

Optimal Reconfiguration of Radial Distribution Network for Loss Minimization Using Whale Optimization Algorithm: A Case Study

TAIWO ADEWALE OJO¹, BANKOLE ADEBANJI², EMMANUEL TAIWO FASINA³

^{1, 2, 3}Department of Electrical and Electronic Engineering, Ekiti State University (EKSU),
Ado Ekiti, Nigeria.

Abstract - Most radial distribution networks are plagued with overloaded feeders, poor voltage profiles and high technical losses which usually lead to poor power quality and serious operational inefficiencies. While comprehensive network upgrades-such as conductor replacement and transformer reinforcement-provide long-term structural reinforcement, they require significant capital expenditure that is often unavailable. Consequently, this study proposes network reconfiguration as a cost-effective operational strategy that complements long-term upgrade planning by maximizing the efficiency of existing assets. This work applied Whale Optimization Algorithm (WOA) to the 33 kV radial distribution network, Ado-Ekiti, Nigeria for loss reduction using Network Reconfiguration technique. A backward/forward sweep power flow algorithm integrated with WOA was applied on the bus systems in a MATLAB environment. The Performance was assessed using active/reactive losses, bus voltages, voltage deviation index, and line loading. All simulations were carried out in MATLAB using custom scripts integrated with the MATPOWER toolbox. Following baseline analysis of the original Ado-Ekiti 33 kV radial distribution network, the WOA-based reconfiguration framework was applied. The methodology was also validated on the IEEE 33-bus radial distribution test systems, which are commonly used benchmarks in the literature. The results showed that the active power loss was reduced by 38%, reactive power losses by 33%, and the weakest bus voltage increased from 0.876 to 0.949 p.u. Each of the feeders showed comparable gains, within 3-5 practical switching operations. Reliability was enhanced with a 20%, line overloading reduction. The results confirmed WOA's robustness, with 31% loss reductions when tested on the IEEE 33-bus systems. This work demonstrates WOA's potential as a robust and effective optimization tool for loss reduction and voltage improvement for reconfiguration of radial distribution systems.

Keywords: Distribution network, Loss Minimization, Optimization, Radial, Reconfiguration.

I. INTRODUCTION

Electrical power distribution system is a vital component of the power system architecture, charged

for delivering electric power directly from transmission system to the final consumers. It typically operates at medium and low levels of voltages, as 33 kV belong to a medium voltage network used basically for sub-transmission and distribution of electric power in urban regions (EL-HAwary, 2008).

The distribution system is basically divided into two: radial and ring/mesh. Most developing nations including Nigeria, used radial distribution systems, because it is simple and not too expensive (Nwohu, 2010). Radial distribution systems, however, are susceptible to higher losses and lesser reliability because of its radial topology which disrupts electric power supply in case of a fault on the line. Ring/Mesh distribution systems in contrast, allows for alternative power flow paths (in case of a fault), enhances reliability and easy reduction of losses through reconfiguration (Grainger and Stevenson, 1994). As radial distribution system lacks alternative power pathway (less ideal for load balancing and loss reduction), network reconfiguration has been proposed as a better way of improving performance and minimizing losses (Goswani & Basu, 1992).

Network reconfiguration can be described as a method of changing the topological structure of electrical distribution system by altering the open/closed status of tie switches with the aim of optimizing some performance criteria like load balancing, loss reduction and voltage profile improvement (Baran & Wu, 1989, Merlin & Back, 1975). A backward/forward Sweep method was applied to the Abuja distribution network in order to minimize the losses through network reconfiguration using real-time load data by Sule & Okoye (2020). The research outcome showed that the methodology was able to reduce losses by 25% through optimal switch re-arrangement. The study underscore the importance of feeder balancing and exact load

switching in achieving optimal network reconfiguration.

