PU Journal of Science and Engineering
Purbanchal University Science and Engineering Campus
Biratnagar
ISSN: XXXX-XXXX

Enhancements of Distribution System Performance by Optimal Network Reconfiguration

Dhanraj Bista[1]*, Sandip Neupane[2], Mohamad Zaid[3]

Received: 03 Nov 2025 / Accepted: 15 Jan 2026

Abstract

This study introduces an optimization-based strategy for improving the operational performance of electrical distribution networks through topological reconfiguration. The proposed approach concurrently addresses two primary objectives: reducing real power losses and increasing service reliability. A weighted-sum formulation was used to consolidate these goals into a single objective function. Two population-based metaheuristics, Genetic Algorithm (GA) and particle swarm optimization (PSO), are implemented to identify optimal switching configurations. Network radiality and operational limits are preserved using connectivity rules derived from graph theory, including loop, common branch, and prohibited branch vectors. For each candidate topology, a sweep-based power flow algorithm computes the nodal voltages, branch currents, and total active losses. Reliability is quantified analytically using the minimal cut set technique, with indices such as SAIFI, SAIDI, and ENS evaluated accordingly. The methodology was first tested on the standard IEEE 33-bus network and then deployed on an operational 43-bus, 11 kV feeder. Comparative analysis revealed that the PSO algorithm outperformed the GA in terms of computational efficiency, proving its practical applicability for distribution system optimization.

Keywords: Active power loss • Network reconfiguration • Particle swarm optimization • System average interruption frequency index • System average interruption duration index • Energy not supplied

1. Introduction

Distribution systems face major challenges worldwide, especially in countries such as Nepal, where an unreliable power supply, high technical losses, and frequent voltage drops affect both residential and industrial consumers. In Nepal, distribution losses remain significant because of radial feeder networks, outdated infrastructure, and load imbalances that reduce service quality and efficiency. Among various solutions, network reconfiguration has emerged as an effective method for reducing losses and improving voltage

[1,2,3] Department of Electrical Engineering, School of Engineering, Purbanchal University, Nepal

*Corresponding author: bistaraj45@gmail.com

levels without costly infrastructure upgrades by rearranging the network topology to better balance loads and optimize power flow (Rojas et al., 2018; Ma, 2017).

Network reconfiguration involves changing the status of sectionalizing and tie switches to modify the network topology (Oloulade et al., 2019). The objective is to reduce active power losses, improve voltage stability, balance the loads, and enhance reliability. Large distribution systems contain many switches, making manual reconfiguration impractical and time-consuming. Therefore, metaheuristic optimization algorithms are widely used to efficiently determine optimal configurations.

Both Genetic Algorithm (GA) and particle swarm optimization (PSO) are popular approaches for solving the distribution network reconfiguration (DNR) problem. GA mimics natural evolution to explore diverse solutions, whereas PSO uses swarm intelligence to converge quickly to promising configurations (Oloulade et al., 2019; Kahouli et al., 2021). This study applies both GA and PSO to determine the optimal switch settings while preserving the radial structure of the network using graph theory-based feasibility rules and the branch exchange method (Jaiswal et al., 2021). Load flow analysis using the backward–forward sweep (BFS) method is employed to evaluate losses, bus voltages, and branch currents under different configurations (Gupta et al., 2014). The main steps followed in this study are network modelling, feasibility assessment, optimization using GA and PSO, and comparative analysis of results in terms of loss reduction and reliability improvement.

2. Materials and Methods

This section details the framework used to investigate and optimize the reconfiguration of radial distribution networks. This study employed a standard test network with complete line, load, and reliability data. Power flow analyses were conducted for different switching states to ensure operational compliance with the voltage and current limits. The reconfiguration challenge is framed as a multi-objective optimization problem, where the dual goals of minimizing active power losses and improving reliability (quantified by SAIFI) are combined into a single weighted objective function for an efficient computation. Metaheuristic algorithms implemented in MATLAB were used to generate, evaluate, and select optimal network configurations by adjusting the switch statuses.

2.1 Problem formulation for network reconfiguration

Network reconfiguration can be approached as either a single- or multi-objective optimization problem. Single-objective methods focus on optimizing one key performance indicator, such as power loss and reliability (SAIFI). The multi-objective function is formulated using the weighted-sum method to ensure a balanced trade-off between the two selected objectives (Jaiswal et al., 2021).

2.1.1 Single-Objective Function Formulation

The primary objective is to optimize the system performance by minimizing either the total active power loss (P_T) or the SAIFI index while ensuring compliance with the operational constraints on the voltage levels and branch currents.

a. Total Active Power Losses:

The total power loss in system can be formulated as:

$$\mathrm{OF}_1 = P_T = \sum_{i=1}^{N} \sum_{j=i+1}^{N} R_{ij}\, I_{ij}^2 \tag{1}$$

Where, R_i = branch resistance (Ω)

I_{ij} = branch current (A)

N = number of nodes

b. System Average Interruption Frequency Index (SAIFI):

SAIFI quantifies the average frequency of supply interruptions for customers within a specified timeframe. Its value is derived from the following formula:

$$\mathrm{OF}_2 = \mathrm{SAIFI} = \frac{\sum \lambda_i N_i}{\sum N_i} \tag{2}$$

Where: λ_i = the failure rate at load point i(interruptions/year)

N_i is the number of customers connected to load point i.

2.1.2 Multi-Objective Function Formulation

In this study, equal importance was assigned to minimizing active power loss and reducing SAIFI by using identical weighting factors for both objectives. The combined objective function is formulated as follows:

$$\min F(x) = \begin{cases} K, & \text{configuration not feasible,} \\ w_1 \, \mathrm{OF}_1 + w_2 \, \mathrm{OF}_2, & \text{feasible.} \end{cases} \tag{3}$$

Subject to:

- Radiality constraints,
- Bus voltage constraints,
- Feeder current limitations,

where v_i is the voltage at bus i and I_i is the feeder current in branch i.

The objective function incorporates the following components.

- P_T : Total active power loss in the distribution system, W.
- SAIFI : System average interruption frequency index.
- K : A large penalty value applied when a switch configuration is infeasible.
- w_1, w_2 are the weights assigned to the two objective functions.

2.2 Backward-Forward Sweep Load Flow Method

The backward–forward sweep (BFS) method is widely used for radial distribution networks because it is simple, efficient, and avoids the complex matrix inversions required in conventional Newton-Raphson methods. It calculates the bus voltages, branch currents, and power losses iteratively (Ghosh et al., 2023).

A radial network is one in which each node is connected by only one path to the substation, forming a tree-like structure. BFS works in two main steps: backward and forward sweeps. A simple three-bus system is shown in Figure 1.

