

Performance Enhancement of the Radial Distribution System Through Simultaneous Optimal Feeder Reconfiguration and Distributed Generation Placement

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ABSTRACT- Energy loss in distribution networks significantly impacts system efficiency and operational costs. This work focuses on minimizing power losses and improving voltage profiles in an IEEE 33-bus system using a Genetic Algorithm (GA)-based reconfiguration and DG placement. The GA optimally places Distributed Generators (DGs) and reconfigures switches to achieve loss minimization while ensuring voltage stability. Power flow analysis is conducted using the Forward-Backward Sweep method which is introduced for better system analysis. The proposed method establishes an intelligent framework for modern power distribution optimization. A mathematical model is formulated to define power loss minimization and voltage constraints, ensuring network reliability. The Forward-Backward Sweep power flow method is employed to analyse voltage variations and system losses, while a state-space representation is introduced to model the system dynamics. The proposed GA-based approach iteratively enhances network performance by optimizing DG placement and switch configurations simultaneously, leading to better efficiency in power distribution. Results demonstrate that GA significantly reduces losses and enhances voltage profiles compared to conventional techniques.

Keywords: Distributed Generation, Forward-Backward Sweep Method, Power Loss Minimization, Bus System Optimization, Genetic Algorithm, Voltage Stability.

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1. INTRODUCTION

Traditional power distribution systems follow a centralized generation model, where electricity is generated in large power plants and transmitted over long distances to consumers. However, this approach results in significant power losses, voltage instability and inefficient load distribution. The increased demand for reliability, energy efficiency and sustainability has led to the integration of Distributed Generation (DG) units within the distribution network[1]-[2].

The increasing demand for reliable, sustainable and efficient electricity supply has led to significant transformations in power systems worldwide. One of the most notable advancements is

the integration of Distributed Generation (DG), a concept that refers to small-scale power generation units located close to the point of consumption[3]-[4]. Unlike traditional centralized power plants, DG systems generate electricity near the load centres, reducing transmission losses, enhancing grid stability and contributing to a more resilient energy infrastructure. As modern power systems evolve towards decentralization and smarter grids, DG plays a crucial role in achieving energy security, promoting renewable energy adoption, and improving the overall efficiency of power distribution networks[5].

One of the inherent drawbacks of centralized power generation is the significant loss of electrical energy during transmission and distribution. Long-distance power transmission results in resistive losses, reducing the overall efficiency of the system[6]. DG addresses this issue by generating electricity near the point of consumption, thereby minimizing the need for extensive transmission infrastructure. By reducing transmission losses, DG enhances the efficiency of the power system and ensures that a higher proportion of the generated electricity reaches consumers[7].

Additionally, DG reduces dependency on large-scale grid expansions. In regions with limited access to electricity, setting up centralized power plants and transmission networks can be expensive and time-consuming[8]. DG provides an

economically viable alternative by allowing local communities to generate their own power using renewable sources such as solar, wind and biomass. This not only accelerates electrification efforts but also reduces reliance on fossil fuels, contributing to a more sustainable energy future[9].

Power loss minimization is a critical aspect of modern power system management, as excessive losses in transmission and distribution networks lead to inefficiencies, increased operational costs and environmental concerns. With the rising demand for electricity, optimizing power systems has become a necessity to ensure energy reliability and economic viability[10]. One of the most effective optimization techniques for minimizing losses in distributed networks is the Genetic Algorithm (GA), a robust, nature-inspired computational approach that mimics the principles of natural selection to achieve optimal solutions[11]. By leveraging GA, power utilities can optimize reactive power compensation, network reconfiguration, capacitor placement, and voltage control, among other factors, to enhance system efficiency. This article explores GA-based strategies for loss minimization, common bus issues affecting system performance, and techniques for overcoming these challenges[12].

The increasing demand for energy efficiency and grid stability necessitates optimized power distribution systems. Traditional radial networks suffer from excessive power losses and poor voltage regulation. Integrating Distributed Generators (DGs) and reconfiguring network topology using meta-heuristic algorithms like GA can enhance efficiency. This work presents a mathematical model for loss minimization and voltage profile improvement through GA reconfiguration[13].

