

# Enhancements of Distribution System Performance by Optimal Network Reconfiguration

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## Abstract

This study presents an optimization strategy to improve the operation of electrical distribution networks by altering their topology. The main goals were to reduce real power losses and improve service reliability. These objectives were combined into a single objective using a weighted-sum approach. The study used two meta-heuristic methods, namely, the genetic algorithm (GA) and particle swarm optimization (PSO), to identify the best switching setups. To maintain the network as radial and within operational limits, graph-theoretic connectivity rules, such as loop, common, and prohibited branch vector rules, were applied. For each possible network layout, a sweep-based power-flow algorithm computed the nodal voltages, branch currents, and total active losses. Reliability was measured using the minimal cut set technique, and indices, such as SAIFI, SAIDI, and ENS, were calculated. The method was first tested on the IEEE 33-bus network and then used on a real 43-bus, 11 kV feeder. The results show that PSO is more efficient than GA, making it a practical choice for optimizing distribution systems.

**Keywords:** Active power loss • Network Reconfiguration • Particle Swarm Optimization • System Average Interruption Frequency Index • System Average Interruption Duration Index

## 1. Introduction

Recently, researchers have explored various optimization methods to improve electrical distribution networks. These methods focus on reducing power losses, improving voltage profiles, and increasing system efficiency. Reconfiguring a distribution network is particularly popular because it can improve performance without major infrastructure changes. By selecting the appropriate switches to open or close, the network can operate more efficiently. (Borozan et al., 1995) However, determining the optimal switch configuration is challenging in large systems because of the numerous possible combinations. Therefore, advanced optimization techniques are required

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to address this challenge.(Ma et al., 2017; Rojas et al., 2018)

Genetic algorithms (GAs) and particle swarm optimization (PSO) are two popular optimization methods used in power systems. GAs work by mimicking natural selection, in which solutions are improved through selection, crossover, and mutation. This helps the algorithm search widely and avoid becoming stuck in local optima. PSO is inspired by the motion of birds and fish in groups. In PSO, each particle is a possible solution that learns from its neighbors, which helps the algorithm find good solutions quickly. Both GAs and PSO are simple and effective, making them good choices for reconfiguring distribution networks.(Gwachha et al., 2023)

In this study, GA and PSO were used to determine the optimal switch settings while maintaining the radial topology of the distribution network.Oloulade et al. (2019) The process uses rules from graph theory and the branch exchange method to ensure that the network remains radial and practical. A load-flow analysis was performed using the backward-forward sweep (BFS) method, which is common for radial systems because it is simple and efficient.Kahouli et al. (2021) The results of the load-flow analysis were used to measure key indicators, such as the total power loss, bus voltage, and branch current.Gupta et al. (2014) The approach was tested on two distribution systems. The former is the standard IEEE 33-bus radial system, often used to verify optimization methods. The latter is a real distribution feeder from the Biratnagar Distribution Center of the Nepal Electricity Authority (NEA) (Figure 1). Testing both standard and real systems demonstrates the performance of the method in practice.Oloulade et al. (2019); Kahouli et al. (2021)

The optimized results were compared with the original network to determine the extent of the performance improvement. The comparison examined loss reduction, improved voltage profiles, and overall efficiency. These findings demonstrate that GA and PSO are highly effective for reconfiguring distribution networks and can assist power utilities in selecting appropriate optimization methods to improve their systems.

## 2. Materials and Methods

This section describes the framework used to analyses and optimize the reconfiguration of a radial distribution network. The study considers a standard test system with complete data for the line parameters, load demand, and reliability indices. A power flow analysis is performed for different switching configurations to verify that the operating conditions satisfy the voltage and current limits. The reconfiguration problem was formulated as a multi-objective optimization problem. The objectives were to minimize the total active power loss and improve system reliability. The reliability performance was evaluated using the system average interruption frequency index (SAIFI). Both objectives were combined using a weighted objective function. Metaheuristic optimization techniques implemented in MATLAB were used to search for the optimal switch configuration.Pandey et al. (2021)

### 2.1 Problem formulation for network reconfiguration

Network reconfiguration can be treated as a single- or multi-objective optimization problem. In the single-objective case, only one performance indicator, such as power loss or reliability, is minimized. In the multi-objective case, more than one objective is considered simultaneously.Kahouli et al. (2021)

#### 2.1.1 Single-Objective Function Formulation

The system performance can be improved by minimizing either the total active power loss or SAIFI reliability index.

