

Optimal Reduction of Technical Power Losses in Radial Distribution Networks Using Differential Evolution for Distributed Generation: A Case Study of the Azare Substation in Nigeria

Muhammad B. MUHAMMAD^{1*}, Muhammad Y. ABDULLAHI², Aminu BALA³

^{1*,2,3}Department of Electrical and Electronics Engineering, Federal University Dutsin-Ma, Katsina State, Nigeria

^{1*}mbmuhammad@fudutsinma.edu.ng, ²myabdullahi@fudutsinma.edu.ng, ³abbala@fudutsinma.edu.ng

Abstract

Technical power losses in distribution networks considerably affect the efficiency, reliability, and economic performance of power utilities, especially in developing nations. This study introduces an optimized method to reduce technical power losses in a radial distribution system by optimally placing Distributed Generation (DG). A Differential Evolution (DE) algorithm is used to find the best locations and sizes of DG units in a 9-bus test system representing the Azare distribution substation in Nigeria. Load flow analysis is performed in MATLAB using the Newton-Raphson method within an optimization framework for precise fitness evaluation. At the same time, the optimized DG settings are validated in PowerWorld Simulator to confirm practical relevance and provide system visualization. Results reveal that placing DG units at buses 5 and 9 decreases total system power loss from 0.2927 MW to 0.0352 MW, significantly improving efficiency. Voltage profiles are also enhanced, with all buses maintaining acceptable levels between 0.95 and 1.05 pu. The study demonstrates that combining metaheuristic optimization with power system simulation tools offers a practical solution for reducing technical losses in distribution networks, and the proposed approach provides a scalable framework for enhancing power system performance in similar developing contexts.

Keywords: Differential evolution, Distributed Generation, Distributed Resource, Metaheuristic method, Power loss.

1.0 Introduction

Electrical energy is central to technological and economic growth. Reliable energy systems power industry, business, and daily life. Yet many power systems face significant challenges from transmission and distribution losses, especially in developing countries. Not all electricity generated reaches end users. Distribution losses can be as high as 50%, and transmission losses are about 17% [1]. These losses are typically grouped into the following categories:

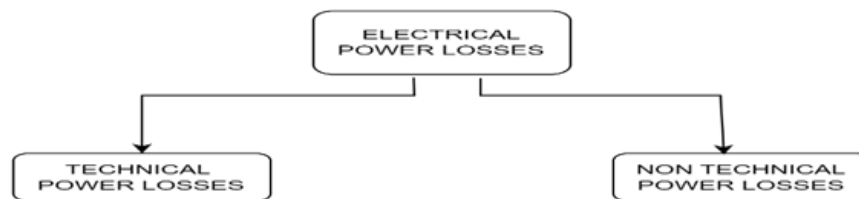


Figure 1: Types of electrical power losses

1.1 Non-technical power losses

Non-technical power losses represent electricity delivered to customers but not billed. They are mainly related to energy theft (fraud and measurement errors) and metering inaccuracies [1, 2]. Non-technical losses are 6.6% and are related to defective meters and errors in meter reading, billing of customer energy consumption, lack of administration, financial constraints, and estimating the unmetered supply of energy [3]. Some of the causes of non-technical losses include power theft, metering inaccuracies, and incorrect meter reading. For instance, in some areas, utility company officers are dispatched to read meters and bill consumers; this is done monthly. Due to human error or sometimes corruption, a different meter reading may be recorded by the officer, leading to unreported usage of electrical power.

1.2 Technical power losses

The technical losses are due to energy dissipated in the conductors, equipment used for the distribution line, and magnetic losses in transformers. Technical losses are normally 22.5% and directly depend on the network characteristics and the mode of operation [1-3]. The major number of losses in a power system is in primary and

secondary distribution lines. Therefore, the primary and secondary distribution systems must be properly planned to ensure within limits. The unexpected load increase was reflected in the increase in technical losses above the normal level. Losses are inherent to the distribution of electricity and cannot be eliminated. They include fixed losses and variable losses.