2. PROPOSED METHOD

Loss minimization in power systems requires a multi-faceted approach that includes reactive power optimization, network reconfiguration, load balancing and capacitor placement. The GA approach offers a unique ability to explore a wide solution space efficiently, identifying near-optimal configurations for reducing system losses while maintaining voltage stability[14]-[15]. By implementing GA-based loss minimization strategies, the 33-bus distribution network can achieve significant reductions in power losses, improved voltage stability and optimized power factor. This approach provides a robust framework for enhancing the performance of modern smart grids and distributed energy systems, ensuring cost-effective and reliable power delivery[16].

Unbalanced loads contribute to higher power losses and reduce system efficiency. GA-based optimization enables the redistribution of loads across different phases and feeders to achieve balance, thereby minimizing losses and preventing voltage fluctuations. By incorporating Optimal Power Flow (OPF) techniques, GA ensures that active and reactive power flows are optimized, reducing overloading of transmission lines and transformers[17]-[18].

The optimization of power distribution networks is crucial for improving efficiency, reducing losses and enhancing voltage

stability. Figure1 represents a 33-bus radial distribution network which is commonly used as a benchmark system in power system studies due to its complexity and real-world applicability. The integration of the Genetic Algorithm (GA) for optimizing this network provides an effective method for loss minimization, reactive power compensation and network reconfiguration. GA, an evolutionary computation technique inspired by natural selection, is well-suited for solving complex optimization problems in power distribution systems[19]-[20].

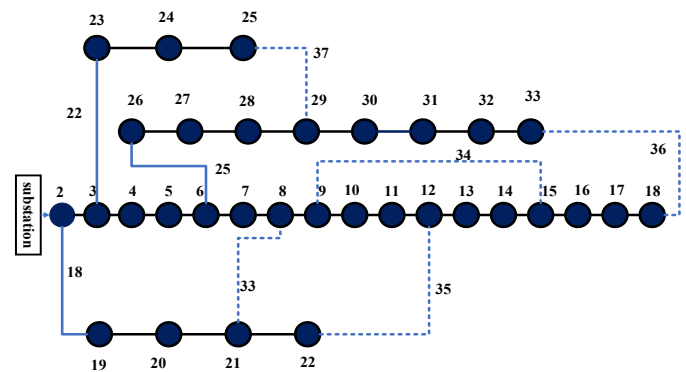


Figure1. Base configuration of IEEE-33 bus DG Network

In a 33-bus distribution network active and reactive power losses primarily arise due to high line resistances, unbalanced loads and suboptimal voltage profiles. GA-based optimization addresses these issues by determining the optimal placement of capacitors, reconfiguring the network topology, and balancing power flows. The algorithm iterates through multiple potential configurations, evaluating the best solution that minimizes total losses while maintaining system constraints such as voltage limits and feeder capacity.

Table1. Switching status for IEEE bus-33

From Bus	To Bus	Switch Status	From Bus	To Bus	Switch Status
1	2	Closed	18	19	Closed
2	3	Closed	19	20	Closed
3	4	Closed	20	21	Closed
4	5	Closed	21	22	Closed
5	6	Closed	22	23	Closed
6	7	Closed	23	24	Closed
7	8	Closed	24	25	Closed
8	9	Closed	25	26	Closed
9	10	Closed	26	27	Closed
10	11	Closed	27	28	Closed
11	12	Closed	28	29	Closed
12	13	Closed	29	30	Closed
13	14	Closed	30	31	Open
14	15	Closed	31	32	Open
15	16	Closed	32	33	Open
16	17	Closed	18	33	Open
17	18	Closed	25	29	Open

2.1. Optimal DG Placement with Network Reconfiguration to Enhance Network Performance

2.1.1. Genetic Algorithm (GA) for Loss Minimization

Genetic Algorithm (GA) is a metaheuristic optimization technique inspired by natural selection. It has been widely used in power system optimization due to its ability to find global optima in complex solution spaces.