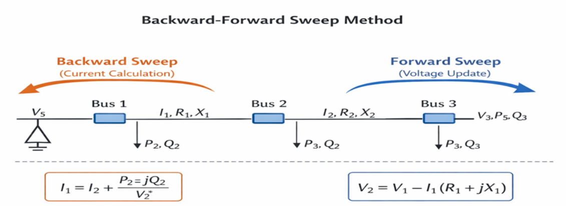

Figure 1: Simple three-bus radial system

Step 1. All bus voltages are initialized (usually set to 1.0 p.u.).

Step 2. Backward Sweep
Perform Backward Sweep to compute the branch currents. In the backward sweep, the branch currents are calculated starting from the end nodes (leaves) towards the substation (root) using the load at each node. For branch j supplying node m_2:

$$I[j] = \frac{P(m_2) - j(Qm_2)}{|Vm_2|*} + \sum_{\text{downstream}} Ik \tag{4}$$

Where:

- Ij = branch current (complex),
- Pm_2, Qm_2 = active and reactive power at the receiving node m_2,
- $Vm_2{}^*$ = complex conjugate of node voltage at m_2,
- $\sum_{\text{downstream}} Ik$ = sum of currents from all downstream branches.

Step 3. Forward Sweep
Perform Forward Sweep to update node voltages. In the forward sweep, bus voltages are updated from the substation to the end nodes using the calculated branch currents:

$$|Vm_2| = [Vm_1 - I[j]\,(r[j] + jx[j])] \tag{5}$$

Where:

- Vm_1 = voltage at the sending node (upstream bus),
- Rj, Xj = resistance and reactance of branch j,
- I_j = branch current calculated in the backward sweep.

Step 4. Check convergence:

$$|V\text{new i} - V\text{old i}| < \epsilon \tag{6}$$

Step 5. Total Power Loss:

$$P_T = \sum_{i=1}^{N} \sum_{j=i+1}^{N} R_{ij} * I_{ij}^2 \tag{7}$$

The total power loss of the system is the sum of the branch power losses. The voltage and the power loss formulae, as mentioned above, are subject to the following constraints:

- Bus voltage constraints, $V_{\min} \leq V_i \leq V_{\max}$,
- Feeder current limitations, $I_j \leq I_{\max}$

2.3 Methodologies for Reliability Evaluation

This study employs an analytical reliability evaluation based on the minimal cut set technique to estimate both load-point reliability and overall system unreliability. The System Average Interruption Frequency Index (SAIFI) is adopted as the primary customer-oriented indicator of service continuity. In addition, the overall system performance was assessed using other standard reliability measures, including the System Average Interruption Duration Index (SAIDI), Average Service Availability Index (ASAI), and Average Energy Not Supplied (AENS).

2.3.1 Computation of Load-Point Reliability Indices

Three basic load-point reliability parameters are used to determine the overall reliability performance of a radial distribution system (RDS) (Gupta et al., 2014).

(a) Average number of outages experienced by a load point per year i, λ_i:

$$\lambda_i = \sum_{j \in Ne} \lambda_{e,j} \tag{8}$$

where:

Ne = set of all elements whose failure will interrupt load point i
$\lambda_{e,j}$ = failure rate of element j (failures/year).

(b) Average annual outage duration at load point i, U_i (h/year): This indicates the total expected outage time experienced at load point iii, per year:

$$U_i = \sum_{j \in Ne} \lambda_{e,j} \cdot r_{i,j} \tag{9}$$

where $r_{i,j}$ = repair time (outage duration) at load point i due to the failure of element j (hours).

c) Average outage duration at load point i, r_i (h): This is the average duration at load point i.

$$r_i = \frac{U_i}{\lambda_i} \tag{10}$$

In general, the reliability of a distribution system is evaluated by examining the frequency of long interruptions and the number of affected customers. The following indices are used to measure the sustained interruption performance in a radial distribution system (RDS):

I. SAIDI (System Average Interruption Duration Index): The average total duration of interruptions per customer:

$$SAIDI = \frac{\text{Sum of total customer interruption durations}}{\text{Total number of customers served}} = \frac{\sum U_i N_i}{\sum N_i} \quad \text{(hours/customer} \cdot \text{year)}$$

II. SAIFI (System Average Interruption Frequency Index): The average number of interruptions per customer:

$$SAIFI = \frac{\text{Total number of customer interruption}}{\text{Total number of customers served}} = \frac{\sum \lambda_i N_i}{\sum N_i} \quad \text{(interruptions/customer} \cdot \text{year)}$$

III. CAIDI (Customer Average Interruption Duration Index): The average duration of an interruption for the affected customers:

$$CAIDI = \frac{\text{Sum of customer interruption durations}}{\text{Total number of customers interrupted}} = \frac{\sum U_i N_i}{\sum \lambda_i N_i} \quad \text{(hr)}$$

IV. ASAI (Average Service Availability Index): The ratio of available service hours to demanded hours:

$$ASAI = \frac{\text{Total number of hours availability}}{\text{Total demanded hours}} = \frac{\sum(8760 \cdot N_i - U_i N_i)}{\sum 8760 \cdot N_i} \quad \text{(P.U)}$$

V. AENS (Average Energy Not Supplied): The average energy not supplied per affected customer:

$$AENS = \frac{\text{Total energy supplied(ENS)}}{\text{Total number of customers served}} = \frac{\sum L_{ai} U_i}{\sum N_i} \quad \text{(MWhr/customer} \cdot \text{year)}$$

2.4 Feasibility of Network Reconfiguration

Reconfiguring a distribution network is challenging because of the vast number of possible switch combinations, which makes exhaustive load flow analysis impractical. To overcome this, efficient methods such as the Branch Exchange Method and the Sequential Switch Opening Method have been developed. In this study, the Branch Exchange Method is employed to maintain a radial network while ensuring all loads remain supplied. To prevent infeasible configurations, such as isolated nodes, loop vectors, common branch vectors, and prohibited group vectors (Jaiswal et al., 2021) are used to guide tie switch selection. Specific rules are applied to avoid node isolation and reduce the search space, enhancing the efficiency of the reconfiguration process while achieving objectives such as loss reduction and reliability improvement.

2.5 Methods for Solving the Optimization Problem

This study applies Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) to determine the optimal network configuration, aiming to reduce power losses and improve system reliability.

2.5.1 GA Approach

The genetic Algorithm (GA) is a population-based optimization technique inspired by the principles of natural evolution. It begins with an initial population of solutions that are iteratively improved through crossover and mutation operations. Elitism is used to preserve the best solutions in each generation. These operations are applied repeatedly in successive generations to create progressively better populations than the previous generation. The overall GA process is shown in Figure 2(Kahouli et al., 2021).