Conventional techniques for loss reduction, such as network reconfiguration and capacitor placement, have been widely applied; however, their effectiveness is often limited in handling the nonlinear and complex nature of modern distribution systems [4]. In recent years, the integration of Distributed Generation (DG) has emerged as a promising solution for improving voltage profiles and reducing power losses by providing localized power support within the network [5, 6].

Despite these advantages, the benefits of DG integration are highly dependent on its optimal placement and sizing. Improper allocation of DG units may lead to increased system losses, voltage instability, and reverse power flow conditions. Consequently, the DG allocation problem has been formulated as a nonlinear optimization problem requiring efficient solution techniques. Metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE) have been widely adopted due to their ability to handle complex search spaces and avoid local optima[7-9]. Among these, Differential Evolution[7] has demonstrated strong convergence characteristics and computational efficiency in solving power system optimization problems[10].

However, many existing studies either rely on a single simulation platform or lack comprehensive validation, limiting the practical applicability of their results. Furthermore, there remains a need for robust optimization frameworks that can reliably determine optimal DG parameters while ensuring system constraints are satisfied under realistic operating conditions.

Therefore, this study addresses the problem of minimizing technical power losses in a radial distribution network through optimal placement and sizing of Distributed Generation units. A Differential Evolution-based optimization approach is employed, integrated with load flow analysis in MATLAB for accurate computation and validated using PowerWorld Simulator for practical verification. The objective is to enhance system efficiency and voltage stability by identifying the optimal DG configuration that yields minimum power loss while satisfying operational constraints.

2.0 Methodology

This study adopts a simulation-based optimization framework to minimize technical power losses in a radial distribution network through optimal placement and sizing of Distributed Generation (DG). The methodology integrates metaheuristic optimization, power flow analysis, and simulation validation using two complementary software tools: MATLAB and PowerWorld Simulator. The overall workflow consists of three major stages: (i) system modelling and data preparation, (ii) optimization using Differential Evolution (DE) implemented in MATLAB, and (iii) validation of results using PowerWorld simulation. This combined approach ensures both computational accuracy and practical applicability of the obtained results.

2.1 Distributed Generation Using Metaheuristic Optimization Technique to Reduce Power Loss

A. Distributed Generation Integration and Load Flow Analysis

In this study, Distributed Generation (DG) units are integrated into a 9-bus radial distribution network to reduce technical power losses and improve voltage profiles. Two DG units are connected to selected buses, and system performance is evaluated before and after DG integration.

Load flow analysis is performed using the Newton–Raphson method implemented in MATLAB. The load flow program is developed as a function that accepts DG locations and sizes as input parameters and computes bus voltage magnitudes, phase angles, real and reactive power flows, and total active power loss. The results obtained serve as the basis for performance evaluation and are subsequently used in the optimization process.

B. Optimization Using the Differential Evolution Algorithm

To determine the optimal placement and sizing of the DG units, a metaheuristic optimization approach based on Differential Evolution (DE) is employed due to its effectiveness in solving nonlinear optimization problems.

The objective is to minimize total active power loss in the distribution system while satisfying operational constraints. These constraints include the power balance between generation and load, bus voltage limits between 0.95 pu and 1.05 pu, and DG size limits relative to total system demand.

Each candidate solution represents a combination of DG locations and corresponding sizes for the two DG units. The DE algorithm iteratively updates these parameters to obtain the configuration that yields the minimum power loss.

