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Optimal Reconfiguration Algorithm of the 33kv Lines and Substations for the Nigerian Electricity Supply Corporation (Nesco) Within Jos and Bukuru Town

Paul P. J.,[1] Dasat M. D.,[1] Maju R. M.,[1] & Ajang B. I.,[2]

[1]Department of Electrical Engineering, Plateau State Polytechnic, Barkin Ladi
[2]Department of Minerals and Petroleum Resources Engineering, Plateau State Polytechnic, Barkin Ladi

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ABSTRACT

The 33 kV embedded distribution network operated by the Nigerian Electricity Supply Corporation (NESCO) within Jos and Bukuru is affected by high technical losses and weak voltage performance under radial operation and increasing load demand. This study develops a comparative distribution network reconfiguration framework based on Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA). A Backward-Forward Sweep load-flow procedure is integrated with binary switch-status optimization, subject to radiality, bus-voltage, branch-current and power-balance constraints. Using the network parameters and study dataset supplied for the analysis, the base configuration produced 514.2 kW active loss, 298.5 kVAr reactive loss and a minimum voltage of 0.78 pu at Bus 18. GA reduced active loss to 400.5 kW and improved the minimum voltage to 0.94 pu, whereas PSO achieved 380.3 kW and 0.95 pu. These values correspond to active-loss reductions of 22.1% and 26.0%, respectively. The convergence behaviour further indicates that PSO attained the lower objective value within the specified iteration limit. The framework therefore provides a practical basis for selecting candidate switching configurations, although field switching studies and protection checks remain necessary before operational deployment.

1. Introduction

Distribution networks form the final electrical link between bulk supply points and end users, and their comparatively high resistance-to-reactance ratios make them particularly susceptible to voltage drop and I^2R losses. Distribution network reconfiguration (DNR) changes the status of sectionalizing and tie switches to alter feeder topology while retaining a connected radial structure. The method can redirect current away from heavily loaded or electrically long branches, improve load sharing and reduce losses without the immediate construction of new lines. The foundational formulation of Baran and Wu (1989) established reconfiguration as a loss-reduction and load-balancing problem, while recent reviews show that modern DNR increasingly combines economic, voltage-quality, reliability and distributed-generation objectives (Lotfi et al., 2024).

The operational relevance of DNR is pronounced in developing electricity systems where feeder expansion, switch automation and real-time monitoring may not keep pace with demand growth. NESCO is a privately operated embedded electricity network whose 33 kV facilities serve important residential, commercial and industrial loads around Bukuru and Jos. The network is supplied from the Kura Falls hydroelectric scheme and is operated predominantly in radial form. Under such conditions, the location of open points strongly influences branch currents, end-of-feeder voltage and the loading of injection substations. A switching decision based only on operator experience may restore supply successfully but may not produce the configuration with the lowest steady-state loss or the best voltage profile.

This study addresses the identified need by formulating a constrained, multi-objective reconfiguration problem for the NESCO 33 kV network and comparing two established population-based algorithms. PSO is used because of its rapid information sharing and continuous search dynamics, adapted here to binary switch decisions, while GA provides a widely used evolutionary benchmark based on selection, crossover and mutation. The study contributes a network model, a repeatable load-flow/optimization workflow, candidate open-switch sets and a comparative interpretation of loss, voltage and convergence performance.

1.1 Statement of the Problem

The supplied base-case model of the NESCO 33 kV network indicates a technically inefficient operating state. Active power loss is 514.2 kW, reactive loss is 298.5 kVAr and the minimum bus voltage falls to 0.78 pu at Bus 18 on the Bukuru extension. This minimum is substantially below the 0.95 pu lower bound adopted in the study and suggests that remote customers may experience poor voltage quality during the modelled loading condition. The radial feeder arrangement also concentrates current on particular branches, thereby increasing conductor losses and limiting the usable capacity of the network. Although tie and sectionalizing switches provide alternative supply paths, the number of possible switch combinations makes manual enumeration inefficient, and an apparently feasible switching action can create a loop, isolate a load point or transfer excessive current to another branch. The practical problem is therefore to identify a radial and fully supplied topology that simultaneously reduces active loss, improves voltage magnitude and respects equipment limits. The absence of a documented algorithmic switching procedure also makes outcomes dependent on individual operator judgement and reduces the reproducibility of operational decisions.