2.5.2 PSO Approach

Particle swarm optimization (PSO) is inspired by the collective foraging behavior of birds and fish. In PSO, each particle represents a potential solution characterized by its position (xi) and velocity (vi). A group of particles, known as a swarm, explores the search space to identify optimal solutions. In this study, each particle encodes the switch configuration as a binary vector. The position of each particle is updated based on its previous experience, the best solution found by the swarm, and its current velocity. The update process is governed by the following equation:

$$v_i^{k+1} = w \cdot v_i^k + c_1.r_1(p_i^k - x_i^k) + c_2.r_2(g_i^k - x_i^k) \tag{7}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{8}$$

In these equations, w represents the inertia weight, c1 and c2 are acceleration coefficients, and r1 and r2 are random numbers between 0 and 1. The term pi(k) denotes the best position achieved by an individual particle, and gi(k) represents the best position found by the entire swarm. The complete computational procedure is summarized in the flowchart in Figure 3.

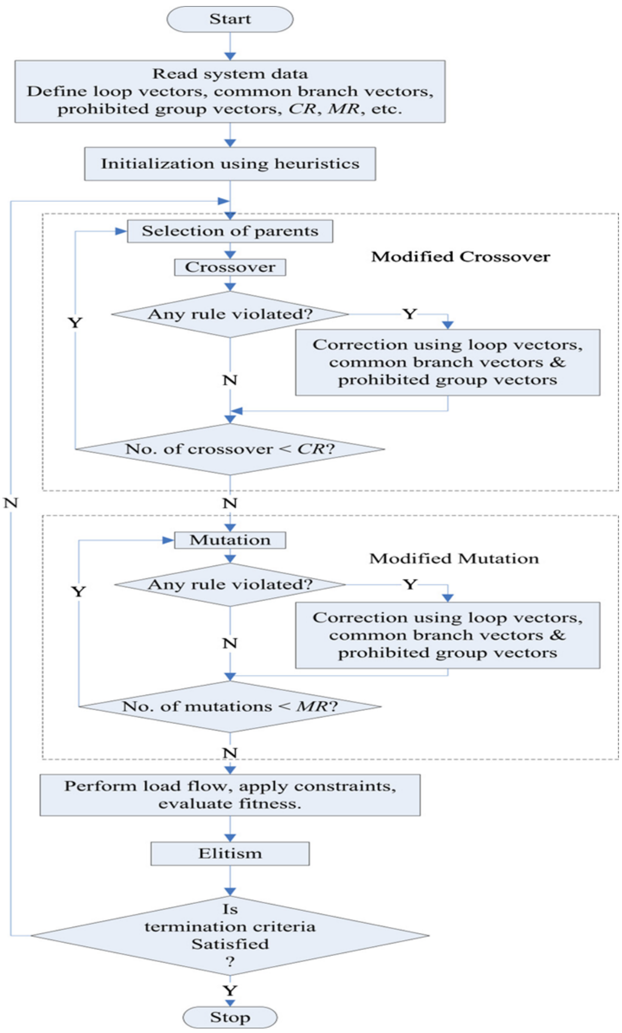

Figure 2: Network reconfiguration by Genetic algorithm optimization (GA) approach

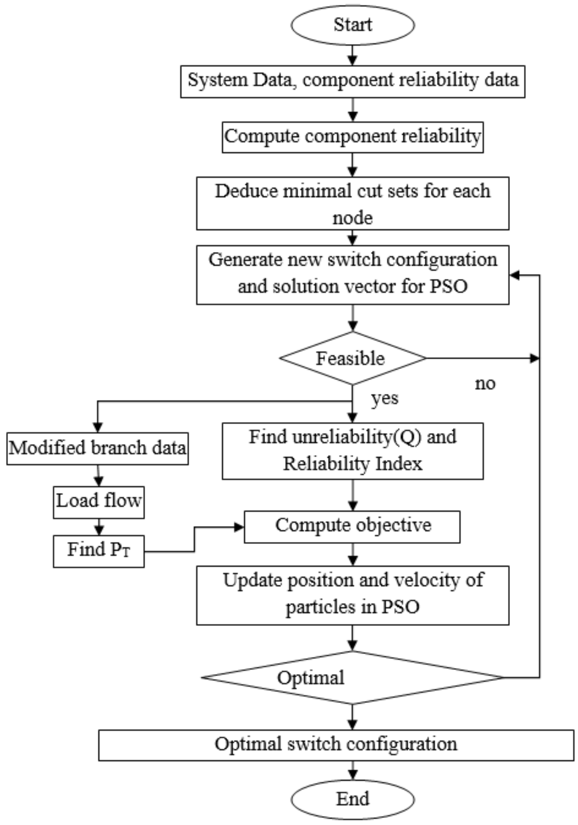

Figure 3: Network Reconfiguration by Particle swarm optimization approach.

3. Simulation Result

The effectiveness of the proposed reconfiguration approach was assessed by comparing the system performance between the original network (base case) and the optimized configuration obtained using both Genetic Algorithm (GA) and particle swarm optimization (PSO). A MATLAB program was developed to implement the optimization procedure for the distribution network reconfiguration. The proposed methodology was tested on the IEEE 33-bus radial system and the 43-bus feeder from the Biratnagar Distribution Center of NEA.

3.1 IEEE 33-Bus Test System

The analysis in this study employed the IEEE 33-bus test network, which is a common benchmark for distribution system studies. This network, illustrated in Figure 4, comprises 33 buses interconnected by 37 branches. Standard line and bus parameters, referenced from sources (**??**), were utilized in the model. In this configuration, every bus serves as a load connection point, except for the substation located at bus 1. The standard nominal data for each bus in this radial distribution system (RDS) are detailed in Table 1.

Table 1: Bus Data for IEEE-33 Bus Radial Distribution System

Parameter	Value
Base voltage (kV)	12.66
Number of nodes	33
Branches	32
Number of tie lines	5
Total active load (kW)	3715
Total reactive load (kvar)	2300
Tie lines available	33, 34, 35, 36, 37