An empirical research using Reinforcement Learning (RL) for an independent network reconfiguration was conducted by Gholani (2020). This methodology allowed the system to adapt to dynamic load variations, and achieving loss reduction in real-time without human help. Though, the research was conducted using Smart-grid context, the results of the study showed that intelligent adaptive algorithms may be implemented incrementally in developing nations, particularly with growing interest in smart technologies. A research work carried out on 33 kV Nigerian distribution network by Adeoye & Adebiyi (2022) using Genetic Algorithm showed a major decrease in real power losses and an improvement in system dependability. Thus, a flexible and adaptive reconfiguration method is needed in maintaining voltage stability in presence of Distributed Energy Resources (Omorogiuwa & Adewumi, 2023).

Early studies by Baran and Wu (1989), Nara et al. (1992), and Abido (2002) justified the effectiveness of heuristic and metaheuristic algorithms in technical loss reduction without requiring significant infrastructural upgrades. In order to accomplish this, sophisticated optimization algorithms like Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), and Genetic Algorithm (GA),

and have been created (Kennedy & Eberhart, 1995; Wolpert & Macready, 1997; Mirjalili & Lewis, 2016).

All these methods have shown significant improvements in voltage profiles and minimization of power losses. Nevertheless, most of these studies focussed mainly on isolated feeders or few sections of distribution networks and depend on outdated/static load profiles. This may not reflect the current operational realities of very fast expansion of urban centres like Ado-Ekiti (where load growth, network topology and load demand by teeming customers have grown significantly). Hence, the need for updated, location-specific studies that use current load data and reflects the dynamic characteristics of modern distribution systems. This work applied Whale Optimization Algorithm (WOA) for optimal reconfiguration of 33 kV radial distribution network of Ado-Ekiti, Nigeria, for loss minimization and voltage profile improvement.

II. MATERIALS AND METHODS

2.1 Study Distribution Network Description

The Ado-Ekiti radial distribution network comprises of four major feeders-Ajilosun, Okesha, Adebayo, and Basiri, supplying a mix of residential, commercial, and institutional loads, and collectively forming a 108-bus medium-voltage system. The single-line diagram of the Ado-Ekiti 108-bus 33 kV radial distribution network is as in Figure 1.

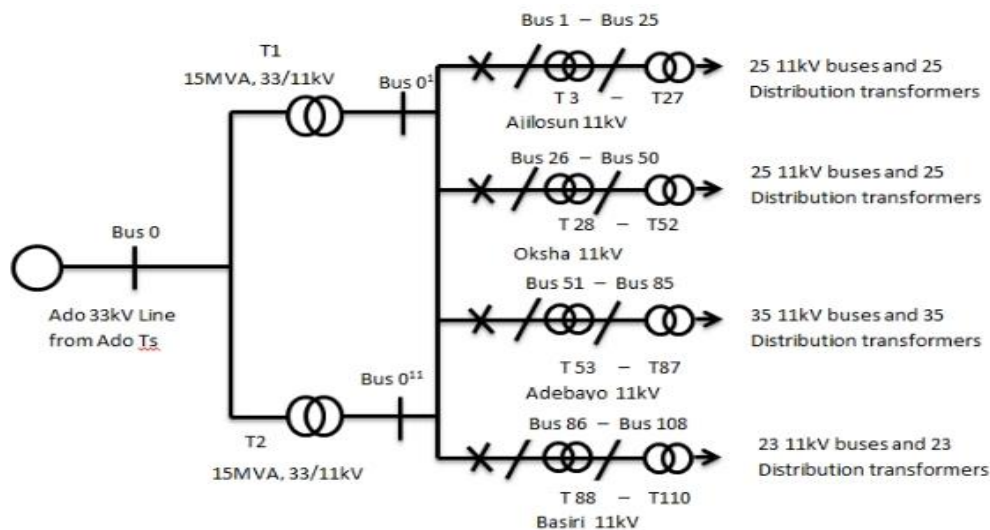


Figure 1. Single-line diagram of the Ado-Ekiti 33 kV radial distribution network.