2.1.2. GA Workflow

- **Initialization:** Generate a population of candidate DG placement solutions.
- **Fitness Evaluation:** Evaluate each solution based on power loss reduction and voltage stability.
- **Selection:** Choose the best solutions for reproduction.
- **Crossover and Mutation:** Generate new solutions by combining parent solutions and introducing variations.
- **Convergence:** Repeat the process until an optimal DG configuration is achieved.

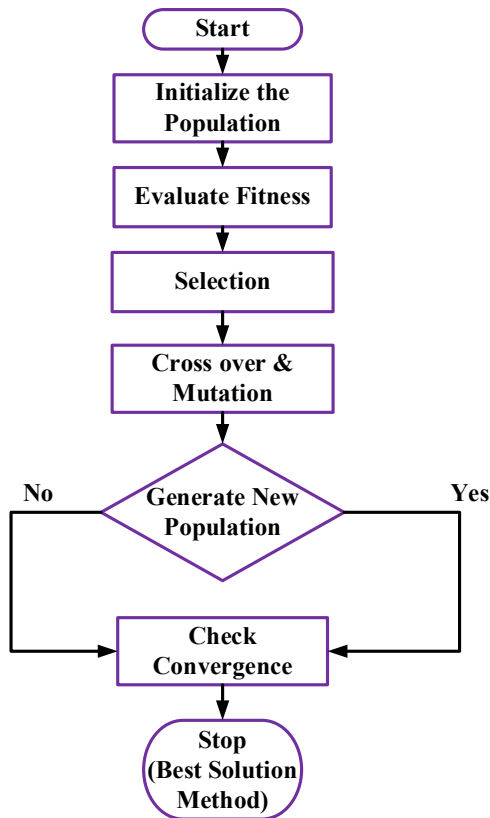


Figure 2. Flowchart for GA

2.2. Mathematical Model

2.2.1. Power Loss Minimization Equation

Power Loss in a Line Section ($i-j$)

The real power loss $P_{loss(i,j)}$ in a line connecting node i to node j is

$$P_{loss\ i\ j} = R_{ij} * \frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \quad (1)$$

Where R_{ij} is Resistance of the line between node i and j , P_{ij} , Q_{ij}

are Active and reactive power flowing through the line, V_i is Voltage magnitude at the sending end (node i)

The total active power loss is given by:

$$P_{loss} = \sum_{i=1}^N I_{ij}^2 R_{ij} \quad (2)$$

$$I_{ij} = \frac{\sqrt{P_{ij}^2 + Q_{ij}^2}}{V_i} \quad (3)$$

Where P_{loss} = total power loss,

I_{ij} = current in ij branch,

R_{ij} = Resistance of ij branch,

N = Number of branches

2.2.2. Constraints

Equality Constraints: These ensure system feasibility and satisfy power flow laws

(a) Nodal Power Balance (Kirchhoff's Law)

At each bus i

$$P_i - P_{DGi} = \sum_{j \in \text{downstream } i} P_{ij} + R_{ij} * \frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \quad (4)$$

$$Q_i - Q_{DGi} = \sum_{j \in \text{downstream } i} Q_{ij} + X_{ij} * \frac{P_{ij}^2 + Q_{ij}^2}{V_i^2} \quad (5)$$

(b) Voltage Drop Along Each Line

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

$$V_j = V_i - R_{ij} + j X_{ij} * I_{ij}, \quad (7)$$

Inequality Constraints: These constraints enforce system limits and design feasibility

(a) Voltage Limits at Each Bus

$$V_{min} \leq V_i \leq V_{max} \quad \forall i \in \{1, 2, 3, \dots, 33\} \quad (8)$$

Where V_i = voltage magnitude at bus i , V_{min} , V_{max} = Allowable voltage range

(b) Branch current limits

$$I_{ij} \leq I_{ij}^{max} \quad (9)$$

(c) DG Capacity Constraints

For each bus with a DG

$$0 \leq P_{DGi} \leq P_{DGi}^{max}; 0 \leq Q_{DGi} \leq Q_{DGi}^{max} \quad (10)$$

2.2.3. Power Balance Equations

$$P_{gen,i} - P_{load,i} = P_{loss,i} \quad (11)$$

$$Q_{gen,i} - Q_{load,i} = Q_{loss,i} \quad (12)$$

Where $P_{gen,i}$, $Q_{gen,i}$ = Active/reactive power generation.