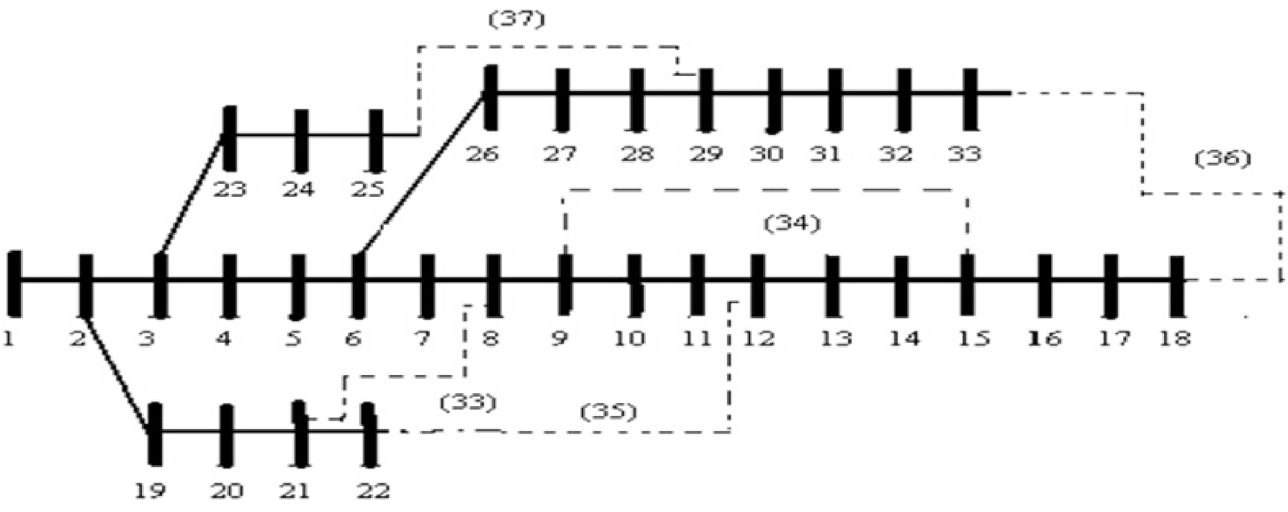

Figure 4: Single line diagram for IEEE 33 bus radial distribution system.

3.1.1 Base Case Results

The baseline performance of the IEEE 33-bus system was assessed by calculating the initial power loss, voltage profile, and key reliability indices. The results are presented in Table 2.

Table 2: Base Case Results for IEEE 33-Bus Distribution System

Parameter	Value
Active Power Loss	211.00 kW
Minimum Voltage	0.9038 p.u.
System Unreliability	0.001392
SAIFI	2.0918 interruptions/customer/year
SAIDI	2.0748 hours/customer/year
CAIDI	0.9919 hours/interruption
ASAI	0.999763
AENS	8.69 kWh/customer/year

3.1.2 Active Power Loss Reduction as the Optimization Objective

For the single-objective case focused solely on minimizing active power loss (w1=1, w2=0), the GA and PSO converged on the same optimal topology: open branches 7, 9, 14, 32, and 37. This configuration achieved a power loss of 139.55 kW and improved reliability, lowering the SAIFI to 1.8666 interruptions/customer/year. However, PSO demonstrated markedly faster computational performance, reaching the solution in 10.79 s compared to GA's 32.80 s, a difference of 38 iterations. The outcomes are presented in Table 3 and Figure 5.

Table 3: Comparison of Algorithm Performance for Active Power Loss Minimization

Optimization Approach	Open Branches	Power Loss (kW)	SAIFI(interruptions/customer/year)	Calculation Time (s)
GA	7-9-14-32-37	139.55	1.8666	32.80
PSO	7-9-14-32-37	139.55	1.8666	10.79

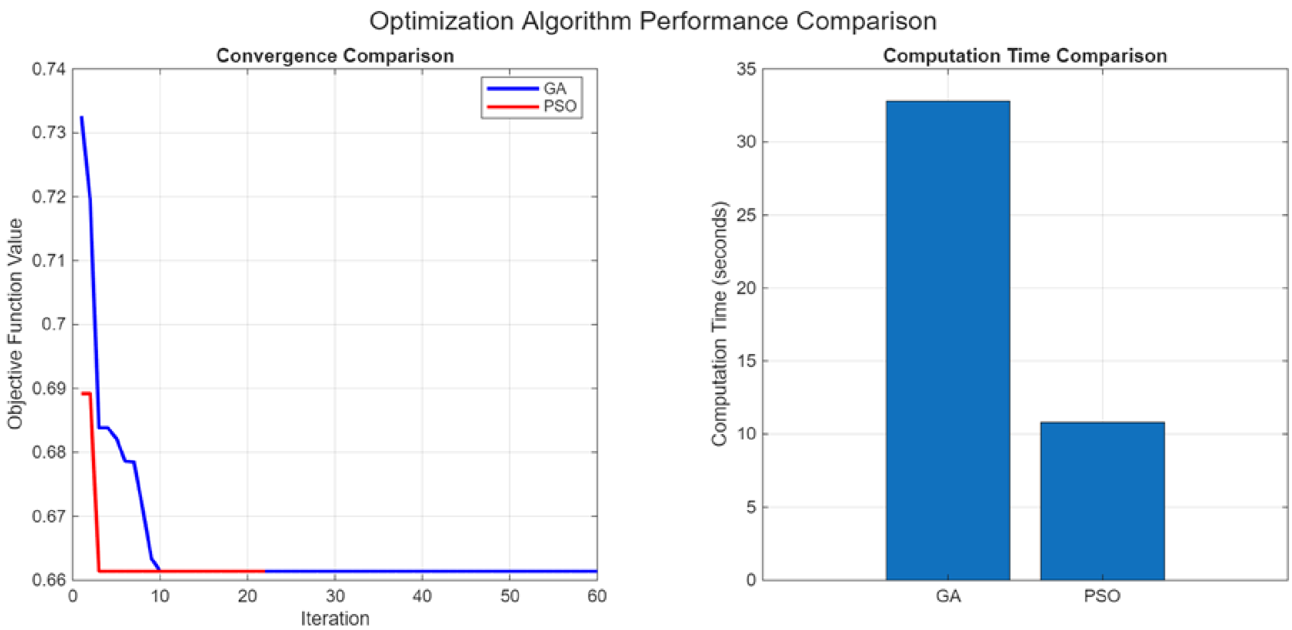

Figure 5: Convergence characteristics of the GA and PSO for active power loss minimization.

3.1.3 System average frequency interruption (SAIFI) as an optimization objective

To minimize only SAIFI (w1=0, w2=1), GA and PSO found the same optimal network state with open branches at 7, 10, 14, 17, and 27. This state lowered the SAIFI to 1.7274 interruptions/customer/year, increasing reliability at the expense of a higher power loss (150.35 kW). PSO proved computationally faster, finding the solution in 13.90 s, whereas GA required 28.76 s and 23 more iterations. The results are presented in Table 4 and Figure 5.