2.2 Data Acquisition and Network Modelling

The dataset employed in this study consists of bus data, branch data, and load demand information

corresponding to peak operating conditions. Network parameters, including line resistance, reactance, transformer ratings, and feeder loading, were

obtained from the Benin Electricity Distribution Company (BEDC). All network parameters were converted into the per-unit system to enhance numerical stability and facilitate comparison with benchmark systems. Detailed datasets are included in the Appendix.

2.3 Load Flow Analysis

Due to the radial topology and high resistance-to-reactance (R/X) ratio characteristic of medium-voltage feeders, the Backward/Forward Sweep (BFS) algorithm was selected for this study. In the backward sweep, branch currents were calculated starting from the terminal buses toward the substation by aggregating downstream load currents. Subsequently, in the forward sweep, bus voltages are updated sequentially from the source node toward the end buses using calculated branch currents and line impedances. This iterative process continues until convergence is achieved within a specified tolerance. The analytical flow of the BFS method as implemented in this study is shown in Figure 2.

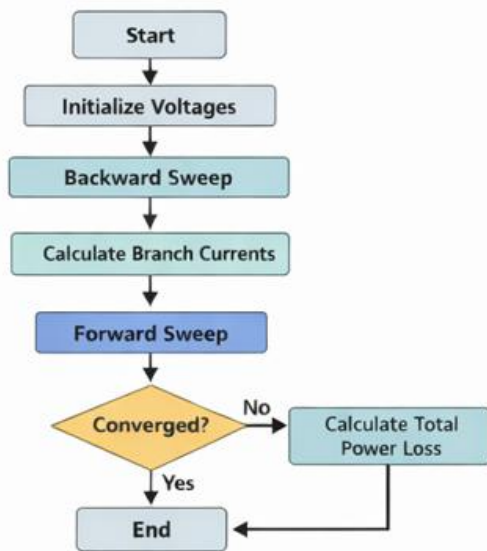


Figure 2. Backward/Forward Sweep load flow algorithm.

The total real power loss computed using Equation (1):

$$P_{loss} = \sum_{k=1}^{N_b} I_k^2 R_k \quad (1)$$

where I_k and R_k denote the current and resistance of branch k , respectively, and N_b represents the total number of branches. Equation (1) is used consistently to quantify losses before and after reconfiguration.

2.4 Optimization Problem Formulation

In this study, the objective function is defined as the minimization of network losses subject to voltage, thermal, and topological constraints.

The optimization objective is expressed as in Equation (2):

$$\min f = P_{loss} \quad (2)$$

Voltage magnitude constraints are enforced using Equation (3):

$$V_{min} \leq V_i \leq V_{max} \quad \forall i \in N \quad (3)$$

where V_i is the voltage magnitude at bus i , and V_{min} and V_{max} define acceptable operating limits. Maintaining radial topology is a critical constraint, as loop formation can compromise protection coordination in distribution networks.

2.5 Whale Optimization Algorithm (WOA) for Network Reconfiguration

This is a nature-inspired metaheuristic based on the bubble-net hunting behaviour of humpback whales (Mirjalili & Lewis, 2016). WOA has demonstrated strong performance in solving non-linear, constrained optimization problems, including power system reconfiguration.

The mathematical model governing the encircling behaviour of whales is given by Equation (4), while the spiral updating mechanism is described by Equation (5):

$$\begin{aligned} \vec{X}(t+1) &= \vec{X}^* \\ &- A \cdot |\vec{C} \cdot \vec{X}^* - \vec{X}(t)| \end{aligned} \quad (4)$$

$$\begin{aligned} \vec{X}(t+1) &= |\vec{X}^* - \vec{X}(t)| e^{bl} \cos(2\pi l) \\ &+ \vec{X}^* \end{aligned} \quad (5)$$

where X^* is the position of the best solution found so far. The coefficient vectors A and C regulate the balance between exploration and exploitation, ensuring effective convergence.

2.6 Performance Evaluation Indices

In order to assess the performance of the network, improvement in voltage profile, loss reduction, voltage deviation index (VDI) and branch loading levels, which are widely used metrics in distribution system studies (Kundur, 1994). Voltage deviation Index is quantified using Equation (6):

$$\begin{aligned} VDI &= \sum_{i=1}^N |V_i \\ &- 1.0| \end{aligned} \quad (6)$$

Lower VDI values indicate improved voltage regulation and a more balanced network.