C. Implementation of Differential Evolution Algorithm

The Differential Evolution algorithm is implemented in MATLAB to solve the optimization problem. The DE/rand/2 mutation strategy is adopted in this study. The implementation procedure is as follows:

1. Initialize a population of candidate solutions representing DG locations and sizes
2. Perform a mutation to generate donor vectors
3. Apply crossover to produce trial vectors
4. Evaluate each solution using load flow analysis to compute power loss
5. Apply selection based on fitness (minimum power loss)
6. Repeat the process until the maximum number of generations is reached or convergence is achieved

To ensure robustness, the optimization process is applied to the 9-bus system and executed iteratively. The optimal DG locations and sizes obtained from MATLAB are subsequently validated using PowerWorld Simulator to confirm the reduction in power losses and improvement in voltage profile. Figure 2: Flowchart of the DG optimization and simulation procedure

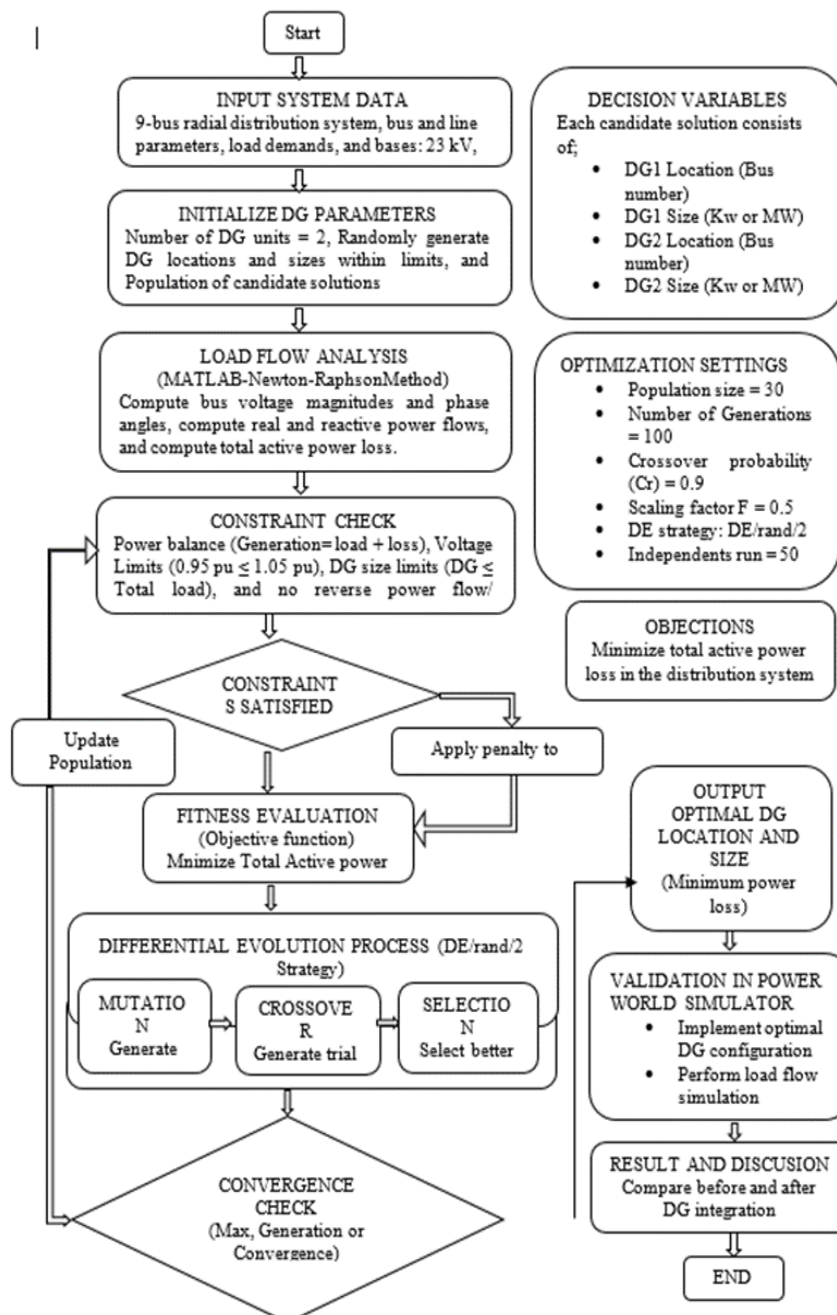


Figure 2: Flowchart of the proposed methodology showing load flow analysis, Differential Evolution-based optimization, and validation using MATLAB and PowerWorld Simulator

2.1.1 Bus Data and Line Data

Table 1: Initial Bus Data for a 9-bus system.