##### a. Total active power loss

The total power loss in a distribution system is calculated as follows:

$$OF1 = PT = \sum_{i=1}^N \sum_{j=i+1}^N R_{ij} I_{ij}^2 \quad (1)$$

Where,  $R_{ij}$  = branch resistance ( $\Omega$ )

$I_{ij}$  = branch current (A)

$N$  = number of nodes

### b. System Average Interruption Frequency Index (SAIFI):

The SAIFI measures the average number of interruptions experienced by customers in a year. It is calculated as

$$\text{OF}_2 = \text{SAIFI} = \frac{\sum \lambda_i N_i}{\sum N_i} \quad (2)$$

Where:  $\lambda_i$  = failure rate at load point  $i$  (interruptions/year)

$N_i$  number of customers connected to load point  $i$ .

#### 2.1.2 Multi-Objective Function Formulation

In this study, both objectives were given equal importance using equal weighting factors. The combined objective function is expressed as

$$\min F(x) = \begin{cases} K, & \text{if the configuration not feasible,} \\ w_1 \text{OF1} + w_2 \text{OF2}, & \text{feasible.} \end{cases} \quad (3)$$

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 (?).

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.

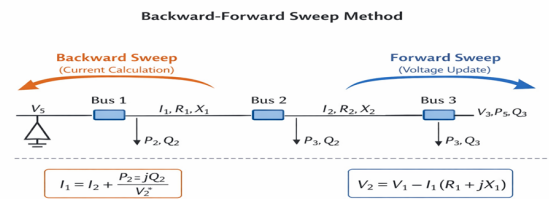


Figure 1: Simple three-bus radial system

**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  $m_2$ :

$$I[j] = \frac{P(m_2) - j(Qm_2)}{|V_{m_2}|^*} + \sum_{\text{downstream}} I_k \quad (4)$$

Where:

- $I_j$  = branch current (complex),
- $P_{m_2}, Q_{m_2}$  = active and reactive power at the receiving node  $m_2$ ,
- $V_{m_2}^*$  = 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:

$$|Vm_2| = [Vm_1 - I[j](r[j] + jx[j])] \quad (5)$$

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:

$$|V_{\text{new } i} - V_{\text{old } i}| < \epsilon \quad (6)$$

### Step 5. Total Power Loss:

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

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) (?).

(a) **Average number of outages experienced by a load point per year  $i$ ,  $\lambda_i$ :**

$$\lambda_i = \sum_{j \in Ne} \lambda_{e,j} \quad (8)$$

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  $i$ , per year:

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

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  $i$ .

$$r_i = \frac{U_i}{\lambda_i} \quad (10)$$

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 (?) 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(?).

### 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:

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

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

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.