2.7 Implementation and Benchmark Validation

All simulations were carried out in MATLAB using custom scripts integrated with the MATPOWER toolbox. The methodology was validated on the IEEE 33-bus radial distribution test systems, which are commonly used benchmarks in the literature (Baran and Wu, 1989).

III. RESULTS AND DISCUSSION

This section presents and discusses the results of the methodology applied in the previous section.

3.1 Ado-Ekiti 33 kV Test Distribution Network

The total active power loss of the network decreased from 7.89 MW to 4.88 MW (38.13% loss reduction) while the reactive power loss decreases from 4.46 MVar to 3.00 MVar (32.73% loss reduction) as shown in Table 1. The improvement in voltage profile before and after reconfiguration process is as shown in Figure 3. It can be deduced that all the bus voltages were maintained above 0.94 p.u. The VDI was reduced from 0.120 to 0.058, implying an improved balanced and secured voltage distribution all over the network.

Table 1: Real and Reactive Power Loss Comparison for the Ado-Ekiti 33 kV Radial Distribution Network

Parameter	Before Reconfiguration	After Reconfiguration	Reduction (%)
Total real power loss (MW)	7.89	4.88	38.13
Total reactive power loss (MVar)	4.46	3.00	32.73
Minimum system voltage (p.u.)	0.876	0.949	–
Voltage deviation index (VDI)	0.120	0.058	51.67

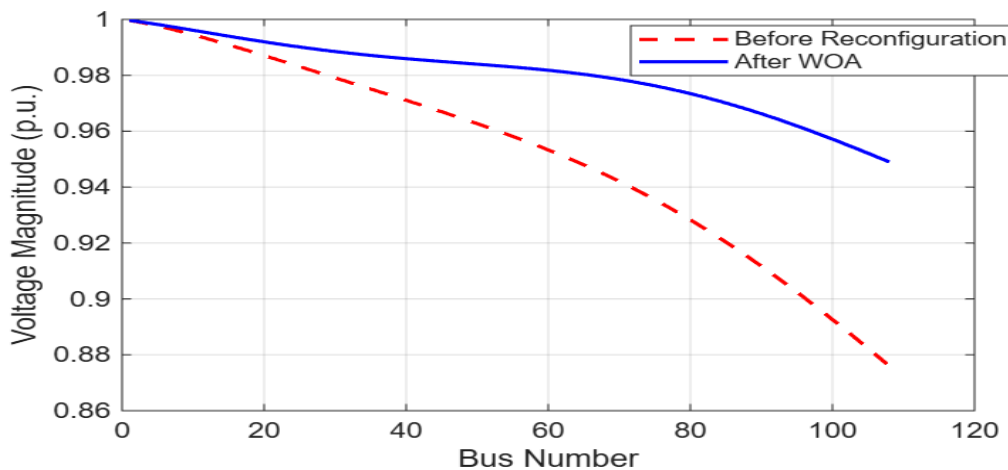


Figure 3: Voltage profile of the Ado-Ekiti 33 kV Radial Distribution Network before and after reconfiguration.

Thermal performance of the network was also assessed through line loading analysis as shown in Table 2 and Figure 4. The branches that were heavily loaded (29–30, 52–53, 63–64) experienced loading relief of 15–20% after reconfiguration. This reduction in thermal stress promotes operational

safety and ensures equipment lifespan extension. It is to be noted that all the four feeders achieved 37–39% active power loss reduction and 5–8% voltage improvement. This confirms WOA’s consistency all over the different load and feeder lengths.

