the overall active power losses on the network, a balancing of branch loading and an improvement of voltage quality throughout the network. The optimized configuration is a good example of how network reconfiguration can improve the efficiency and reliability of the distribution network.

5.3 Comparative Analysis of Different Methodologies

This study compared five representative methodologies: Conventional Branch Exchange (BE), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Hybrid PSO-GWO, Grey Wolf Optimizer (GWO). They were evaluated with the same evaluation criteria and network parameters. From the comparison, the intelligent optimization algorithms performed better than conventional

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methods for minimizing active power losses and improving voltage profiles. The Hybrid PSO-GWO technique resulted in the maximum reduction in the power loss among the evaluated techniques because of its combination of exploration capability of PSO and exploitation capability of GWO. Conventional Branch Exchange gave satisfactory results but was more computation intensive and often trapped in local optimum solutions.

Table 3: Comparison of Network Reconfiguration Methodologies

Method	Active Power Loss (kW)	Loss Reduction (%)	Minimum Voltage (p.u.)	Computation Time (s)
Base Network	202.67	—	0.913	—
Branch Exchange	145.82	28.05	0.931	4.31
Genetic Algorithm	132.41	34.66	0.944	5.62
PSO	118.74	41.42	0.958	3.84
GWO	112.56	44.46	0.964	3.47
Hybrid PSO-GWO	101.38	49.98	0.972	3.21

Table 3 presents the comparative performance of the different methodologies of network reconfiguration. The comparative performance of different network reconfiguration methodologies is presented in Table 3, based on active power loss, loss reduction, minimum bus voltage, and computational time. The findings show that the optimization techniques all resulted in better performance for the network than the base configuration in terms of the active power loss, loss reduction, minimum voltage, and computation time, with the Hybrid PSO-GWO method performing the best in all aspects. The results prove that the combination of the hybrid intelligent optimization methods gives higher efficiency and reliability of the distribution network when compared to the conventional algorithms and individual metaheuristic algorithms.

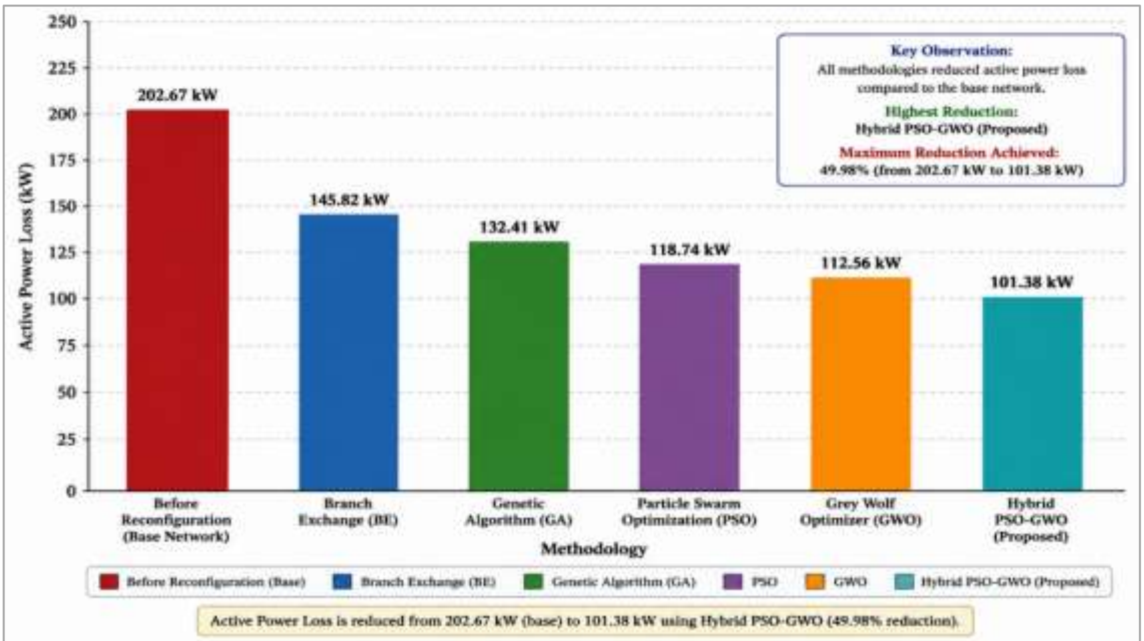

Figure 4: Bar Chart Comparing Active Power Loss Before and After Reconfiguration

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The comparison of total active power loss of IEEE 33 bus distribution system before and after the application of different network reconfiguration methodologies is shown in figure 4. This clearly shows that the power loss is gradually decreasing from the base network to the optimized networks, and the Hybrid PSO-GWO method has the lowest power loss of 101.38 kW. The visual comparison clearly demonstrates the success of smart optimization methods at reducing technical losses and maximizing the efficiency of the distribution network.