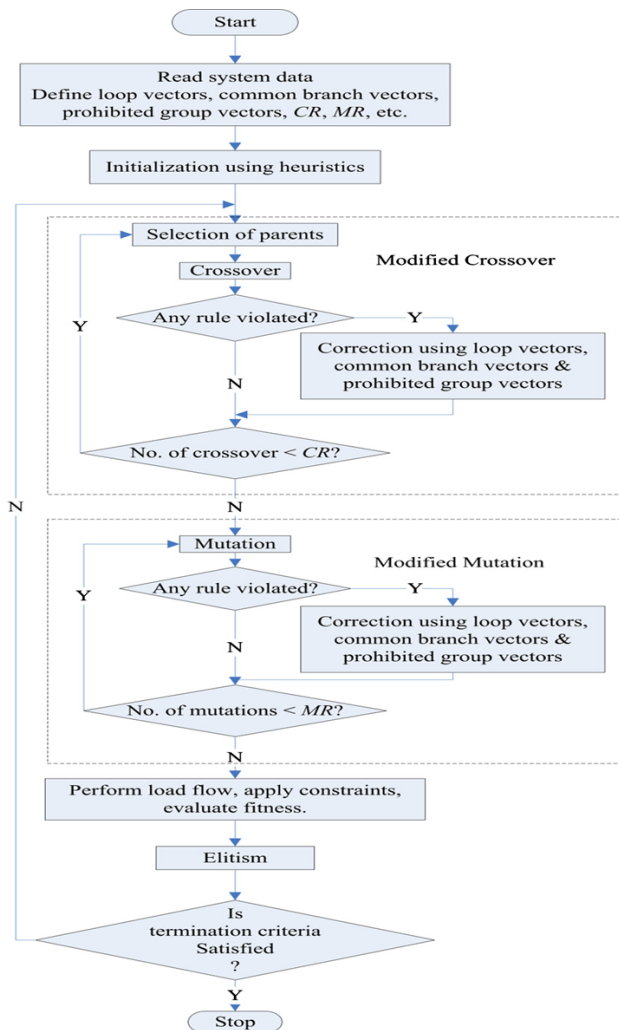


Figure 2: Network reconfiguration by Genetic algorithm optimization (GA) approach

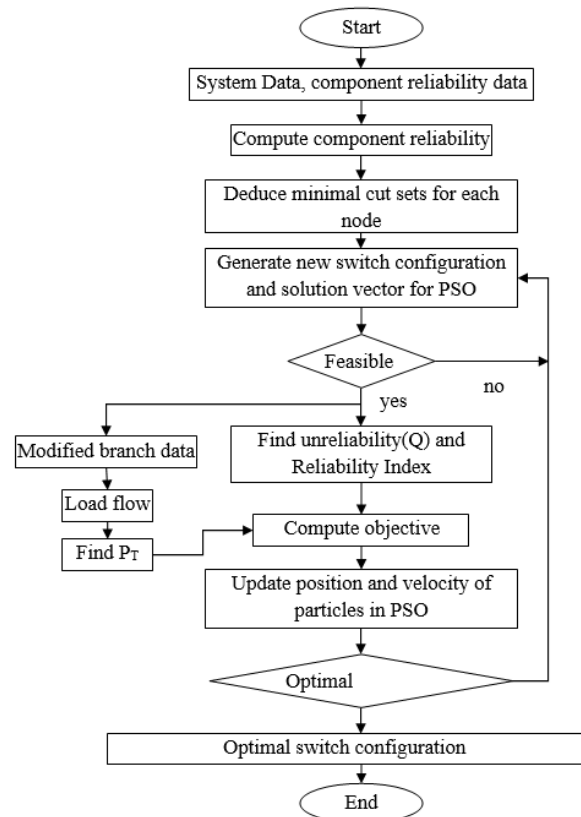


Figure 3: Network Reconfiguration by Particle swarm optimization approach.

### 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 (Amanulla et al., 2012; Aryal et al., 2021), 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