$P_{load,i}$, $Q_{load,i}$ = Active/reactive power demand.

$P_{loss,i}$, $Q_{loss,i}$ = Active/reactive power losses.

2.2.4. Power Flow Equations

Forward-Backward Sweep (FBS) is a widely used technique

in radial distribution networks due to its simplicity and robustness.

Power Flow Equations (at bus i)

$$S_i = P_i - P_{DG_i} + j(Q_i - Q_{DG_i}) \quad (13)$$

$$S_i = V_i * I_i^* \quad (14)$$

$$I_i = \frac{S_i^*}{V_i^*} \quad (15)$$

Backward Sweep (Calculation of Branch Currents)

Start from the leaf nodes and move toward the source, which calculates all the branch currents using the load power and voltages from the previous iteration

$$I_{ij} = \sum_{k \in \text{child } j} I_{jk} + \frac{S_{ij}^*}{V_i^*} \quad (16)$$

Forward Sweep (Bus Voltages Update)

Start from the source and move downstream, which updates the voltages using the current obtained from the backward sweep

$$V_j = V_i - Z_{ij} * I_{ij}, \quad (17)$$

$$V_j = V_i - R_{ij} + j X_{ij} * I_{ij}, \quad (18)$$

Where V_i : Voltage at bus i^{th} ,

I_{ij} : Current flowing in the branch from bus i to j ,

R_{ij}, X_{ij} : Resistance and Reactance of the branch from i to j ,

P_i, Q_i : Active and Reactive power demand at bus i ,

P_{DG_i}, Q_{DG_i} : Active and Reactive power generated by DG at bus i

2.2.5. Genetic Algorithm (GA) Formulation Chromosome Representation

Each GA chromosome is structured as

$$C = [P_{DG1}, P_{DG2}, P_{DG3}, S_{SW1}, S_{SW2}, S_{SW3}] \quad (19)$$

Where, P_{DG} = DG power injection

S_{SW} = Switch state

$$\text{Fitness Function} = \frac{1}{P_{loss} + \omega \cdot \sum (|V_i - 1.0|)} \quad (20)$$

where ω is a weight factor balancing loss minimization and voltage regulation.

3. RESULTS AND DISCUSSION

In order to demonstrate the effectiveness of the proposed method (simultaneously reconfiguring the network and installation of DG units) using GA, it is applied to 33 bus. In the simulation of network, five approaches are considered to analyse the superiority of the proposed method.

3.1. Case Studies

Case1 (Base case): The system is without reconfiguration and distributed generators.

Case 2: same as approach 1 except that system is reconfigured

by the available sectionalizing and tie switches

Case3: same as approach 1 except that DG units are installed at candidate buses in the system;

Case 4: DG units are installed after reconfiguration of network

Case 5: System with simultaneous feeder reconfiguration and DG allocation.