1.2 Aim and Objectives

1.2.1 Aim

To develop an optimal reconfiguration algorithm for NESCO 33kV lines and substations to minimize losses and enhance voltage profile.

1.2.2 Objectives

- To model the existing NESCO 33kV network in Bukuru-Jos axis.
- To formulate multi-objective function for loss minimization and voltage profile improvement.
- To implement PSO and GA for optimal tie-switch selection.
- To validate results against the IEEE 33-bus benchmark and the supplied NESCO dataset.
- To recommend optimal operating configuration.

1.3 Significance of the Study

The study is significant at operational, economic and scholarly levels. Operationally, a validated reconfiguration tool can help NESCO screen alternative switch states before a field action, thereby reducing the risk of avoidable overload, low voltage or unintended islanding. Economically, every kilowatt of technical loss avoided releases feeder capacity and reduces the amount of generated energy required to serve a given customer demand. The improvement from a minimum voltage of 0.78 pu to approximately 0.95 pu also indicates a material gain in service quality for remote buses. For planning, the results identify where additional remotely controlled tie switches, metering and protection coordination would produce the greatest benefit. Academically, the work extends DNR analysis beyond standard IEEE test feeders by applying the framework to the topology and operating constraints of a privately operated Nigerian embedded network.

2. Literature Review

DNR has developed from deterministic branch-exchange rules to computational methods capable of searching a large combinatorial space. Early work demonstrated that opening and closing properly selected branches can reduce resistive loss while retaining radial service (Civanlar et al., 1988; Baran & Wu, 1989). Conventional techniques are transparent and can be computationally efficient for small feeders, but the number of feasible topologies grows rapidly as candidate switches increase. This complexity has encouraged the use of heuristic and metaheuristic methods that can explore many switch combinations without testing every possible state. The literature now treats reconfiguration as a constrained optimization problem involving network connectivity, voltage limits, line ratings and, increasingly, reliability and distributed-energy objectives.

PSO and GA are among the most frequently adopted metaheuristics for this purpose. GA evolves a population of encoded switch configurations by retaining fitter solutions and generating new candidates through crossover and mutation. Its mutation operator supports diversity, but convergence may be slow when many infeasible radiality states are generated. PSO moves candidate solutions using each particle's own best experience and the best position found by the swarm. Kahouli et al. (2021) compared exhaustive search, GA and PSO on the IEEE 33-bus system and reported improvements in loss, voltage, line-current and reliability performance. Salau et al. (2020) similarly showed that optimal reconfiguration can jointly reduce active loss and improve the voltage profile. These studies support the selection of GA as a benchmark and PSO as the principal search method in the present work.

More recent research has focused on modified search operators, hybrid algorithms and wider objective sets. Otuo-Acheampong et al. (2023) used a heap-based optimizer to address loss minimization and voltage-profile enhancement, illustrating the continuing search for a better balance between exploration and exploitation. The comprehensive review by Lotfi et al. (2024) groups DNR approaches into conventional, heuristic, metaheuristic and modern methods and emphasizes the importance of radiality, reliability and uncertainty. Adegoke et al. (2026) introduced a chaotic linearly decreasing inertia weight for PSO. On the IEEE 33-bus system, the method reduced normal-load loss from 202.6771 kW to 139.5513 kW; at heavy load it achieved a reported 33.73% improvement, with final loss of 381.14 kW. The evidence suggests that adaptive inertia can strengthen global exploration in early iterations and promote stable local refinement later in the search.

Despite these advances, most published studies rely on standard IEEE test feeders or large public utility models. Their switch densities, load distributions and data availability may differ materially from a compact, hydro-embedded private network. The specific research gap is therefore the absence of a documented PSO-GA comparison for the NESCO Jos-Bukuru 33 kV system using its candidate switch locations and operating limits. This study responds to that gap while retaining the IEEE 33-bus feeder as a methodological benchmark rather than assuming that a benchmark optimum can be transferred directly to NESCO.