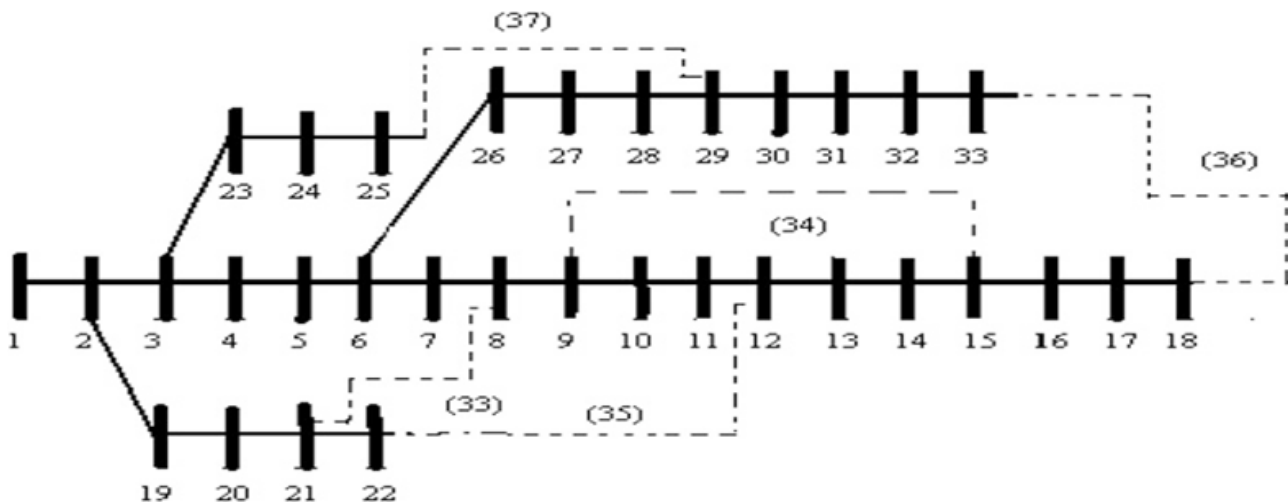


Figure 4: Single line diagram for IEEE 33 bus radial distribution system.

##### 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 ( $w_1=1, w_2=0$ ), 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(interruption- s/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

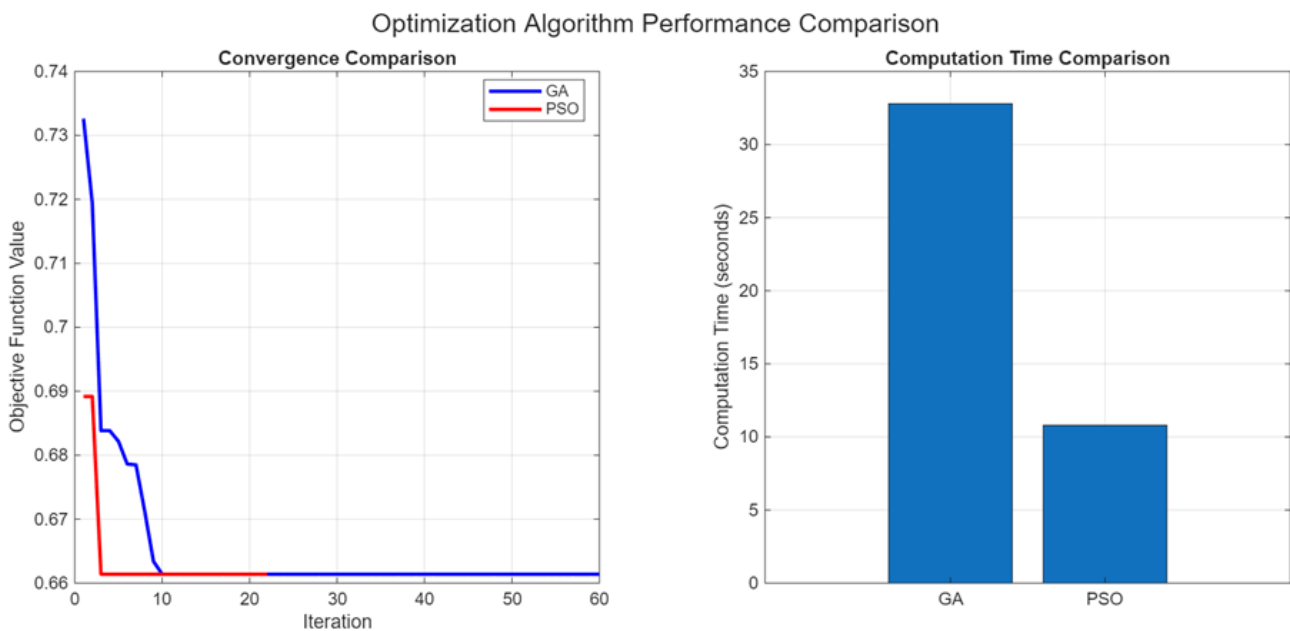


Figure 5: Convergence characteristics of the GA and PSO for active power loss minimization.