Table 2: Line Loading Comparison of Critical Branches under Baseline and WOA-Optimized Configurations

Branch	Loading Before (%)	Loading After (%)	Relief (%)
29 – 30	High	Moderate	≈ 18
52 – 53	High	Moderate	≈ 15
63 – 64	High	Moderate	≈ 20

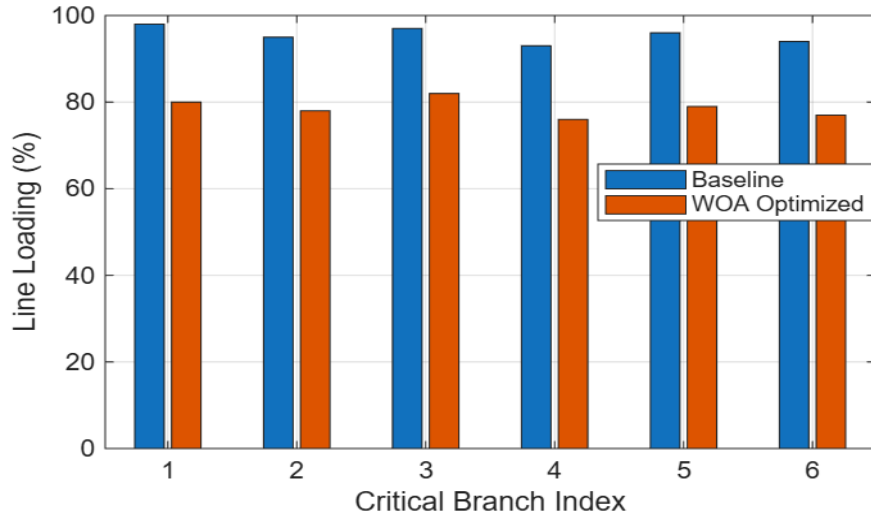


Figure 4: Line loading distribution of the Ado-Ekiti network under baseline and WOA-optimized configurations.
 3.2 IEEE 33-Bus Distribution Test Systems

The test results conducted using the IEEE 33-bus distribution system is as shown in Table 3. The results showed that active power loss is reduced from 0.203 MW to 0.140 MW (31% improvement). The voltage profile enhancement before and after reconfiguration is as in Figure 5.

Table 3: Power Loss and Voltage Profile Comparison for the IEEE 33-Bus Test System

Parameter	Before Reconfiguration	After WOA Reconfiguration	Improvement (%)
Active power loss (MW)	0.203	0.140	31.03
Minimum bus voltage (p.u.)	0.913	0.941	–
Network type	Radial	Radial	–

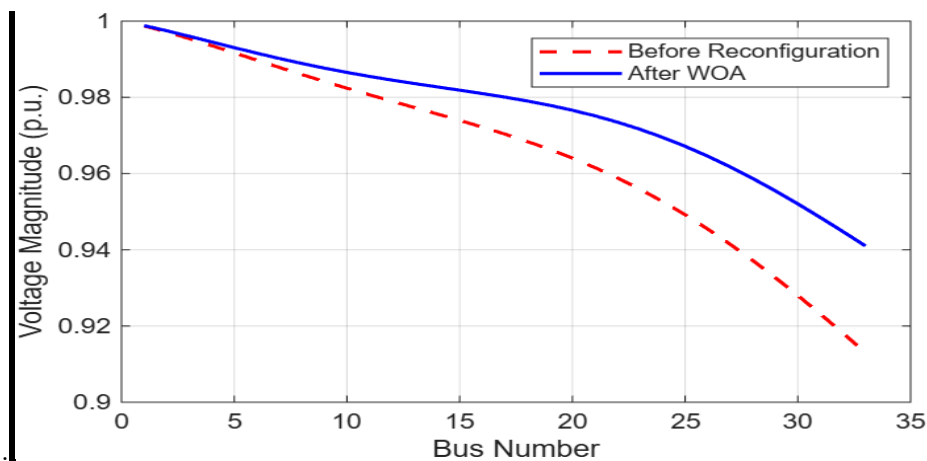


Figure 5: Voltage profile of the IEEE 33-bus distribution system before and after WOA Reconfiguration.