Table 4: Comparison of Algorithm Performance for SAIFI Minimization

Optimization Approach	Open Branches	Power Loss (kW)	SAIFI(interruptions/customer/year)	Calculation Time (s)
GA	7-10-14-17-27	150.35	1.7274	28.76
PSO	7-10-14-17-27	150.35	1.7274	13.90

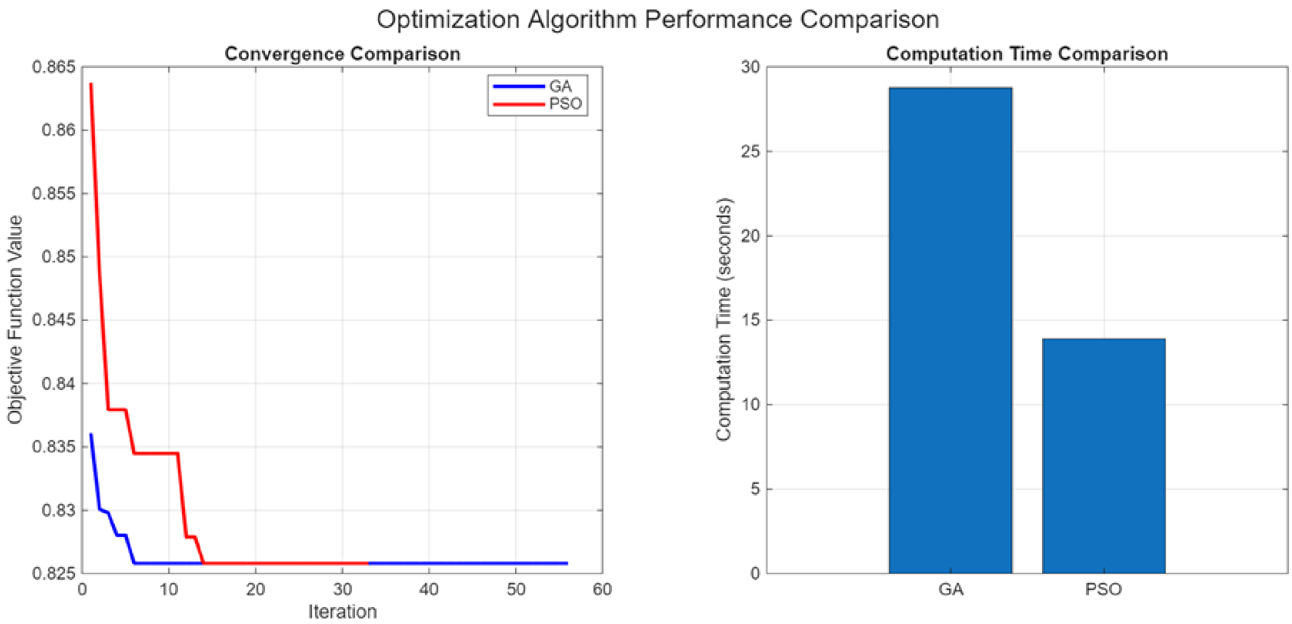

Figure 6: Convergence characteristics of the GA and PSO for the minimization of the SAIFI criterion.

3.1.4 Minimization of both objective active power losses and SAIFI.

In the bi-objective optimization scenario with equal weighting (w1=0.5, w2=0.5), both the Genetic Algorithm (GA) and particle swarm optimization (PSO) converged to an identical Pareto-optimal configuration, opening branches 7, 9, 14, 28, and 32. This configuration yielded a balanced compromise, reducing the active power loss to 139.98 kW and the SAIFI index to 1.7559 interruptions per customer annually. These figures represent improvements of 33.66% and 16.06%, respectively, compared to the base case. This solution illustrates a fundamental tradeoff. The earlier single-objective focus on power-loss minimization achieved a slightly lower loss (139.55 kW) at the expense of a higher SAIFI, indicating worse reliability. Conversely, optimizing solely for SAIFI produced a better reliability index (1.7274) but required the acceptance of higher power losses (150.35 kW). The bi-objective result thus provides a practical middle ground, offering substantial gains in both metrics without the extremes of either a single-objective outcome. Computationally, PSO maintained its efficiency advantage, converging in 13.73 s for this bi-objective case, whereas GA required 25.38 s. The complete comparative results are presented in Table 5, which demonstrates the compromise nature of the multi-objective solution. Table 5. Comparison of algorithm performance for the minimization of active power loss and SAIFI criterion (with w1=0.5 and w2=0.5).

Table 5: Comparison of Algorithm Performance for Active Power Loss and SAIFI Minimization (w_1=0.5, w_2=0.5)

Optimization Approach	Optimal Configuration	Power Loss (kW)	SAIFI(interruptions/customer/year)	Calculation Time (s)
GA	7-9-14-28-32	139.98	1.7559	25.38
PSO	7-9-14-28-32	139.98	1.7559	13.73

For the bi-objective case, a broader set of performance indices was evaluated to fully assess the impact of network reconfiguration on the IEEE 33-bus radial distribution system. This extended analysis included the System Average Interruption Duration Index (SAIDI), Unreliability, Average Service Availability Index (ASAI), and Average Energy Not Supplied (AENS). The values of these indices, both before and after reconfiguration, are listed in Table 6 and illustrated in Figure 6. Furthermore, a direct comparison between the base case and reconfigured network is presented in Table 6 and visualized in Figure 7, focusing on node voltage magnitudes and branch-level power losses. The reconfiguration led to a substantially improved voltage profile, with the minimum bus voltage rising from 0.9038 p.u. to 0.9413 p.u. at bus 18. This enhancement indicates a more balanced and stable voltage distribution throughout the system. Concurrently, the analysis of branch power losses confirmed a notable reduction, demonstrating that the optimal switching configuration achieved a more efficient load sharing among feeder sections.

Table 6: Variation in the Performance Indices after Network Reconfiguration

Description	**Base Case**	**After Reconfiguration (w_1=0.5, w_2=0.5)**	
		Value	**% Reduction**
SAIDI (hours/customer. Year)	2.0748	1.4220	31.47%
Unreliability	0.001392	0.001095	21.37%
ASAI (p.u)	0.999763	0.999838	31.47%
Min. Voltage in p.u.	0.9038	0.9413	38.99%
Average energy not supplied (AENS)	8.69	5.92	31.97%
(kWh/customer)			
Energy loss per year (kWh)	1823040	1209427.20	33.67%
Final switch open	33-34-35-36-37	7-9-14-28-32	–