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

To minimize only SAIFI ( $w_1=0$ ,  $w_2=1$ ), 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(interruption- s/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

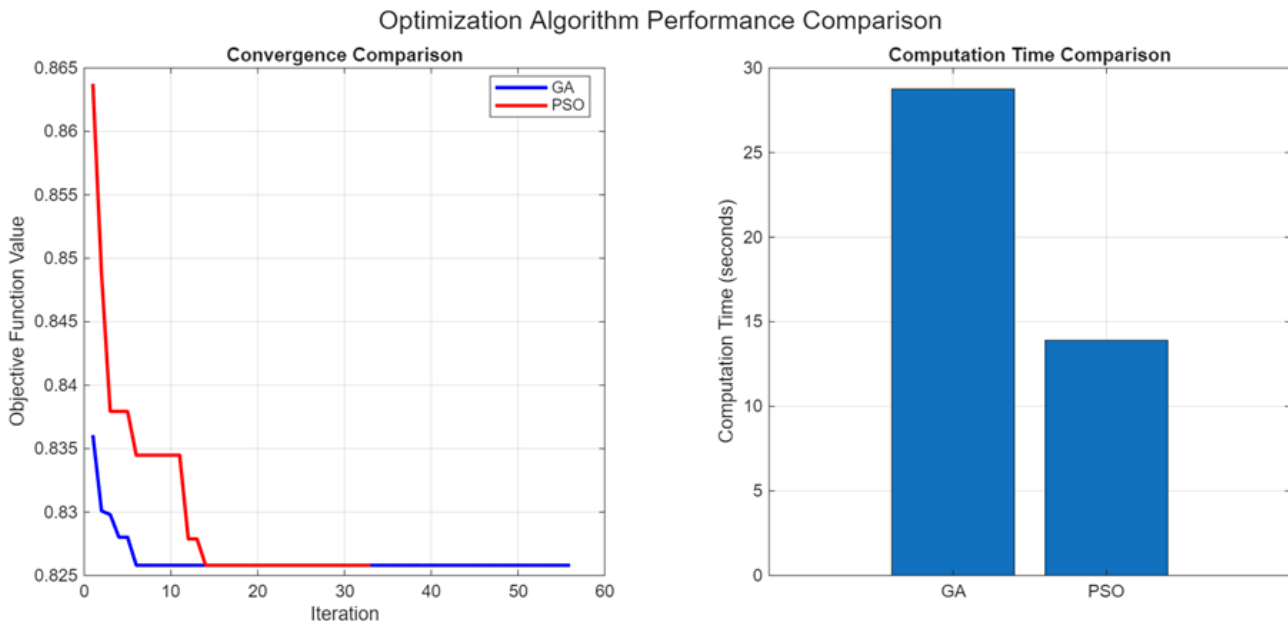


Figure 6: Convergence characteristics of the GA and PSO for the minimization of the SAIFI criterion.

### 3.1.4 Minimization of both objective active power losses and SAIFI.

In the bi-objective optimization scenario with equal weighting ( $w_1=0.5$ ,  $w_2=0.5$ ), 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  $w_1=0.5$  and  $w_2=0.5$ ).

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

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

<b>Description</b>	<b>Base Case</b>	<b>After Reconfiguration (<math>w_1=0.5</math>, <math>w_2=0.5</math>)</b>	
		<b>Value</b>	<b>% Reduction</b>
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) (kWh/customer)	8.69	5.92	31.97%
Energy loss per year (kWh)	1823040	1209427.20	33.67%
Final switch open	33-34-35-36-37	7-9-14-28-32	–