% %	Bus No	Bus code	Voltage Mag.	Angle Degree	---Load--- MW Mvar	-----Generator----- MW Mvar Qmin Qmax	Injected Mvar
busdata=[1 0 1.0 0.0 1.840 0.460 0 0 0 0 0							
	2	0	1.0	0.0	0.980 0.340	0 0 0 0	0
	3	0	1.0	0.0	1.790 0.446	0 0 0 0	0
	4	0	1.0	0.0	1.598 1.840	0 0 0 0	0
	5	0	1.0	0.0	1.610 0.600	0 0 0 0	0
	6	0	1.0	0.0	0.780 0.110	0 0 0 0	0
	7	0	1.0	0.0	1.150 0.060	0 0 0 0	0
	8	0	1.0	0.0	0.980 0.130	0 0 0 0	0
	9	0	1.0	0.0	1.640 0.200	0 0 0 0	0
	10	1	1.0	0.0	0.000 0.000	0 0 0 0	0];

Table 2: Initial Line Data for a 9-bus system

% %	Bus nl	bus nr	R p.u.	X p.u.	1/2 B p.u.	= 1 for lines > 1 or < 1 tr. tap at bus nl
linedata=[10 1 0.1233/zbase 0.4127/zbase 0 1						
	1	2	0.0140/zbase	0.6050/zbase	0	1
	2	3	0.7463/zbase	1.2050/zbase	0	1
	3	4	0.6984/zbase	0.6084/zbase	0	1
	4	5	1.9831/zbase	1.7276/zbase	0	1
	5	6	0.9053/zbase	0.7886/zbase	0	1
	6	7	2.0552/zbase	1.1640/zbase	0	1
	7	8	4.7953/zbase	2.7160/zbase	0	1
	8	9	5.3434/zbase	3.0264/zbase	0	1];

Bus data column 7 (Generation Power) will be modified accordingly depending on the chosen DG location and size. The voltage base is set to 23kV, and the power base is set to 10 MVA.

2.1.2 Overview of The Program

An individual consists of 4 parameters - DG 1 location, DG 1 size, DG 2 location, DG 2 size. The MATLAB code is used to find the bus location and DG size. Fitness evaluation consists of 2 parts - load flow analysis function, as the first stage of evaluation, its output will be given to the constraint function to get the fitness value. 8 outputs will be obtained from the DE program as follows: DG 1 location, DG 1 size, DG 2 location, DG 2 size, total power loss, power equality violation flag, reverse power violation flag, and voltage violation flag. The best individual with the lowest fitness value in each generation will be shown in the output. Each row of the output corresponds to a certain generation, with the earliest generation at the top of the matrix and the newest generation at the bottom of the matrix.

2.1.3 Load Flow Analysis Function

Newton-Raphson load flow analysis program was used to perform the load flow analysis based on the modified bus and line data -A. The original load flow program was transformed into a function. This function will be called by the DE programme for fitness evaluation. Random parameters (DG size and location) will be passed to the function, and load flow analysis output, then power loss, bus voltage, total DG size, total generation size, and total load will be returned as function output for further evaluation by the DE program.

2.1.4 Constraint Function

Output from the load flow function will be passed to the constraint function in the DE program to check for any violation of the constraints stated. The constraints are – the sum of generation and DG size should be equal to the sum of load and power loss; DG size must not be bigger than total load size, and bus voltage must be within the specified range from 0.95pu to 1.05pu. If any of these constraints is violated, a flag will be raised to show which constraint has been violated, and a penalty will be added to the power loss. If all constraints are met,

the power loss will be returned without penalty. Power loss with or without the penalty will be used as a fitness value to compare and select the next generation's individuals.

2.1.5 Parameter Selection

Typical values used in previous studies will be selected for crossover probability and scaling factor [2, 3]. Bus boundaries are set from 1 to 9 because only 9 buses are available in the test case. The DG size boundary is set from 0.01 to 11 because the total load of 12MW should not be exceeded to prevent unnecessary computation.