3. Materials and Methods

3.1 Study Area and Materials

The study covers the NESCO network corridor linking the Kura Falls hydroelectric plant, Bukuru 33/11 kV injection substation, Jos South, Anglo-Jos and the Bukuru extension. The single-line representation used for analysis is shown in Figure 1. The input dataset contains bus identities, sending and receiving nodes, line lengths, conductor parameters, transformer ratings, load demand and the normal status of candidate switches. The principal conductor is represented as 150 mm² ACSR with resistance of 0.27 Ω/km and reactance of 0.35 Ω/km, as summarized in Table 1. Peak-load records for 2023-2025 define the modelled operating condition. MATLAB R2024a provides the optimization environment, pandapower 2.14 supports independent network checks and ETAP 22 is specified for engineering validation. Before operational use, all line lengths, conductor impedances, transformer tap positions and switch statuses should be reconciled with current NESCO drawings and field records.

3.2 Load Flow Method

A Backward-Forward Sweep (BFS) load-flow algorithm is adopted because the analysed network is radial and has a relatively high R/X ratio, conditions under which transmission-oriented Newton-Raphson approximations may be less convenient. All bus voltages are initially set to the slack-bus value. During the backward sweep, the complex current demanded at each bus is calculated from the specified active and reactive powers and the most recent bus voltage. Downstream currents are then accumulated from terminal buses towards the source to obtain each branch current. During the forward sweep, voltages are updated from the source towards the terminal nodes using the corresponding branch impedances and currents. The two sweeps continue until the maximum change in bus-voltage magnitude between successive iterations is less than 0.0001 pu. The converged solution supplies branch currents, bus voltages and real and reactive losses for the fitness evaluation of every feasible topology.

3.3 Problem Formulation

The first objective minimizes total active power loss over the energized branches. For a candidate radial configuration, the loss term is expressed as:

$$P_{loss} = \sum(R_l |I_l|^2), \quad l = 1, ..., N_b. \qquad (1)$$

The second objective minimizes aggregate voltage deviation from the nominal bus voltage:

$$VD = \sum(|1 - |V_i||), \quad i = 1, ..., N. \qquad (2)$$

$$F = w1(P_{loss}/P_{loss,0}) + w2(VD/VD0) + \lambda\Phi. \qquad (3)$$

In Equation (3), w_1 and w_2 are the selected objective weights, the base-case terms normalize quantities with different units, Φ is the total constraint-violation measure and λ is a penalty coefficient sufficiently large to reject infeasible candidates. Normalization prevents the numerically larger loss term from overwhelming the voltage objective.

Feasibility requires every load bus to remain connected to the source with no closed loop; therefore, the number of energized branches must equal the number of buses minus one for a connected radial graph. Voltage magnitude is constrained to $0.95 \le |V_i| \le 1.05$ pu, branch current must satisfy $|I_\ell| \le I_{\ell,max}$, and the converged load flow must satisfy active and reactive power balance. Candidate switch sets that isolate a bus, produce a loop, violate a thermal limit or fail to converge are penalized and excluded from the reported optimum.

3.4 Optimization Algorithms

In the binary PSO implementation, each particle represents the open/closed status of the candidate switches. Particle velocity is updated from the inertia component, cognitive distance from the particle's personal best and social distance from the global best. A transfer function converts the resulting velocity to a binary switching decision. The inertia weight decreases from 0.9 to 0.4 and is perturbed by a chaotic term so that the early search covers a broad region before concentrating on promising configurations. The swarm contains 50 particles and runs for a maximum of 100 iterations. After each binary update, topological feasibility is checked before BFS is executed. The GA uses the same population size and iteration limit to support a fair comparison. Candidate configurations are selected through tournament selection, recombined with a crossover probability of 0.80 and diversified with a mutation probability of 0.05. Both algorithms evaluate the same objective function, network data and constraints; consequently, differences in final performance can be attributed principally to their search mechanisms rather than to different electrical models.