Table 2. Results analysis with power loss and voltage with proposed method

Bus No.	Power Loss Case1 (kW)	Power loss after reconfiguration without DG Placement (kW)	Voltage Case1 (p.u.)	Voltage After reconfiguration on without DG Placement (p.u.)
1	93.65	54.42	0.928	0.952
2	66.96	29.74	0.933	0.97
3	90.09	36.12	0.894	0.914
4	71.75	46.32	0.925	0.968
5	136.21	89.8	0.896	0.939
6	72.66	44.41	0.891	0.915
7	138.29	63.8	0.917	0.958
8	72.32	48.48	0.925	0.949
9	118.47	55.85	0.945	0.973
10	64.83	31.86	0.919	0.947
11	93.06	55.73	0.904	0.929
12	92.99	47.52	0.897	0.934
13	96.47	57.64	0.943	0.99
14	84.15	44.81	0.944	0.981
15	80.48	55.27	0.891	0.919
16	85.49	54.01	0.889	0.913
17	93.23	39.57	0.934	0.975
18	86.94	41.87	0.925	0.957
19	52.46	25.93	0.933	0.958
20	81.21	47.46	0.918	0.964
21	114.23	57.6	0.897	0.924
22	79.79	47.41	0.881	0.912
23	113.79	47.05	0.924	0.955
24	74.11	34.25	0.938	0.968
25	146.35	82.47	0.889	0.924
26	129.5	65.45	0.928	0.965
27	115.59	67.84	0.916	0.942
28	117.02	68.83	0.917	0.966
29	82.03	44.76	0.905	0.936
30	74.39	34.01	0.944	0.979
31	126.58	63.72	0.884	0.923
32	143.4	87.73	0.935	0.969
33	95.28	41.41	0.942	0.982

Table 2 shows the analysis of results for optimally reconfiguring the 33-bus radial distribution network using a Genetic Algorithm (GA) for reduce power loss and improve the voltage profile. Two distinct approaches are considered: Approach 1, which represents the base case scenario where the system operates without reconfiguration and distributed generators, and Approach 2, where the system undergoes reconfiguration using sectionalizing and tie switches. In Approach 1, the power losses across different buses are significantly higher, with the highest recorded value at 146.35 kW at Bus 25 and the lowest at 52.46 kW at Bus 19. The overall distribution of power losses shows inefficiencies in power transmission, which contribute to increased operational costs and potential system instability. With the implementation of Approach 2, the system undergoes a structural reconfiguration using available sectionalizing and tie switches. The switching status of this approach 2, 31-32, 18-33, 25-29 are opened. This strategic modification leads to a significant reduction in power losses across all buses. The highest power loss after reconfiguration drops to 89.8 kW at Bus 5, while the lowest power loss decreases to 25.93 kW at Bus 19. This improvement suggests that reconfiguring the network optimally redistributes the load and minimizes losses due to resistance in the distribution lines.

Table 3. Optimized matrix for optimal placement of DG using GA

Bus No.	Power Loss after optimal DG Placement without reconfiguration (kW)	Voltage (p.u.) after optimal DG Placement without reconfiguration	DG Placement (MW) location
1	68	0.96	0
2	105.76	0.995	0
3	50.17	0.994	0
4	130.66	1.013	0
5	123.09	0.966	0
6	78.41	1.015	0
7	99.46	1.013	1.85
8	147.96	0.987	0
9	55.73	0.995	0
10	70.3	0.979	0.85
11	59.51	0.999	0
12	70.73	0.991	0
13	75.01	1.002	0
14	66.34	0.977	0
15	81.52	0.956	0
16	120.13	1.003	0
17	87.88	0.999	0
18	84.73	0.976	0
19	106.75	0.954	0
20	128.2	1.004	0
21	98.15	0.95	0
22	149.18	0.999	0
23	131.97	0.958	0
24	123.98	0.952	0

25	112.06	0.963	0
26	53.29	0.99	0
27	69.77	0.951	0
28	81.65	1.012	0
29	85.49	0.962	0
30	82.86	1.002	1.73
31	109.15	0.966	0
32	133.59	0.963	0
33	113.75	1.012	0

Table 3 shows case3 further improves the system performance by incorporating Distributed Generation (DG) units at candidate buses. DG placement significantly impacts power loss reduction and voltage enhancement by supplying localized power and reducing dependency on central generation. The implementation of DG units results in lower power losses across multiple buses, with substantial improvements observed in buses with optimal DG placement. For instance, Bus 7, bus 10 and Bus 30 show improved voltage profiles at 1.013 p.u.0.979 p.u and 1.002 p.u., respectively, due to the installation of DG units with capacities of 1.85 MW,0.85 MW and 1.73 MW. Approach 4 takes the optimization further by installing DG units after reconfiguring the network. This combined strategy leverages the benefits of both network restructuring and localized power generation. The results indicate that this approach yields the most efficient power distribution, as it minimizes power losses to an even greater extent and ensures voltage stability across all buses.