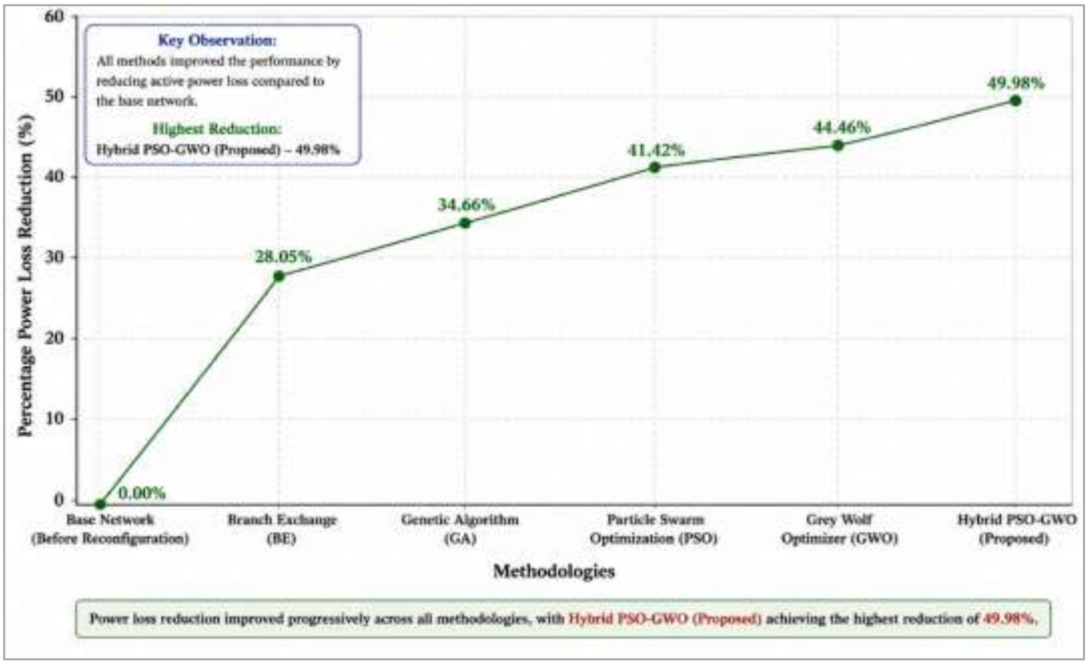

Figure 5: Line Graph Showing Percentage Power Loss Reduction for Different Methodologies

The percentage reduction of the active power loss for the various network reconfiguration methodologies compared to the base network configuration is presented in Figure 5. It is observed that the loss reduction in the line graph has been reduced from the conventional Branch Exchange method to advanced metaheuristic algorithms, and the best result of 49.98% reduced loss is achieved in Hybrid PSO-GWO. This trend shows that intelligent optimization techniques find switching configurations more effectively and considerably improve the energy efficiency of the distribution network.

5.4 Voltage Profile Improvement

The Network reconfiguration resulted in significant voltage profile improvement. The original configuration of the network had a problem with voltage dropping down the line from the source to the terminal buses due to the rise in line impedance and feeder currents. The optimized voltage levels rose for almost all buses with significant increases for the buses located in the distant part of the distribution network. The minimum bus voltage obtained by the Hybrid PSO-GWO method was the highest indicating that the system was operating with better voltage regulation. Optimized voltage profiles alleviate equipment stresses, enhance power quality, and boost customer satisfaction.