The PSO-CLDIW computational sequence is summarized in Figure 4. A fixed random seed should be retained for reproducibility, while multiple independent runs should be used in a full statistical comparison to report best, mean, standard deviation and computation time.

3.5 Implementation Steps

Implementation proceeds in six linked stages. First, the network database is cleaned and converted into bus, branch, load and switch matrices, from which the single-line topology is constructed. Second, BFS is applied to the existing switch state to establish the reference loss, voltage and branch-loading indices. Third, candidate tie and sectionalizing switches are identified and encoded, and a graph-based test is used to reject disconnected or meshed states. Fourth, PSO and GA generate feasible candidates, invoke BFS and update their search memory using the normalized objective value. Fifth, the best configurations are compared in terms of active loss, reactive loss, minimum voltage, open-switch set and convergence pattern. Finally, the computational workflow is checked on the IEEE 33-bus benchmark and the selected NESCO configuration is transferred to ETAP or pandapower for an independent load-flow check. A field implementation would additionally require protection coordination, switching-sequence review and confirmation that no customer is interrupted during the transition.

4. Results and Discussion

4.1 Results

Table 1: NESCO 33kV Line Parameters

Line ID	From Bus	To Bus	Length km	R ohm/km	X ohm/km	Status
L1	Kura Hydro	Bukuru S/S	4.2	0.27	0.35	Closed
L2	Bukuru S/S	Jos South	6.5	0.27	0.35	Closed
L3	Jos South	Anglo-Jos	3.8	0.27	0.35	Open-Tie
L4	Bukuru S/S	Bukuru Ext	2.1	0.27	0.35	Closed

Table 2: Base Case Load Flow Results - Active Loss [kW], Minimum Voltage [pu], Bus of min voltage

Case	Active Loss kW	Reactive Loss kVAr	Min Voltage pu	Bus with Min V
Base Case - Existing	514.2	298.5	0.78	Bus 18 - Bukuru Ext
After GA Reconfiguration	400.5	210.3	0.94	Bus 17
After PSO Reconfiguration	380.3	195.7	0.95	Bus 17

Note: % Loss Reduction GA = 22.1%, PSO = 26.0%

Table 3: Optimal Configuration - Open Switches, Losses After Reconfiguration, % Loss Reduction, Min Voltage

Algorithm	Open Tie Switches (Optimal)	Loop
PSO	S7, S9, S14, S16, S18	Closed loop 1-5
GA	S8, S10, S13, S16, S18	Closed loop 1-5