3.2. Combined Approach: DG Placement and Network Reconfiguration

A hybrid approach combining GA-based DG placement and feeder reconfiguration can maximize power loss reduction while maintaining system reliability.

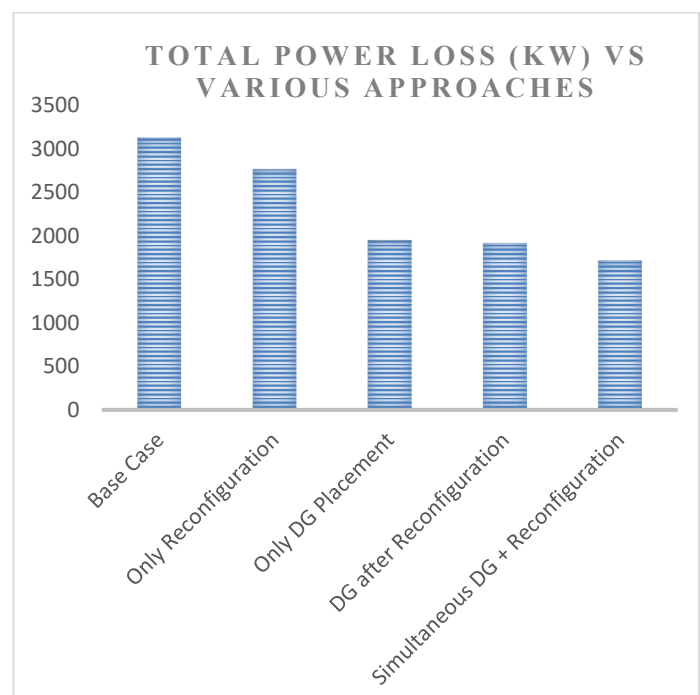


Figure 5. Power loss reduction with various cases

Table 4. Proposed method results analysis of power loss reduction with various cases

Bus No.	Base Case (kW)	Only Reconfiguration (kW)	Only DG Placement (kW)	Simultaneous DG + Reconfiguration (kW)	% Loss Reduction (from case1 to case5)
1	93.65	54.42	68	68.08	27.3
2	66.96	29.74	105.76	71.62	-6.95
3	90.09	36.12	50.17	72.86	19.12
4	71.75	46.32	130.66	72.3	-0.77
5	136.21	89.8	123.09	70.4	48.32
6	72.66	44.41	78.41	67.63	6.92
7	138.29	63.8	99.46	64.48	53.37
8	72.32	48.48	147.96	61.41	15.08
9	118.47	55.85	55.73	58.9	50.28
10	64.83	31.86	70.3	57.43	11.41
11	93.06	55.73	59.51	57.47	38.25
12	92.99	47.52	70.73	58.4	37.2
13	96.47	57.64	75.01	60.59	37.19
14	84.15	44.81	66.34	59.89	28.83
15	80.48	55.27	81.52	58.54	27.26
16	85.49	54.01	120.13	56.84	33.51
17	93.23	39.57	87.88	55.06	40.94
18	86.94	41.87	84.73	53.49	38.48
19	52.46	25.93	106.75	52.4	0.12
20	81.21	47.46	128.2	52.07	35.88
21	114.23	57.6	98.15	52.79	53.78
22	79.79	47.41	149.18	54.84	31.27
23	113.79	47.05	131.97	45.26	60.23
24	74.11	34.25	123.98	33.46	54.85
25	146.35	82.47	112.06	26.4	81.96
26	129.5	65.45	53.29	24.74	80.9
27	115.59	67.84	69.77	29.15	74.79
28	117.02	68.83	81.65	40.28	65.58
29	82.03	44.76	85.49	55.19	32.71
30	74.39	34.01	82.86	57.64	22.51
31	126.58	63.72	109.15	77.74	38.58
32	143.4	87.73	133.59	134.82	5.98
33	95.28	41.41	113.75	248.22	-160.51