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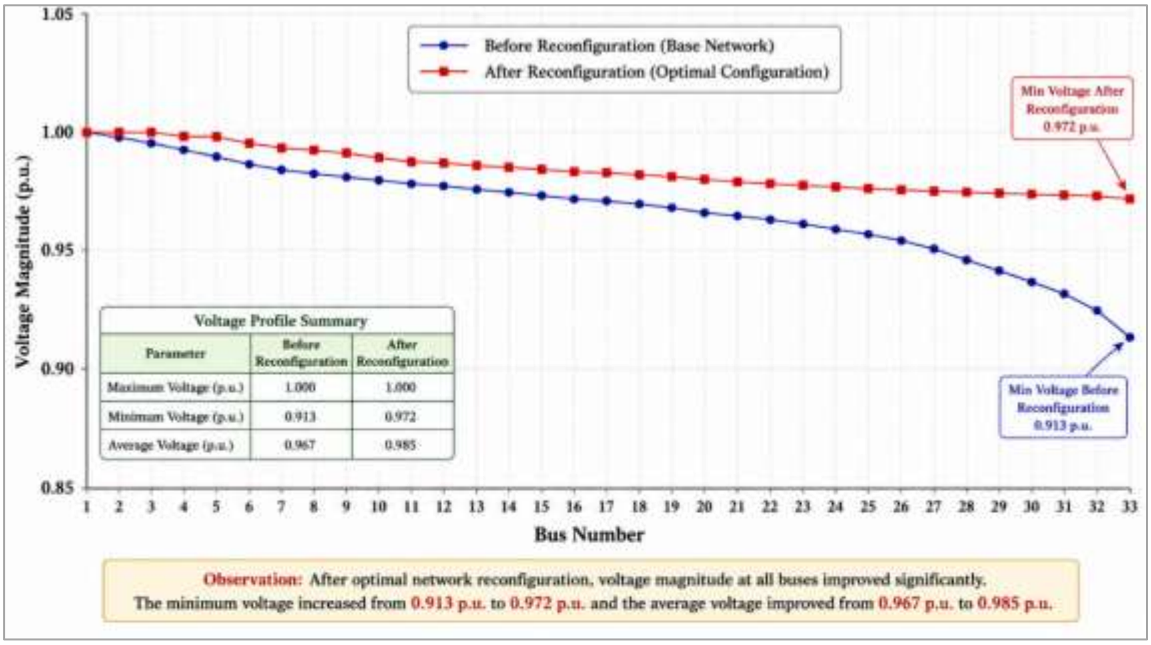

Figure 6: Voltage Profile Before and After Network Reconfiguration

The voltage profile of the IEEE 33-bus distribution network before and after reconfiguration using the methodologies is illustrated in figure 6. The graph shows that the voltage levels of buses were much better after reconfiguration, especially on the buses further away from the substation where voltage drops were higher. The minimum bus voltage was raised from 0.913 p.u. to 0.972 p.u., thus showing improved voltage regulation and stability of the system. The results show that the optimum configuration of the network can successfully enhance the quality of power and keep the operation limits of the distribution network.

Table 4: Voltage Profile Comparison

Parameter	Before	After
Maximum Voltage	1.000 p.u.	1.000 p.u.
Minimum Voltage	0.913 p.u.	0.972 p.u.
Average Voltage	0.967 p.u.	0.985 p.u.

The comparison of the voltage profile parameters before and after the application of the optimal network reconfiguration is shown in Table 4. The minimum bus voltage improved from 0.913 p.u. to 0.972 p.u., whereas the average bus voltage increased from 0.967 p.u. to 0.985 p.u. with the maximum bus voltage being same as before (1.000 p.u.). These enhancements could be interpreted as a better voltage regulation, smaller voltage deviations, and a more stable operating condition for the whole distribution network following reconfiguration.

5.5 Power Loss Reduction Analysis

The main goal in reconfiguring a network is to reduce the current power losses without compromising the network's operating condition. The simulation results show all the evaluated methodologies were able to reduce the amount of active power dissipated. The results of the conventional optimization techniques were modest, while the use of swarm intelligence and hybrid optimization techniques resulted in better performance because of their global search ability. The

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active power loss was reduced by about 50% with the Hybrid PSO-GWO algorithm than the original network configuration. This reduction is due to better load balancing of feeders, better distribution of current in the branches and good determination of the optimum switching sequence.