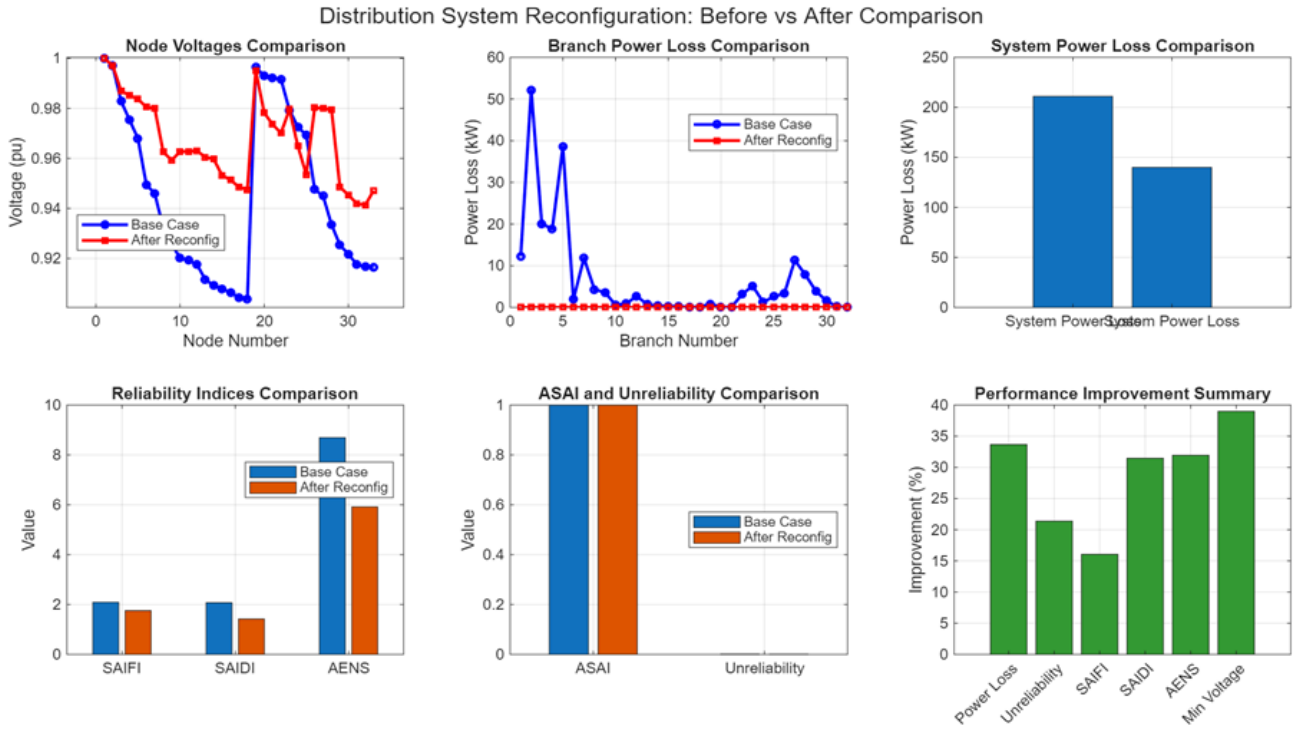


Figure 7: Variation in the different performance indices after network reconfiguration.

### 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.

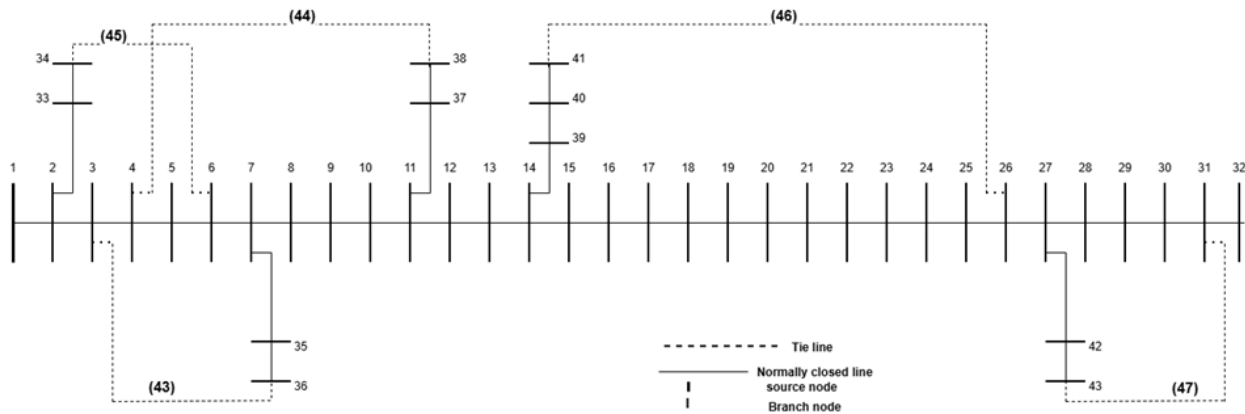


Figure 8: Bus Data for NEA-43 bus radial distribution system.