IV. CONCLUSION

This work examined the effectiveness of optimal reconfiguration of a radial distribution network for loss minimization with application of WOA, using the Ado-Ekiti 33 kV radial distribution network as a case study. The simulation results showed significant reductions in both active and reactive

power losses across individual feeders and the overall network, while ensuring acceptable voltage levels at all buses. The reconfiguration process improved voltage stability by eliminating under voltage conditions and redistributing power flows more evenly across the network.

The IEEE 33-bus benchmark results further confirms its scalability and general applicability. The study establishes WOA-based feeder reconfiguration as a practical, low-cost, and effective strategy for improving efficiency and power quality in radial distribution networks, particularly in developing power systems.

REFERENCES

- [1] El-Hawary, M. E. (2008). Introduction to electrical power systems. Wiley-IEEE Press.
- [2] Nwohu, M. N. (2010). Voltage stability improvement using static VAR compensator in power systems. *Nigerian Journal of Technology (NIJOTECH)*, 29(2), 10–20. <https://doi.org/10.4314/njt.v29i2>
- [3] J. J. Grainger and W. D. Stevenson, *Power System Analysis*. New York, NY, USA: McGraw-Hill, 1994.
- [4] Goswami, S. K., & Basu, S. K. (1992). A new algorithm for the reconfiguration of distribution feeders for loss minimization. *IEEE Transactions on Power Delivery*, 7(3), 1484–1491. <https://doi.org/10.1109/61.141858>
- [5] 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, Apr. 1989.
- [6] Merlin, A., & Back, H. (1975). Search for a minimal-loss operating spanning tree configuration in an urban power distribution system. In *Proceedings of the 5th Power System Computation Conference (PSCC)* (pp. 1–18). Cambridge, UK.
- [7] Sule, A., & Okoye, C. A. (2020). Feeder reconfiguration for technical loss reduction in Abuja distribution network. *Nigerian Journal of Technology (NIJOTECH)*, 39(4), 1192–1202. <https://doi.org/10.4314/njt.v39i4>
- [8] Gholami, M., Ahmadi, M., & Shayeghi, H. (2020). Reinforcement learning-based reconfiguration of distribution networks for loss minimization. *Applied Energy*, 277, 115556. <https://doi.org/10.1016/j.apenergy.2020.115556>
- [9] Adebisi, A. A., & Adeoye, A. A. (2022). Loss reduction in Nigerian 33 kV distribution networks using genetic algorithm-based reconfiguration. *Nigerian Journal of Technology (NIJOTECH)*, 41(2), 152–162. <https://doi.org/10.4314/njt.v41i2>
- [10] Omorogiwa, O., & Adewumi, O. (2023). Adaptive reconfiguration techniques for distribution networks with distributed energy resources. *Heliyon*, 9(3), e13721. <https://doi.org/10.1016/j.heliyon.2023.e13721>
- [11] N. Nara, K. Shiose, M. Kitagawa, and T. Ishihara, “Implementation of genetic algorithm for distribution systems loss minimum reconfiguration,” *IEEE Transactions on Power Systems*, vol. 7, no. 3, pp. 1044–1051, Aug. 1992.
- [12] Abido, M. A. (2002). Optimal power flow using particle swarm optimization. *International Journal of Electrical Power & Energy Systems*, 24(7), 563–571. [https://doi.org/10.1016/S0142-0615\(01\)00067-9](https://doi.org/10.1016/S0142-0615(01)00067-9)
- [13] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of IEEE International Conference on Neural Networks* (pp. 1942–1948). IEEE. <https://doi.org/10.1109/ICNN.1995.488968>
- [14] Wolpert, D. H., & Macready, W. G. (1997). No free lunch theorems for optimization. *IEEE Transactions on Evolutionary Computation*, 1(1), 67–82. <https://doi.org/10.1109/4235.585893>
- [15] S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” *Advances in Engineering Software*, vol. 95, pp. 51–67, May 2016
- [16] J. A. Momoh, *Electric Power System Applications of Optimization*. New York, NY, USA: Marcel Dekker, 2001.