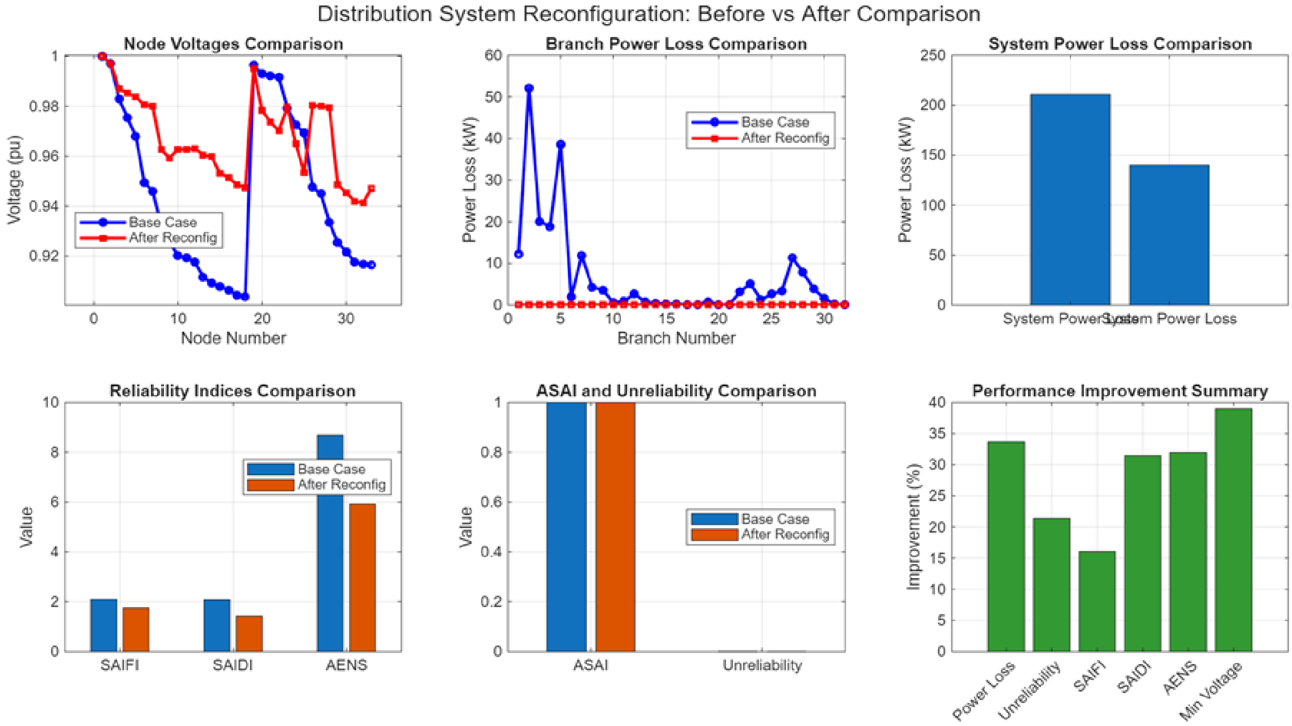

Figure 7: Variation in the different performance indices after network reconfiguration.

3.2 NEA-43 bus radial distribution feeder of Biratnagar Distribution center

We further tested the practical viability of the proposed technique by applying the reconfiguration algorithm to an actual operational feeder, the NEA 43-bus system at the Biratnagar Distribution Centre (see Figure 8). The necessary data, including general system information, line and bus parameters, and customer counts per node, were sourced from the utility and are compiled in Table 7.

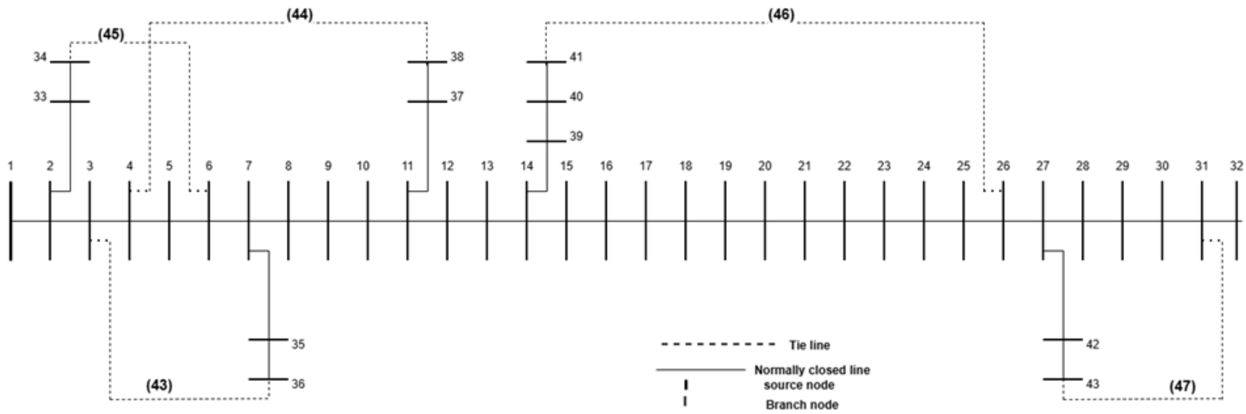

Figure 8: Bus Data for NEA-43 bus radial distribution system.

Table 7: Bus Data for NEA-43 Bus Radial Distribution System

Description	**Value**
DCS Name	NEA Biratnagar Distribution Center
Total Number of 11kV feeders under DCS	26
Test Feeder Name	11kV Bhirkuti feeder
Length of feeder	16 Km
Base MVA	1000
Base kV	11 kV
Number of buses	43
Number of branches	42
Number of tie lines	5
Total active load	5000 kW
Total reactive load	1000 kvar
Tie lines	43, 44, 45, 46, & 47

To further inform the reliability analysis, monthly tripping and shutdown records were obtained from the Tanki substation. These data were used to derive the feeder's annual outage duration and failure frequency. Subsequent calculations yielded specific failure metrics: a failure rate of 3.75 failures per kilometer per year and an annual outage duration of 89.95 h for the 16-kilometer feeder section. These computed values served as foundational inputs for estimating load-point unavailability and calculating customer-oriented reliability indices. For the scope of this study, all other system components, including transformers, circuit breakers, protective switches, and connection nodes, were modelled as perfectly reliable to simplify the analysis.

3.2.1 Base Case Results

The base case results of the load flow and reliability assessment using the cut-set approach are presented in Table 8.

Table 8: Base Case Results Summary

Parameter	**Base Case**
Optimization Approach	–
Power Loss (kW)	78.67
System Unreliability	0.255740
SAIFI (interruptions/customer/year)	27.7750
SAIDI (hours/customer/year)	55.5500
CAIDI (hours/interruption)	2.0000
ASAI	0.993659
AENS (kWh/customer/year)	85.60
Minimum Voltage (p.u.)	0.9497
Final Switches Opened	43, 44, 45, 46, 47

3.2.2 After network reconfiguration

A multi-objective optimization study was conducted on a 43-bus distribution network, simultaneously targeting the minimization of active power loss and the System Average Interruption Frequency Index

(SAIFI). The Particle Swarm Optimization (PSO) algorithm was employed for this purpose, with equal weighting factors (w = 0.5 and w = 0.5) assigned to balance both objectives.