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	–

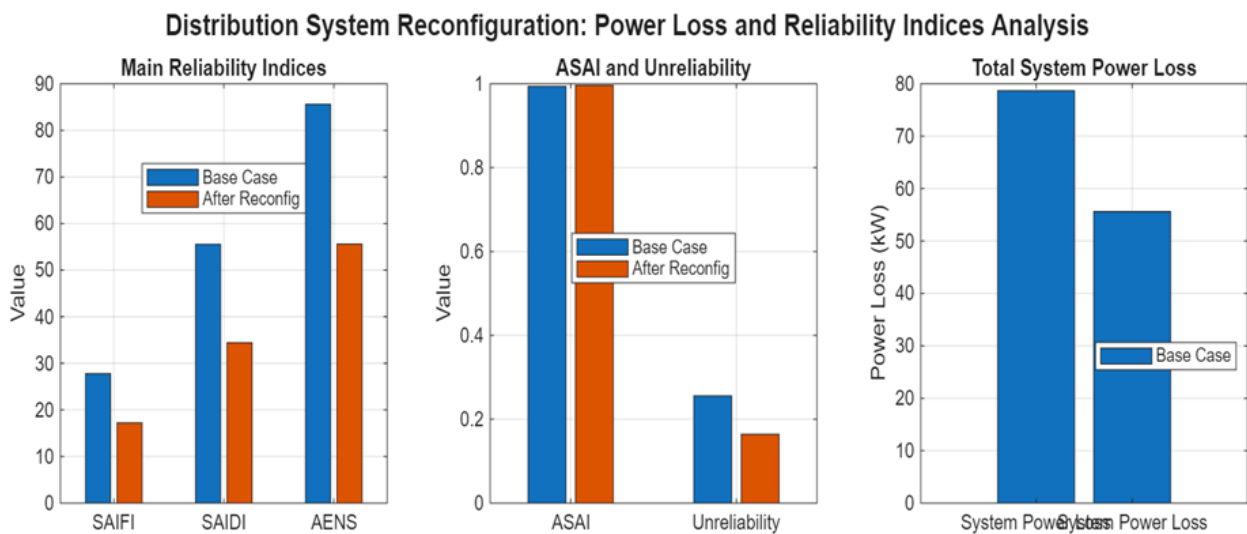


Figure 9: Performance indices before and after the reconfiguration.