Table 3:DE Parameters

Parameter	Value
Crossover Probability, Cr	0.9
Scaling Factor, F	0.5
Individuals	30
Generation	100
Minimum Bus Location No	1
Maximum Bus Location No	9
Minimum DG Size	0.01
Maximum DG Size	11

2.1.6 Experimental Setup

1. The DE program will run using 30 individual populations for 100 iterations to check if the solution will converge. If it doesn't converge to a fixed value, the iteration will be increased to ensure the convergence is achieved.
2. If the solution converges within 100 iterations, the 100th iteration's output will be recorded (DG locations and size, power loss).
3. The last iteration's power loss value will be used as a reference to check at which iteration the program converged to the optimum solution.
4. Constraint violation flags raised by the best individual of each iteration will also be summed up.
5. Steps 2 to 4 are repeated for 50 runs to see any variation of the optimum solution, how fast DE converges to the optimum solution, and the number of constraint violations by the best individual of each generation.
6. Optimum solutions found by the DE program will be transferred to the Power World simulation for visualization.

3.0 Results and Discussion

This section presents and analyzes the results obtained from the proposed optimization framework for minimizing technical power losses in the distribution network. The Differential Evolution (DE) algorithm implemented in MATLAB is first used to determine the optimal locations and sizes of Distributed Generation (DG) units based on power loss minimization. The convergence characteristics and consistency of the optimization results are evaluated across multiple simulation runs. The optimal DG configuration obtained is then implemented in PowerWorld Simulator to validate its effectiveness under practical operating conditions. A comparative analysis of system performance before and after DG integration is carried out, focusing on total power loss reduction and improvement in bus voltage profiles. The combined results from MATLAB and PowerWorld provide a comprehensive assessment of the proposed approach.

3.1 Distributed Generation with Optimization to Reduce Power Loss

The results and solutions of 50 runs of DE with 30 individual populations and 100 iterations for each run are outlined in the table above. Only the 100th iteration is shown in the DG columns.

Table 4: 50 Trials of Differential Evolution for 30 Individuals in 100 Generations