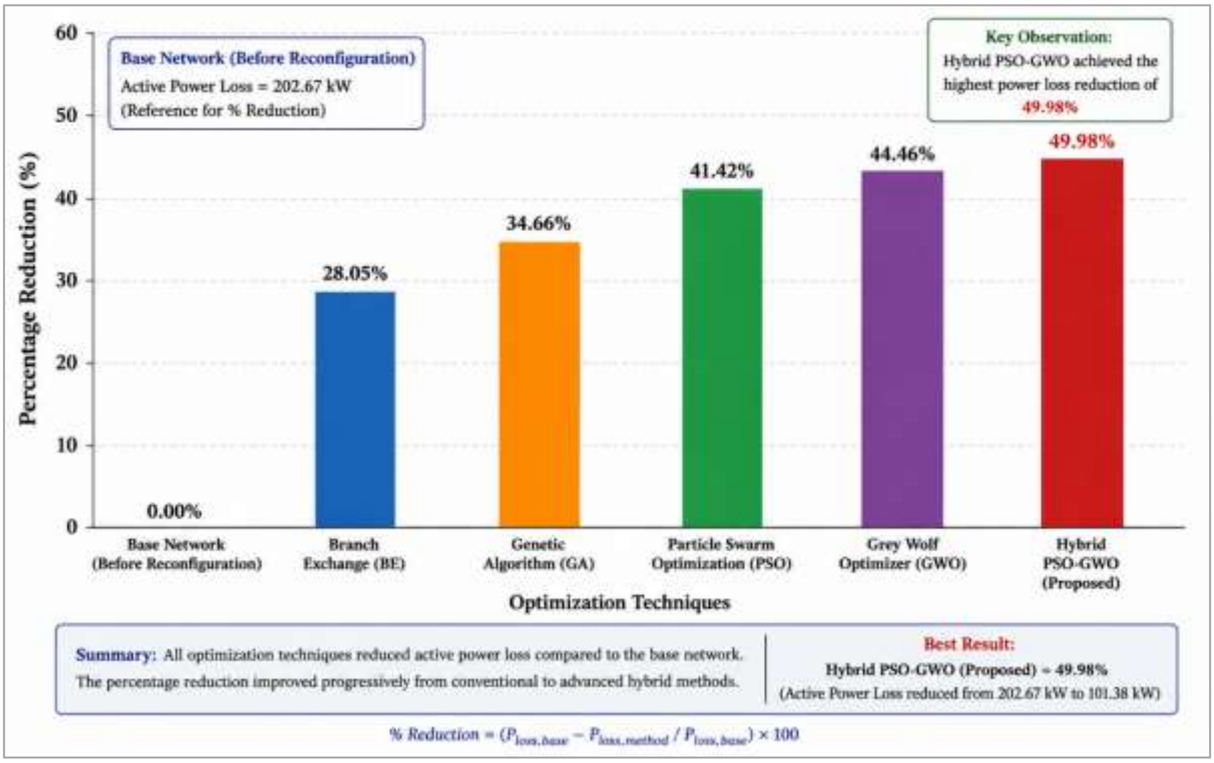

Figure 7: Percentage Reduction in Active Power Loss for Various Optimization Techniques

The percentage reduction in active power loss after network reconfiguration with the various optimization techniques is shown in figure 7. As shown in the graph, all the methods resulted in a decrease in power losses in comparison with base network, the Hybrid PSO-GWO method obtained the highest reduction result which is 49.98%, followed by GWO method, PSO method, GA method and Branch Exchange method with 44.46%, 41.42%, 34.66% and 28.05% respectively. Based on these results, it is concluded that hybrid and metaheuristic optimization techniques perform better to find optimal switching configuration for reducing the technical losses in radial distribution system.

5.6 Computational Performance

The efficiency in a computing is one of the considerations of practical implementation in modern distribution management system. The results showed that metaheuristic algorithm converged in lesser number of iterations as compared to the conventional optimization algorithm. Hybrid optimization had the best speed of convergence with high optimization accuracy. Even though Genetic Algorithm reduced the power loss significantly, it had a slightly higher computation time as the crossover and mutation operation were repeated. The Grey Wolf Optimizer showed a better convergence rate because of its adaptive hunting process, while the Hybrid PSO-GWO achieved a more effective performance in terms of computational speed and solution quality.