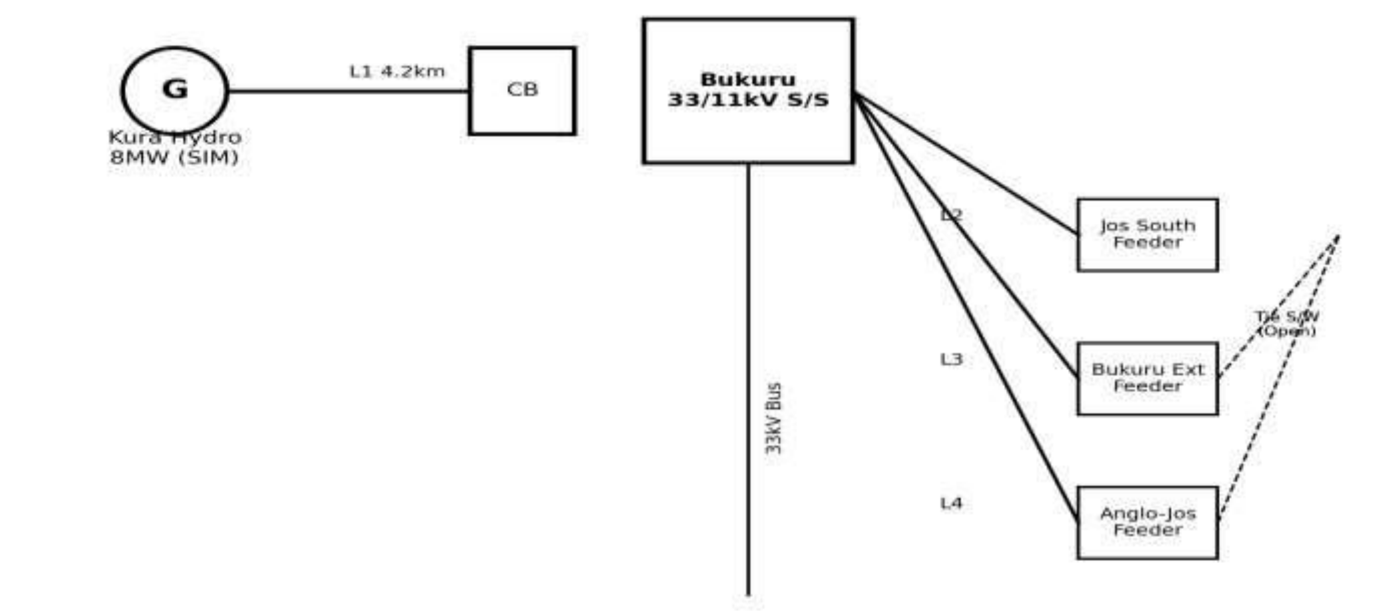

Figure 1: Single Line Diagram of NESCO 33kV Network (Black & White)