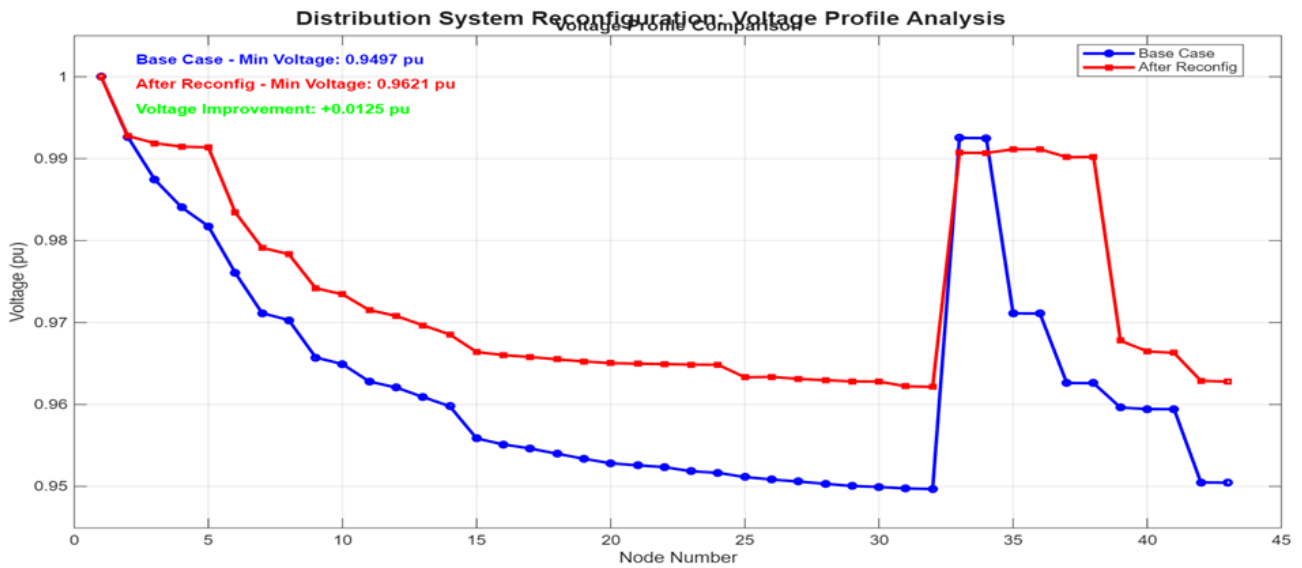


Figure 10: voltage profiles, before and after reconfiguration.

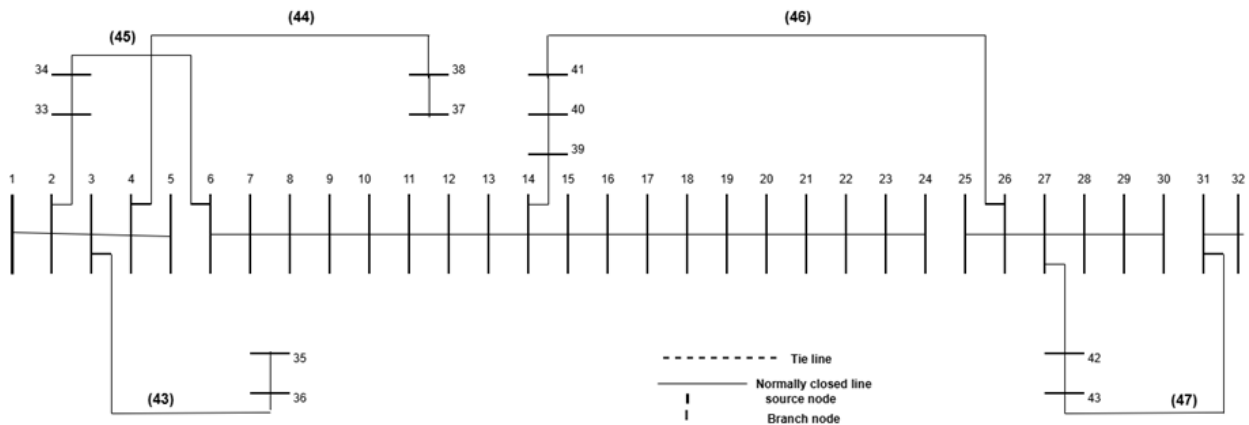


Figure 11: NEA-43 bus RDS reconfiguration.

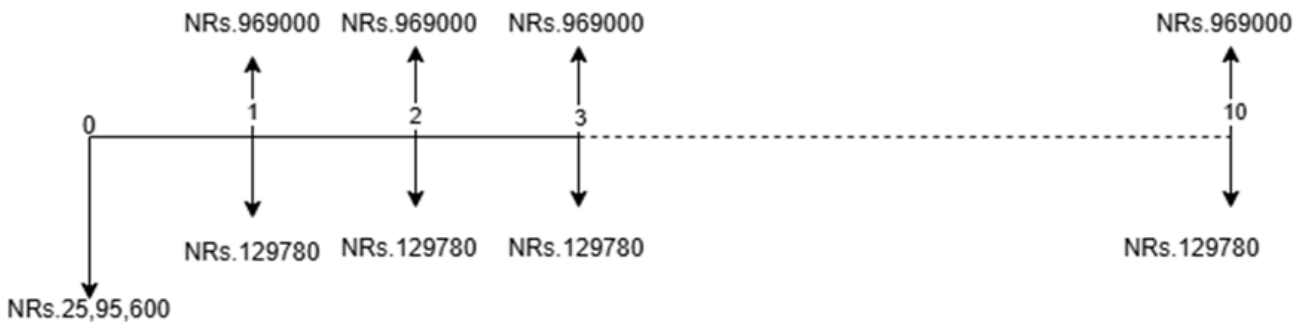


Figure 12: cash flow diagram for the economic analysis.

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.

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