Run No	DG 1 Bus	DG 1 Size	DG 2 Bus	DG 2 Size	Power Loss	Power Equality Constraint	Reverse Power Constraint	Bus Voltage Constraint	Converged at Generation
1	5	4.921914	9	2.549683	0.0835569	19	0	0	82
2	5	4.927155	9	2.548758	0.0835569	32	0	0	83
3	5	4.924124	9	2.549349	0.0835569	11	0	0	47
4	5	4.924996	9	2.549044	0.0835568	18	0	0	63
5	5	4.924999	9	2.549043	0.0835568	28	0	0	55
6	5	4.924759	9	2.549151	0.0835568	8	0	0	76
7	5	4.924996	9	2.549046	0.0835568	21	0	0	45
8	5	4.927816	9	2.548670	0.0835569	4	0	0	64
9	5	4.925916	9	2.549696	0.0835570	19	0	0	84
10	5	4.924317	9	2.549651	0.0835569	8	0	0	67
11	5	4.922389	9	2.547093	0.0835571	20	0	0	93
12	5	4.924995	9	2.549046	0.0835568	18	0	0	28
13	5	4.925487	9	2.549262	0.0835569	18	0	0	78
14	5	4.924994	9	2.549045	0.0835568	19	0	0	49
15	5	4.916787	9	2.550524	0.0835572	15	0	0	80
16	5	4.924996	9	2.549042	0.0835568	17	0	0	53
17	5	4.923546	9	2.550681	0.0835569	10	0	0	75
18	5	4.924995	9	2.549045	0.0835568	12	0	1	24
19	5	4.924995	9	2.549045	0.0835568	9	0	0	49
20	5	4.924995	9	2.549045	0.0835568	21	0	0	48
21	5	4.924801	9	2.548973	0.0835568	23	0	0	66
22	5	4.925006	9	2.548522	0.0835569	17	0	0	51
23	5	4.924995	9	2.549045	0.0835568	25	0	0	48
24	5	4.924994	9	2.549046	0.0835568	23	0	0	49
25	5	4.924995	9	2.549045	0.0835568	18	0	0	43
26	5	4.924995	9	2.549046	0.0835568	17	0	0	36
27	5	4.925015	9	2.549062	0.0835568	21	0	0	68
28	5	4.924994	9	2.549046	0.0835568	28	0	1	41
29	5	4.924882	9	2.548998	0.0835568	28	0	0	77
30	5	4.924995	9	2.549045	0.0835568	26	0	0	49
31	5	4.924997	9	2.549055	0.0835568	25	0	0	65
32	5	4.921677	9	2.548518	0.0835570	22	0	0	73
33	5	4.924993	9	2.549045	0.0835568	14	0	0	53
34	5	4.924993	9	2.549046	0.0835568	24	0	0	55
35	5	4.924996	9	2.549046	0.0835568	23	0	0	60
36	5	4.932047	9	2.546120	0.0835572	22	0	0	72
37	5	4.925004	9	2.549044	0.0835568	6	0	0	59
38	5	4.924131	9	2.549010	0.0835569	15	0	0	82
39	5	4.924994	9	2.549046	0.0835568	21	0	0	60
40	5	4.928341	9	2.549268	0.0835569	21	0	0	75
41	5	4.925577	9	2.549406	0.0835569	13	0	0	61
42	5	4.925020	9	2.549038	0.0835568	17	0	0	71
43	5	4.930434	9	2.550540	0.0835572	19	0	0	88
44	5	4.924969	9	2.549049	0.0835568	10	0	0	66
45	5	4.924942	9	2.548303	0.0835569	0	0	0	75
46	5	4.924994	9	2.549045	0.0835568	10	0	0	52
47	5	4.924996	9	2.549048	0.0835568	20	0	0	65
48	5	4.924994	9	2.549046	0.0835568	15	0	0	36
49	5	4.924995	9	2.549045	0.0835568	19	0	0	42
50	5	4.924989	9	2.549047	0.0835568	11	0	0	62

From Table 4, all 50 runs of the optimum solutions converged to bus 5 and bus 9. Power loss converged to the minimum value of approximately 0.08356 MW for the given locations and size of DG. Constraint columns show the total number of constraint violations for each constraint by the best individual for each generation during each run. It can be seen that most of the constraint violations occurred at the power equality constraint.

This does not imply that voltage and reverse power violations were not present. Instead, the penalty was set to be cumulative. The penalty would add up if more than one constraint was violated. Further analysis shows that when the bus voltage or reverse power is violated, the power equality constraint would be violated as well. In this scenario, the fitness value will be penalized. During the selection process for the next iteration population, in comparison to the individual that violated only one constraint, which was mostly power equality, an individual with more than 1 constraint violation will be discarded in the selection process because of higher penalty sums. This explains why there is almost no voltage or reverse power violation shown in every run.

The “Converged at generation” column shows at which generation the DE started to converge to the optimum solutions shown in the DG columns. This shows how fast the optimum solution is obtained. On average, DE converged to the solution in 61 iterations. Data in the previous Table 4 is summarized as follows:

Table 5: Statistical Summary of DE Optimization Results.

Parameters	Value
DG 1 Mean Size (Bus No: 5)	4.925019 MW
DG 2 Mean Size (Bus No: 9)	2.548996 MW
Mean Power Loss	0.0835568867169660 MW
Mean Converged at Generation	61
The minimum power loss (out of 50 runs)	0.0835568478664658 MW
DG 1 Size (Bus No: 5) at minimum power loss (out of 50 runs)	4.924994 MW
DG 2 Size (Bus No: 9) at minimum power loss (out of 50 runs)	2.549046 MW

The optimization results obtained from 50 independent runs of the Differential Evolution (DE) algorithm, as summarized in Table 5, demonstrate the consistency and reliability of the proposed approach. The algorithm consistently converges to the same DG placement at bus 5 and bus 9 across all runs, indicating a stable and globally optimal solution for the system. The mean optimal DG sizes are 4.925 MW at bus 5 and 2.549 MW at bus 9, corresponding to a mean total power loss of 0.08356 MW. The minimum power loss recorded is also 0.08356 MW, showing negligible variation and confirming the robustness of the optimization process.