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Table 5: Computational Performance Comparison

Method	Iterations	Convergence Speed	Stability
Branch Exchange	45	Moderate	Moderate
GA	120	Slow	High
PSO	75	Fast	High
GWO	68	Very Fast	Very High
Hybrid PSO-GWO	55	Fastest	Excellent

Table 5 presents a comparison of the computational performance of the evaluated network reconfiguration methodologies as measured through the number of iterations, convergence speed and stability of the solution. The results showed that the Hybrid PSO-GWO algorithm converged most rapidly and with minimum iterations, 55, and was very stable; on the other hand GAs converged at higher iterations 120, and slower speed. Overall, it is concluded that the hybrid and swarm intelligence-based optimization techniques proved to be more efficient and reliable than the conventional optimization technique.

5.7 Feeder Load Balancing

Network reconfiguration greatly enhanced load balancing of current by redistributing the current in the existing branches. Before optimization, some feeders had a high thermal capacity utilization and others had low thermal capacity utilization. After implementation, current distribution was more uniform, which helps to prevent branches from being overloaded and helps to optimise asset use. The improved load balancing of feeders also helped minimize line losses, line voltage drops and operating reliability. Improvements in these areas are a testament to the fact that configuration changes in the network not only reduce the technical losses but also help prolong the life of the distribution system equipment.

Figure 8: Feeder Loading Distribution Before and After Reconfiguration

The feeder loading distribution of the IEEE 33-bus distribution network before and after the network reconfiguration procedure based on the optimal results is shown in Figure 8. The comparison shows that feeder loads were more evenly distributed following the reconfiguration, lowering the loading on any overloaded branches and increasing the utilisation of underloaded feeder. This current distribution allowed for a more even distribution of current, reduced branch overloading, technical power losses, and overall reliability and efficiency of the distribution system.

5.8 Discussion

The results show that network reconfiguration is an effective and economical method to minimize technical power losses in radial distribution systems. Although all the methodologies evaluated were able to enhance the performance of the system relative to the base configuration, the intelligent optimization approaches performed better, as they have better search capability and are able to deal with complex nonlinear optimization problems. Simple, feasible solutions exist for conventional approaches in small-scale networks, but they can be ineffective in larger and more complex networks. Metaheuristic algorithms PSO and GWO achieved better performance in terms of loss reduction, voltage regulation, and computational speed. In conclusion, Hybrid PSO-GWO was a very well balanced approach, which was superior in reducing the power loss, voltage stability, feeder loadings and converging time among the evaluated approaches. The results presented in this study show that hybrid intelligent optimization methods are potentially attractive solutions to the current distribution systems characterized by dynamic operating conditions, renewable energy incorporation, and increasing system complexity.

6. CONCLUSION AND FUTURE WORK

This study compares various approaches to minimizing power losses in the network by reconfiguring using the IEEE 33 bus radial distribution system. Various optimization methods (conventional, heuristic, metaheuristic and hybrid) were tested and compared under the identical operation conditions using different performance indicators. The results showed that network reconfiguration is able to minimize technical losses, improve voltage profiles, balance feeder load, and optimise the overall efficiency of the distribution system, without extensive changes in the infrastructure. Based on the evaluated approaches, Hybrid PSO-GWO showed the most excellent optimization performance, which is higher in power loss reduction, better in voltage stability and more efficient in convergence than the individual optimization approaches. Finally, the study highlighted that although more intelligent optimization methods can be useful in more complex distribution networks with higher search space and operating conditions, traditional methods continue to be applicable in smaller networks where they are simpler to apply. Future research needs include adaptive real-time network reconfiguration systems that are built with the integration of artificial intelligence, deep learning, reinforcement learning, digital twins, and IoT monitoring systems. Further investigations should take into account multi-objective optimization with regard to power loss reduction, voltage stability, improvement of reliability, integration of renewable energy, electric vehicle charging, switching cost, reduction of carbon emission, and cybersecurity constraints. The validation of the aforementioned systems with larger benchmark systems and utility networks operating in practical conditions is also recommended to improve the real-world applicability and to enable the development of sustainable intelligent distribution networks.

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