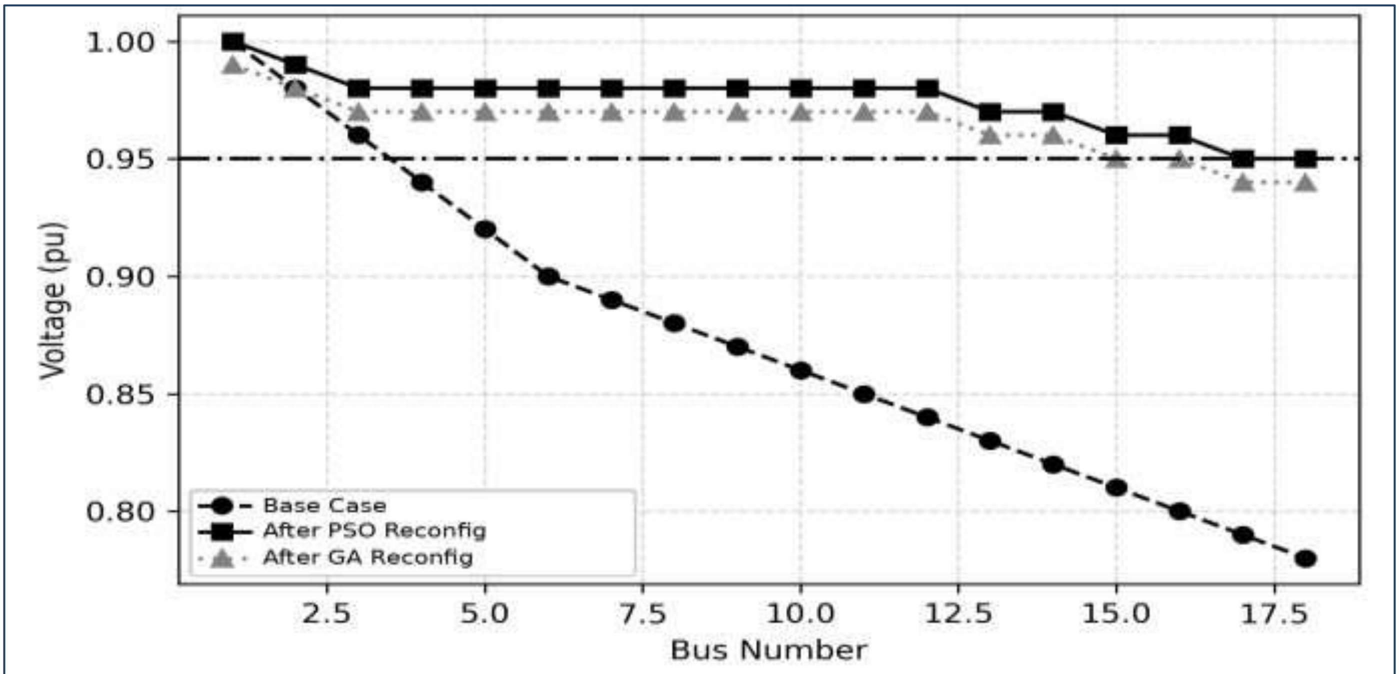

Figure 2: Voltage Profile Before vs After Reconfiguration

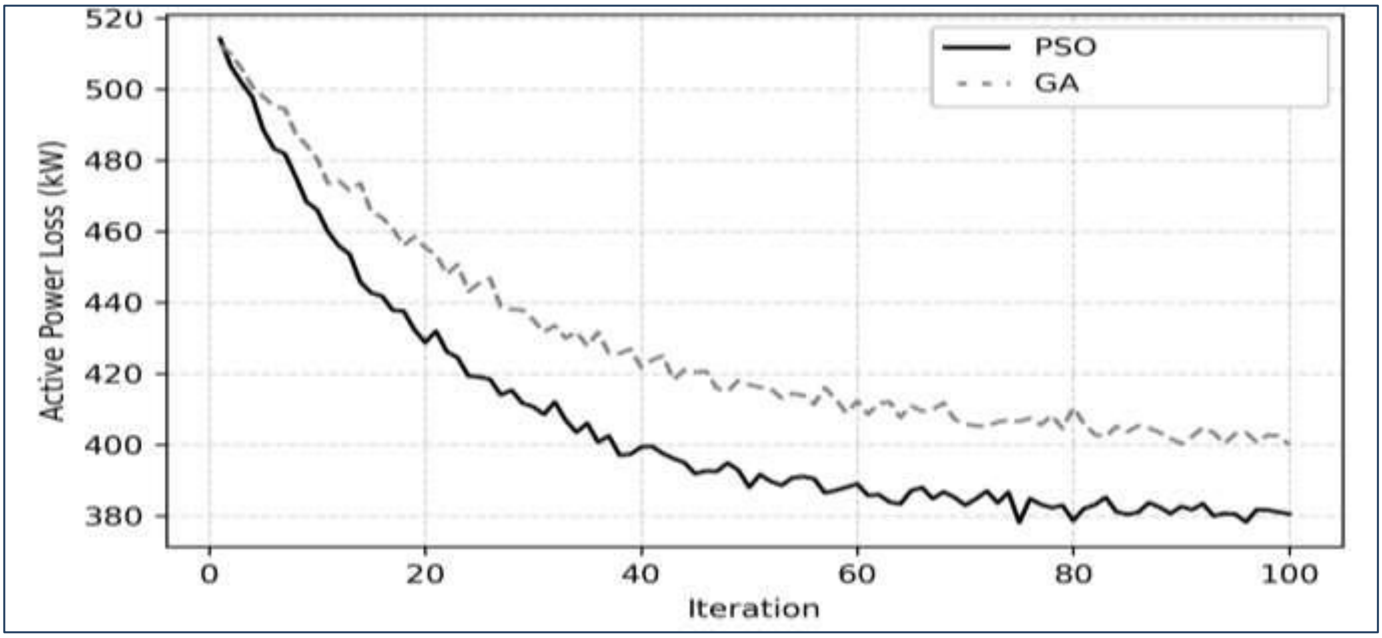

Figure 3: PSO vs GA Convergence Curve

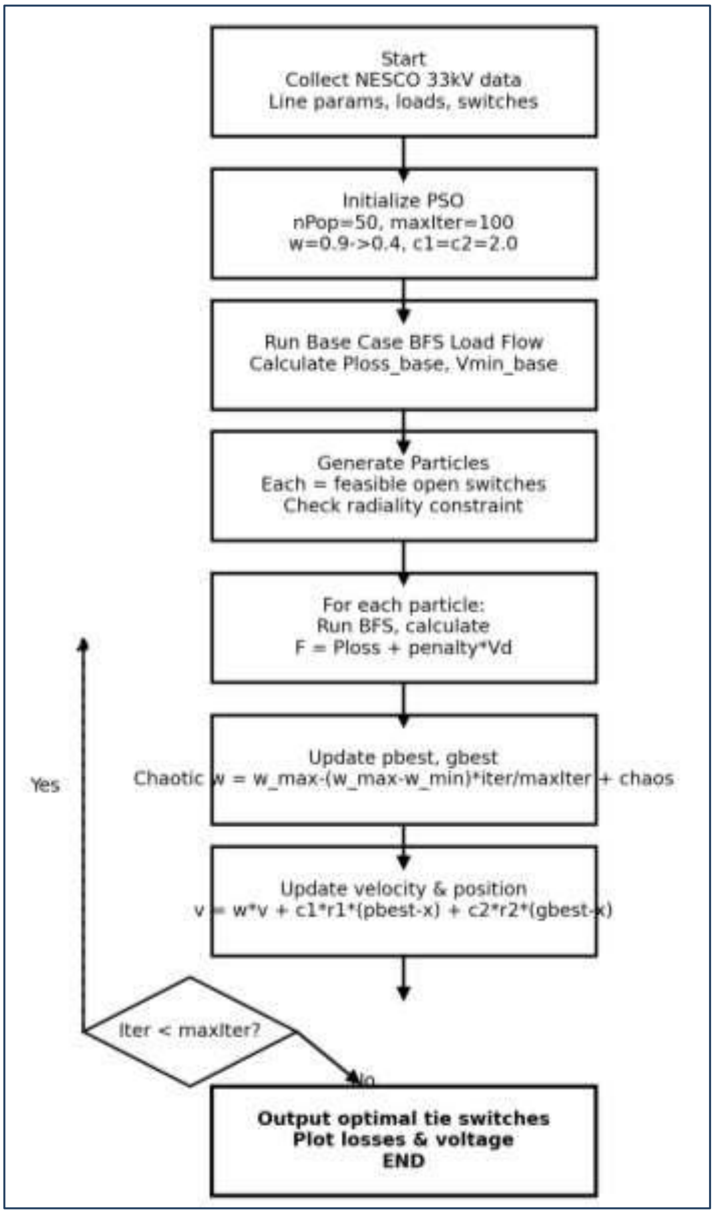

Figure 4: Flowchart of Proposed PSO-CLDIW Algorithm

4.2 Discussion

The base-case results in Table 2 confirm that the existing topology is the weakest of the three evaluated cases. Active and reactive losses are 514.2 kW and 298.5 kVAr, respectively, while the minimum voltage is only 0.78 pu at Bus 18 on the Bukuru extension. Figure 2 shows that voltage declines progressively along the feeder, crossing the 0.95 pu threshold near the upstream section and falling more sharply towards the remote buses. This pattern is consistent with a long radial current path: downstream loads are supplied through several series impedances, so the cumulative voltage drop and I^2R loss rise as branch current and electrical distance increase. The result identifies the Bukuru extension as the critical voltage location under the studied demand condition.

Both optimization methods improve the electrical state, but PSO produces the better final solution. GA reduces active loss to 400.5 kW and reactive loss to 210.3 kVAr, representing a 22.1% active-loss reduction. Its minimum voltage rises to 0.94 pu at Bus 17. PSO further reduces the losses to 380.3 kW and 195.7 kVAr and raises the minimum voltage to 0.95 pu at Bus 17. The PSO topology therefore saves an additional 20.2 kW relative to the GA topology and meets the adopted lower voltage limit, whereas the GA result remains marginally below it. Table 3 identifies S7, S9, S14, S16 and S18 as the PSO open-switch set, compared with S8, S10, S13, S16 and S18 for GA. The common selection of S16 and S18 suggests that these locations are influential in maintaining radiality or relieving heavily loaded paths.