In addition, the algorithm achieves convergence at an average of 61 generations, demonstrating its computational efficiency within the defined iteration limit. The consistency in both DG placement and power loss values across multiple runs indicates that the optimization process is not sensitive to initial population randomness and can reliably identify the optimal configuration. These results validate the effectiveness of the DE-based approach in determining optimal DG integration parameters for minimizing technical power losses in the distribution system.

3.0 Power World Simulation

A. Before Adding Distributed Generator (DG)

Power World was simulated without adding any DG to the system, and the following results from the simulation without DG were obtained, as shown in Tables 6 and 7.

Table 6: Bus Voltage Before Adding DG.

Bus No	1	2	3	4	5	6	7	8	9
Voltage PU	1.00	1.00	0.99	0.98	0.97	0.96	0.96	0.94	0.94

Table 7: Generation, Total Load, and Power Loss Before Adding DG.

Generation	12.6607 MW
Total Load	12.3680 MW
Power Loss	0.2927

B. After adding a Distributed Generator (DG)

Results from the simulation after adding DG are summarized in Tables 8 and 9

Table 8: Bus Voltage After Adding DG as per Optimum Solutions

Bus No	1	2	3	4	5	6	7	8	9
Voltage PU	1.00	1.00	0.99	0.99	0.99	0.99	0.99	0.98	0.99

Table 9: Generation, Total Load, and Power Loss After Adding DG

Generation	4.9292 MW
DG 1 at Bus 5	4.925 MW
DG 2 at Bus 9	2.549 MW
Total Load	12.3680 MW
Power Loss	0.0352 MW

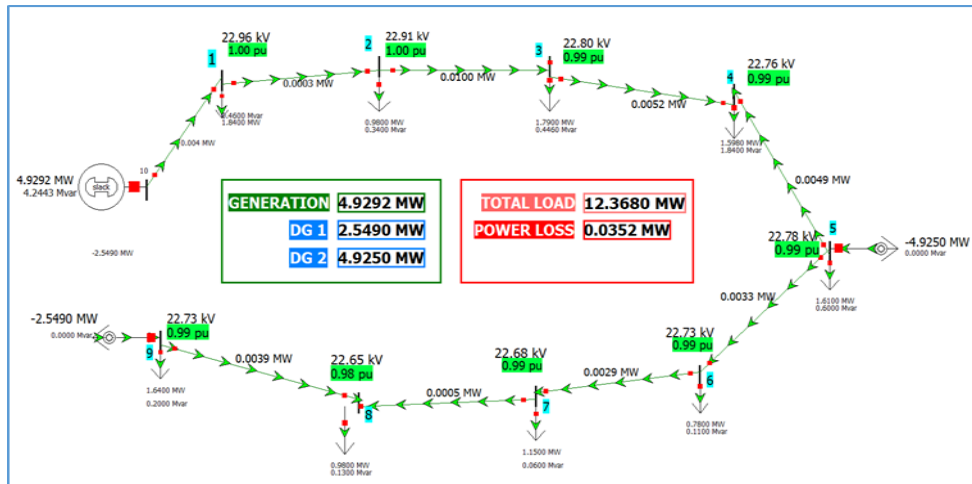


Figure 3: Simulation in Power World

From the power world simulation, power loss in the system was 0.2927MW. The voltage at bus 8 and bus 9 was also below the tolerance acceptable limit, 0.94 pu.