The outcomes of network reconfiguration are presented in Table 3.8 and Figure 9, revealing substantial enhancements in both technical and reliability performance. Following optimization, the total real power losses declined from 78.67 to 55.60 kW, marking a reduction of 29.32%. The system unreliability was reduced by 35.88%, falling from 0.255740 to 0.163982. Key reliability metrics also showed major improvement: SAIFI and SAIDI both decreased by 38.01%, indicating fewer and shorter customer interruption. Although the Customer Average Interruption Duration Index (CAIDI) remained unchanged, the Average Service Availability Index (ASAI) increased slightly from 0.993659 to 0.996069, reflecting enhanced service continuity. Furthermore, the Average Energy Not Supplied (AENS) improved by 35.07%, signifying a marked decrease in unmet energy demand. The system voltage profiles also improved, with the minimum bus voltage increasing from 0.9497 per unit to 0.9621 per unit, as shown in Figure 10.

These gains were achieved through optimal adjustment of the network layout. The set of open switches changed from the initial configuration of 43, 44, 45, 46, 47 to an optimized set of 34, 36, 5, 24, 30, as illustrated in Figure 11. In summary, the PSO-driven reconfiguration strategy successfully improved the overall system efficiency, strengthened reliability, and promoted more effective distribution network operation.

Table 9: Variation in the Performance Indices for the 43-Bus Distribution System

Parameter	**Base Case**	**After Reconfiguration**	**Improvement (%)**
Optimization Approach	–	PSO	–
Power Loss (kW)	78.67	55.60	29.32
System Unreliability	0.255740	0.163982	35.88
SAIFI (interruptions/customer/year)	27.7750	17.2165	38.01
SAIDI (hours/customer/year)	55.5500	34.4331	38.01
CAIDI (hours/interruption)	2.0000	2.0000	0.00
ASAI	0.993659	0.996069	0.25
AENS (kWh/customer/year)	85.60	55.58	35.07
Minimum Voltage (p.u.)	0.9497	0.9621	1.26
Final Switches Opened	43, 44, 45, 46, 47	34, 36, 5, 24, 30	–

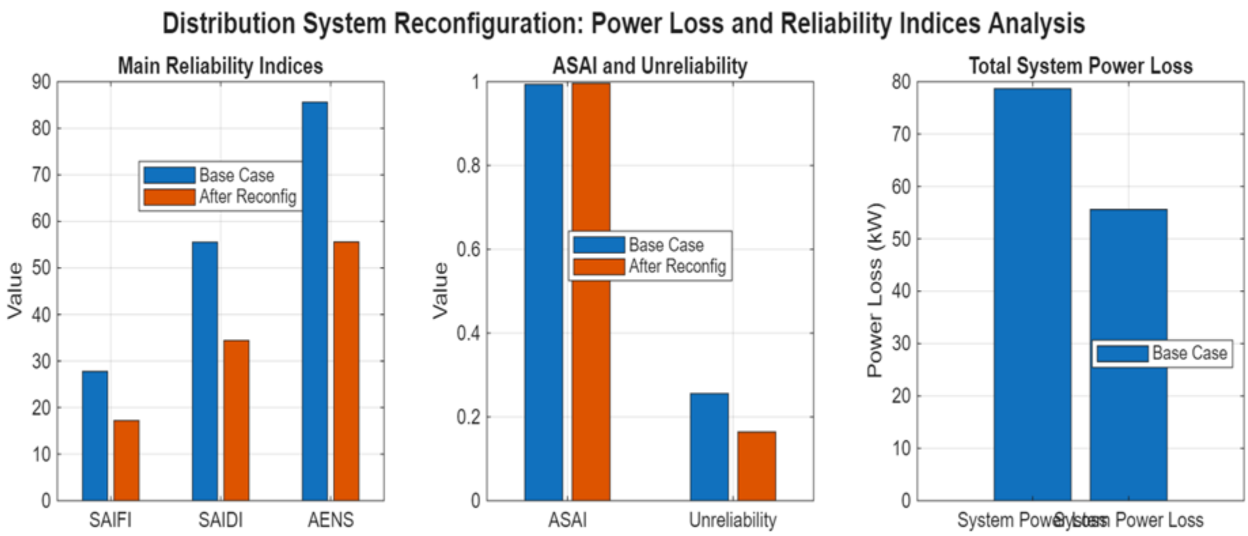

Figure 9: Performance indices before and after the reconfiguration.

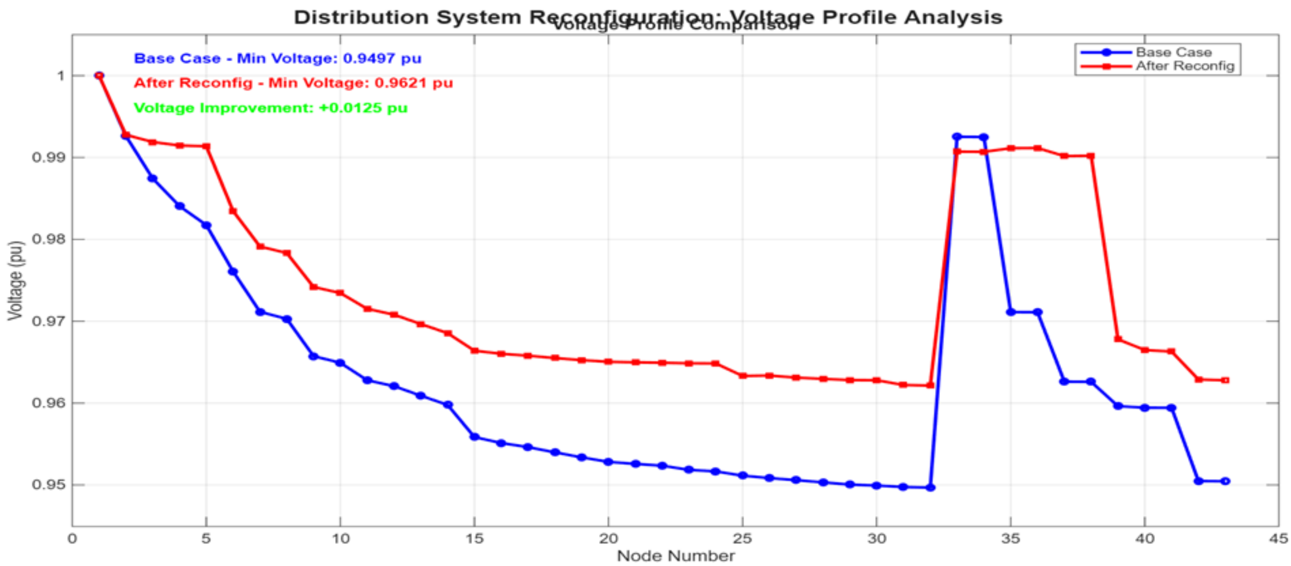

Figure 10: voltage profiles, before and after reconfiguration.