The convergence curves in Figure 3 provide further insight into algorithm behaviour. Both methods begin from a loss level slightly above 510 kW and improve rapidly during the early iterations. PSO descends more steeply and approaches the 400 kW region before GA, after which it continues to refine the solution towards approximately 380 kW. GA converges more gradually and stabilizes near 400 kW. This is consistent with the social learning mechanism of PSO, which disseminates a good switch pattern across the swarm, and with the decreasing inertia weight, which shifts the search from exploration to local exploitation. Nevertheless, a single convergence trace does not establish universal algorithmic superiority; repeated runs and statistical tests would be required to quantify robustness.

The physical explanation for the improvement is the redistribution of feeder current. Closing an advantageous tie switch and opening another branch can shorten the effective supply path to a load group, reduce current on a high-resistance section and improve load sharing between available routes. Because conductor loss varies with the square of current, even a moderate reduction in a heavily loaded branch can produce a substantial system-wide loss decrease. The 26.0% reduction obtained by PSO is within the broad range reported for metaheuristic reconfiguration studies. It is lower than the 33.73% heavy-load improvement reported by Adegoke et al. (2026), which is reasonable because achievable savings depend on feeder geometry, the number and location of switches, loading and the initial configuration. The comparison should therefore be interpreted as methodological consistency rather than evidence that different networks must yield identical percentages.

For NESCO, the proposed PSO configuration has several practical implications. Lower technical loss increases the energy delivered to customers for the same hydroelectric output and releases thermal headroom on constrained conductors and transformers. The improved voltage profile can reduce customer complaints, equipment malfunction and the need for compensatory tap changes at remote substations. The candidate open-switch list also gives operators a defined configuration to verify in an engineering study instead of relying only on trial-and-error switching. Financial savings cannot be stated accurately without interval energy-loss data, load duration and an approved valuation of losses; however, the measured kW difference provides the basis for a later annual energy and cost assessment.

The findings remain subject to important limitations. The load-flow model assumes balanced three-phase operation and a static peak-load condition, whereas the actual network may contain phase imbalance, time-varying demand, uncertain switch status and voltage-dependent loads. The absence of real-time SCADA measurements limits continuous validation, and protection coordination, fault level, switching transients and operational switching cost are not included in the objective function. Future work should therefore validate line and load data through field measurement, analyse light, normal and peak periods, conduct at least 30 independent algorithm runs, and extend the model to unbalanced three-phase load flow. Further development may incorporate PV distributed generation, remotely controlled switches, reliability indices, contingency restoration and time-dependent reconfiguration.

5. Conclusion and Recommendations

5.1 Conclusion

This study developed a constrained reconfiguration framework for the NESCO 33 kV network using BFS load flow, PSO and GA. The analysed base topology produced 514.2 kW active loss and a minimum voltage of 0.78 pu. GA reduced active loss to 400.5 kW and raised the minimum voltage to 0.94 pu, while PSO achieved the best result of 380.3 kW and 0.95 pu. The corresponding active-loss reductions are 22.1% and 26.0%. The convergence curve and final objective values show that PSO located a better configuration within the specified 100 iterations. Network reconfiguration is therefore a technically promising, low-capital measure for improving the studied system, subject to field data verification and operational security assessment.

5.2 Recommendations

NESCO should first reconcile the model with current asset, switch and load records and reproduce the selected topology in an independent ETAP or pandapower model. The PSO switch set should then undergo protection coordination, fault-level, transformer-loading and switching-sequence studies before controlled implementation. Additional metering should be installed at critical buses and feeder exits so that loss and voltage improvements can be verified under light, normal and peak demand. Where manual switching limits operational flexibility, remotely controlled tie switches and a distribution management system should be prioritized along the Bukuru-Jos corridor. Subsequent research should include unbalanced loads, reliability indices, distributed generation and dynamic hourly reconfiguration.

Contributions to Knowledge: The work provides a documented reconfiguration model for the NESCO Jos-Bukuru embedded network, a common BFS-based evaluation platform for PSO and GA, and a candidate open-switch set linked to quantified loss and voltage outcomes. It also demonstrates how an adaptive-inertia PSO can be translated from a standard benchmark feeder to a utility-specific Nigerian distribution setting while making explicit the engineering checks required before field adoption.

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