After adding the optimum solutions DG at bus 5 and bus 9 with sizes of 4.925 MW and 2.549 MW, respectively, the power loss was decreased to 0.0352 MW. This power loss is even lower than the optimum power loss found by DE. The bus voltages have been improved, with most bus voltages at 0.99pu. All constraints have been met – all bus voltages within 0.95pu to 1.0pu, total power generation and DG sizes equal to total load, and total power loss and DG size must be less than total load.

4.0 Conclusion

This study presented an optimization-based approach for minimizing technical power losses in a radial distribution network through optimal placement and sizing of Distributed Generation (DG) using the Differential Evolution (DE) algorithm. The methodology integrated MATLAB-based optimization with PowerWorld simulation to ensure both computational accuracy and practical validation.

The results obtained demonstrate a significant improvement in system performance. Without DG integration, the total system power loss was 0.2927 MW, with voltage levels at buses 8 and 9 dropping to 0.94 pu, which is below the acceptable operational limit. After applying the optimized DG configuration, with DG units placed at bus 5 (4.925 MW) and bus 9 (2.549 MW), the total power loss was reduced to 0.0352 MW, representing a reduction of approximately 88%. In addition, the voltage profile of the system improved substantially, with all bus voltages maintained within the acceptable range of 0.95 pu to 1.05 pu, and most buses operating close to 0.99 pu.

The DE algorithm consistently converged to the optimal solution across multiple runs, with an average convergence at 61 generations and a minimum computed power loss of 0.08356 MW during the optimization phase in MATLAB. The slight variation between MATLAB and PowerWorld results further confirms the robustness and practical reliability of the proposed approach.

Overall, the findings establish that optimal DG integration using metaheuristic optimization techniques can significantly enhance distribution system efficiency, reduce technical losses, and improve voltage stability. The proposed methodology provides a practical and scalable solution suitable for real-world distribution networks, particularly in developing power systems where loss reduction remains a critical challenge.

References

- [1] U. Jamil, A. Amin, and A. Mahmood, "A comparative study of control techniques for power loss minimization in a distribution network," in *2018 1st International Conference on Power, Energy and Smart Grid (ICPESG)*, 2018: IEEE, pp. 1-5.
- [2] M. F. Akorede, O. Ibrahim, A. O. Otuoze, A. S. Oladeji, A. O. Zubair, and M. O. Tijani, "Technical Losses Computation of a Typical Nigerian Radial Distribution Feeder using the Forward/Backward Sweep Approach," in *2022 IEEE Nigeria 4th International Conference on Disruptive Technologies for Sustainable Development (NIGERCON)*, 2022: IEEE, pp. 1-5.
- [3] R. Biazzi, E. Becker, D. P. Bernardon, L. M. Chiara, and J. A. Silva, "TECHNICAL AND NONTECHNICAL LOSS ESTIMATION USING REAL-TIME ACCESS TO DISTRIBUTION SYSTEM," in *CIREDA 2021-The 26th International Conference and Exhibition on Electricity Distribution*, 2021, vol. 2021: IET, pp. 2324-2328.

- [4] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1401-1407, 2002.
- [5] T. Ackermann, G. Andersson, and L. Söder, "Distributed generation: a definition," *Electric power systems research*, vol. 57, no. 3, pp. 195-204, 2001.
- [6] R. H. Lasseter, "Microgrids," in *2002 IEEE Power Engineering Society Winter Meeting. Conference proceedings (Cat. No. 02CH37309)*, 2002, vol. 1: IEEE, pp. 305-308.
- [7] D. Goldberg, "Genetic Algorithms in Search, Optimization and Machine Learning, Vol. 13 (7)," ed: Addison-Wesley Publishing.
- [8] J. Kennedy and R. Eberhart, "Particle swarm optimization (PSO)," in *Proc. IEEE International Conference on Neural Networks, Perth, Australia*, 1995, vol. 4, no. 1, pp. 1942-1948.
- [9] S. Mirjalili, "Evolutionary algorithms and neural networks," *Studies in Computational Intelligence*, vol. 780, no. 1, pp. 43-53, 2019.
- [10] R. Storn and K. Price, "Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341-359, 1997.