Table 5. Summary of Optimized IEEE 33 bus

Parameter	Value
Optimization Technique	Genetic Algorithm (GA)
Number of Open Switches in case5	5
Open switches status (Bus Pairs)	
Case1(Base Case)	Figure 1 reference
Case2	[6-26, 9-10, 9-21,9-15,18-33]
Case 3	Default (No reconfiguration)
Case 4	[6-26, 9-10, 9-21,9-15,18-33]
Case5*	[6-26, 9-10, 9-21,9-15,18-33]
Optimal location DG Placement in case3	[8,14,31]
Optimal location DG Placement in case5	[6,14,31]
Optimal DG Sizes (MW)	[1.43, 0.58, 1.92]
Total Loss Reduction (%)	46.19%
Minimum Voltage (p.u.) in case1	0.880512238
Minimum Voltage (p.u.) in case5	0.912436175

Table 4 presents a comparative analysis of power losses across different optimization strategies applied to the IEEE 33-bus distribution system. The base case, which operates without any reconfiguration or distributed generation (DG), shows the highest power losses at almost all buses. When only network reconfiguration is applied using sectionalizing and tie switches, a noticeable reduction in losses is observed. For instance, Bus 5 shows a reduction from 136.21 kW in the base case to 89.80 kW after reconfiguration. Further improvements are seen with the integration of DG units alone. At Bus 7, DG-only placement reduces power loss to 99.46 kW compared to 138.29 kW in the base case. However, the most significant enhancement is achieved through the simultaneous application of DG placement and feeder reconfiguration. This combined strategy results in substantial loss reductions at several buses. For example, Bus 25 experiences a drastic drop from 146.35 kW in the base case to just 26.40 kW, achieving a loss reduction of approximately 81.96%. Similarly, Bus 5 benefits from a reduction of over 48%, while Bus 7 shows a 53.37% decrease.

On the contrary, not all buses demonstrate improvement. At Bus 2 and Bus 33, power losses actually increase with the combined approach compared to the base case, suggesting suboptimal DG placement at those locations. Specifically, Bus 33 shows a loss of 248.22 kW in the simultaneous case, compared to 95.28 kW in the base case indicating a need for further refinement in DG sizing or placement strategies at certain nodes.

Table 5 reflects the optimization of the power distribution network using a Genetic Algorithm (GA) has led to a 46.19% reduction in power losses, significantly enhancing system efficiency. This improvement was achieved through a simultaneous feeder reconfiguration and DG allocation approach. The system was optimized by opening five switches

(6-26, 9-10, 9-21,9-15 and 18-33), which restructured the network for better power flow. Additionally, DG units were strategically placed at buses 6, 31, and 14 with capacities of 1.43 MW, 0.58 MW, and 1.92 MW, respectively.

4. CONCLUSION

The implementation of meta-heuristic reconfiguration techniques for power distribution networks has demonstrated significant improvements in loss minimization and voltage profile enhancement. These methods effectively optimize network topology by selecting the best switching combinations, leading to reduced power losses and improved voltage stability. When combined with reconfiguration, DG placement enhances system flexibility, resilience, and efficiency. It also aids in reducing the dependency on centralized generation sources, promoting a decentralized and sustainable power model. GA algorithm exhibits superior performance in finding optimal reconfiguration solutions while maintaining computational efficiency. The adaptability of GA algorithm allows them to handle the nonlinear, complex nature of distribution network optimization, ensuring improved power quality and efficiency. This results in a more resilient and reliable power system with lower energy losses and better voltage regulation. By reconfiguring the network dynamically, the load distribution becomes more balanced, mitigating voltage drops and ensuring a stable supply to consumers.

While the current study demonstrates the effectiveness of meta-heuristic reconfiguration techniques and DG placement, future research can further enhance these methods by integrating Electric Vehicles (EVs) into the distribution network. With the increasing adoption of EVs, their coordinated charging and discharging behaviour can be used as a controllable load or even as distributed energy storage through Vehicle-to-Grid (V2G) technologies.

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