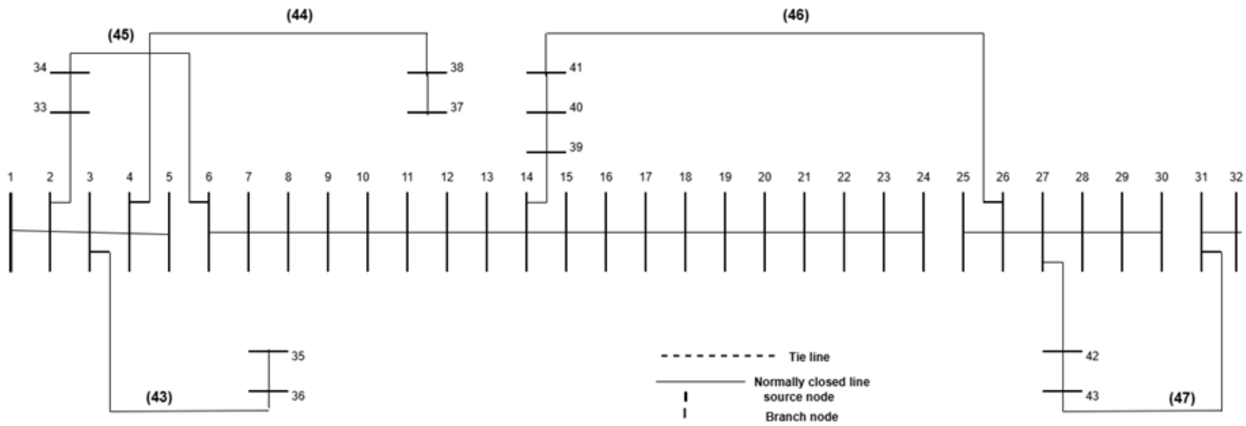

Figure 11: NEA-43 bus RDS reconfiguration.

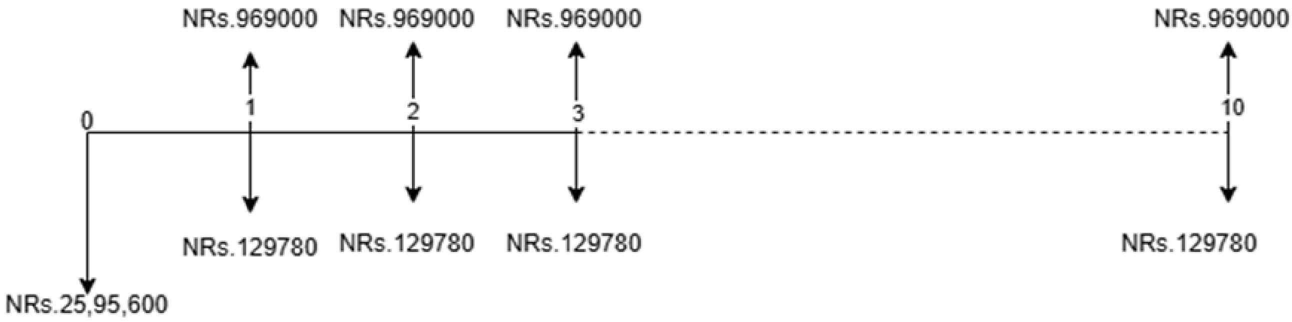

Figure 12: cash flow diagram for the economic analysis.

From the cash flow presented in Figure 12, the total initial investment for implementing the network reconfiguration is estimated at Rs.17,95,600. Additionally, an annual operation and maintenance cost, assumed to be 5% of the initial investment, is expected. The key financial feasibility indicators were calculated. The results show that the investment is highly attractive: the discounted payback period is approximately 3.71 years, the Internal Rate of Return (IRR) is 31.54%, and the Benefit-Cost Ratio (B/C) is 1.88, which is greater than one. All three metrics confirm the project's viability.

3.3 Conclusion

This study presents a developed method for distribution network reconfiguration that simultaneously minimizes active power losses and the System Average Interruption Frequency Index (SAIFI). The methodology evaluates both single- and dual-objective optimization frameworks, comparing the performance of Genetic Algorithm (GA) and particle swarm optimization (PSO) techniques. The analysis determined that the PSO algorithm, configured with equal weighting for the two objectives, yielded the most effective results.

The proposed approach was initially validated using the standard IEEE 33-bus test system and subsequently applied to a practical 11 kV distribution network from NEA Biratangar, confirming its applicability in real-world scenarios. The reconfiguration yielded substantial performance gains, including a significant reduction in active power losses, enhanced reliability indices, and improved voltage profiles. A decrease in SAIFI directly indicates a lower frequency of customer interruption. Concurrent improvements in system downtime, unsupplied energy, and annual energy losses further demonstrate the comprehensive effectiveness of this method.

An economic assessment revealed a favorably short discounted payback period, establishing the financial viability of implementing the proposed reconfiguration strategy. In conclusion, this study verified that the developed technique offers a robust, reliable, and cost-effective solution for enhancing the distribution system performance.

References

Ghosh, B., Chakraborty, A. K., and Bhowmik, A. R. (2023). Reliability and efficiency enhancement of a radial distribution system through value-based auto-recloser placement and network remodeling. *Protection and Control of Modern Power Systems*, 8(1):1–14.

Gupta, N., Swarnkar, A., and Niazi, K. R. (2014). Distribution network reconfiguration for power quality and reliability improvement using genetic algorithms. *International Journal of Electrical Power and Energy Systems*, 54:664–671.

Jaiswal, R., Yadav, N. K., and Khan, S. (2021). Reliability driven network reconfiguration of power distribution system. In *Proceedings of the 9th IOE Graduate Conference*, pages 46–54.

Kahouli, O., Alsair, H., Bouteraa, Y., Ben Ali, N., and Chaabene, M. (2021). Power system reconfiguration in distribution network for improving reliability using genetic algorithm and particle swarm optimization. *Applied Sciences*, 11(7):3092.

Ma, Y. (2017). The review on distribution network reconfiguration. In *2017 29th Chinese Control and Decision Conference (CCDC)*, pages 1–6. IEEE.

Oloulade, A., Imano, A., Fifatin, X., Vianou, A., Tamadaho, H., and Badarou, R. (2019). Multi-objective optimization of the safe operation of the electrical distribution system by placing d-facts and network reconfiguration. *Journal of Power and Energy Engineering*, 7:94–113.

Rojas, A. L., Koziel, S., Abdel-Fattah, M. F., and Gutiérrez-Alcaraz, G. (2018). Distribution network reconfiguration for voltage stability enhancement via feasibility-preserving evolutionary optimization. In *2018 IEEE Electrical Power and Energy Conference (EPEC)*, pages 1–8. IEEE.