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11 kV Distribution Feeder Reconfiguration for Power Loss and Voltage Deviation Reduction Using Different Optimization Algorithms

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Abstract

This paper presents an optimal reconfiguration approach for radial distribution systems (RDS) to minimize power losses and improve voltage profiles using metaheuristic algorithms. Particle Swarm Optimization (PSO), Cuckoo Search Algorithm (CSA), Harmony Search Algorithm (HSA), Whale Optimization Algorithm (WOA), and Grey Wolf Optimization (GWO) are applied to determine optimal switching configurations while maintaining bus voltages within permissible limits. The study is validated on the IEEE 33-bus system and the Airport feeder of Kudhar substation using real load and transformer data. A MATLAB-based platform integrated with the Backward–Forward Sweep load flow method is developed for performance evaluation. For the IEEE 33-bus system, active power loss is reduced from 202.6771 kW to 144.578 kW (28.67%), reactive power loss from 135.1409 kVAR to 100.5318 kVAR (25.61%), and average voltage deviation (AVD) from 0.051544 p.u. to 0.031871 p.u. (38.17%). For the Airport feeder, active power loss decreases from 226.3445 kW to 174.8185 kW (22.76%), reactive power loss from 260.5359 kVAR to 194.6124 kVAR (25.30%), and AVD from 0.055189 p.u. to 0.042897 p.u. (22.27%). Each case is executed 20 times to ensure robustness. Results confirm that metaheuristic-based feeder reconfiguration is an effective and economical solution for enhancing distribution system efficiency and voltage performance.

Keywords

Backward-Forward Sweep Method, Feeder Reconfiguration, Metaheuristic Algorithms Radial Distribution Networks, Voltage Profile

1. Introduction

The distribution system is the largest segment of the electrical power system and the final stage in delivering electricity to consumers [1]. It experiences technical or non-technical power losses due to its radial configuration and connected equipment. Technical losses occur naturally in power systems because electrical energy is converted into heat within conductors and other equipment. In contrast, non-technical losses arise from external factors such as electricity theft or meter tampering. These losses decrease system efficiency and raise operating expenses, making their minimization important for delivering reliable power and improving the revenue of utilities. Technical losses mainly depend on the magnitude of current flowing through the network and are highest during periods of peak demand. Poor power factor, unbalanced phases and improper line connections also contribute to these losses. Power losses are generally categorized into active/real power losses and reactive power losses. Real power losses result from the resistance of conductors, whereas reactive power losses originate from the presence of reactive components in the system. Utilities typically focus more on real power losses because they directly reduce the effectiveness of energy transmission. However, reactive power losses are also significant, as maintaining adequate flow of reactive power is essential for sustaining acceptable voltage levels in the system.

Equally critical is the issue of voltage drop, which occurs due to impedance (resistance and reactance) in distribution lines and components. Voltage drop directly impacts the ability to maintain acceptable voltage levels at consumer endpoints, leading to equipment malfunction, reduced motor efficiency and dim lighting. It is caused by factors such as long feeder lengths, unbalanced phase loading and inadequate reactive power compensation, so voltage drop compromises service quality [2].

Reconfiguration of the radial distribution system (RDS) is one of the ways to reduce losses and improve system voltage. For an RDS, feeder reconfiguration is performed by transferring load from heavily loaded branch to lightly loaded branch there by balancing the load and loss reduction [3]. There are two types of switches: open switches called as tie-switch and close switches called as sectionalizing switch. For the better planning of an RDS, network topology needs to be changed with the help of switches. Reducing power losses while keeping bus voltages within acceptable limits is a key objective of any electrical distribution system to ensure reliable supply to consumers. Many researchers have employed meta-heuristic optimization techniques to determine the optimal configuration of radial distribution systems (RDS) with the objective of minimizing active power loss and improving bus voltage profiles. Early studies investigated various optimization approaches, including Ant Colony Search, Fuzzy Logic, and Genetic Algorithms (GA), for loss minimization and performance enhancement in distribution networks [2]-[4].

Among these techniques, Particle Swarm Optimization (PSO), originally introduced in [5], has been widely adopted for distribution system reconfiguration. Several studies have demonstrated the effectiveness of PSO and its modified variants in achieving minimum power loss while maintaining bus voltages within permissible limits [6-11]. These works highlight the capability of PSO-based approaches to handle the nonlinear and combinatorial nature of the reconfiguration problem efficiently.

The Harmony Search Algorithm (HSA) has also been applied to determine optimal switching configurations in standard IEEE test systems. The studies reported in [12] and [13] confirm that HSA provides significant reduction in power losses and voltage deviation in large-scale radial distribution networks. In addition, Cuckoo Search-based techniques have been utilized for multi-objective distribution network reconfiguration, focusing on simultaneous minimization of power loss and voltage deviation in IEEE standard bus systems [14], [15].

More recently, Grey Wolf Optimization (GWO) has been employed for optimal reconfiguration of IEEE 33-bus and 69-bus radial distribution systems, demonstrating substantial loss reduction and improved voltage stability [16], [17]. Similarly, the Whale Optimization Algorithm (WOA) has been applied to network reconfiguration problems with the objective of minimizing power loss and enhancing voltage profiles, as reported in [18], [19]. Overall, the literature indicates that meta-heuristic algorithms provide robust and efficient solutions for the optimal reconfiguration of radial distribution systems, particularly in minimizing power losses and maintaining acceptable voltage limits under various operating conditions. This paper investigates the application of multiple meta-heuristic optimization techniques for optimal network reconfiguration of radial distribution systems. Specifically, Particle Swarm Optimization (PSO), Harmony Search Algorithm (HSA), Cuckoo Search Algorithm (CSA), Grey Wolf Optimization (GWO), and Whale Optimization Algorithm (WOA) are employed to determine the optimal switching positions that minimize active power loss and voltage deviation while satisfying operational constraints.

The proposed approach is validated on the standard IEEE 33-bus test system as well as on the real distribution network of the Pokhara International Airport feeder, both operating as radial power distribution systems. A comprehensive comparative analysis of all five meta-heuristic algorithms is conducted to evaluate their effectiveness in terms of loss reduction and voltage profile improvement. The results demonstrate the relative performance and robustness of each technique, thereby providing practical insight into the selection of suitable optimization methods for distribution system reconfiguration.

2. Methodology

The overall methodology adopted in this study follows a systematic framework consisting of data collection, system modeling, problem formulation, and optimization-based solution. Initially, an extensive literature review was carried out to identify suitable techniques for distribution system reconfiguration and loss minimization. In the first stage of implementation, data for the standard IEEE 33-bus test system were collected, including the single-line diagram, bus data (active and reactive power), and line data (sending bus, receiving bus, resistance, and reactance). In parallel, real-time data of the Airport feeder were collected and prepared by developing the single-line diagram using QGIS, along with the corresponding bus data, line parameters, and feeder loading information. Both systems were then modeled in MATLAB to perform load flow analysis and establish the base-case performance. Subsequently, the distribution system reconfiguration problem was formulated as a constrained optimization problem with the objective of minimizing power losses while maintaining voltage and operational limits. Finally, the formulated problem was solved using a meta-heuristic optimization algorithm to determine the optimal switch configuration for network reconfiguration, resulting in reduced power losses and improved voltage profile for both the benchmark and practical distribution systems. the overall framework of the study is presented in Figure 1.

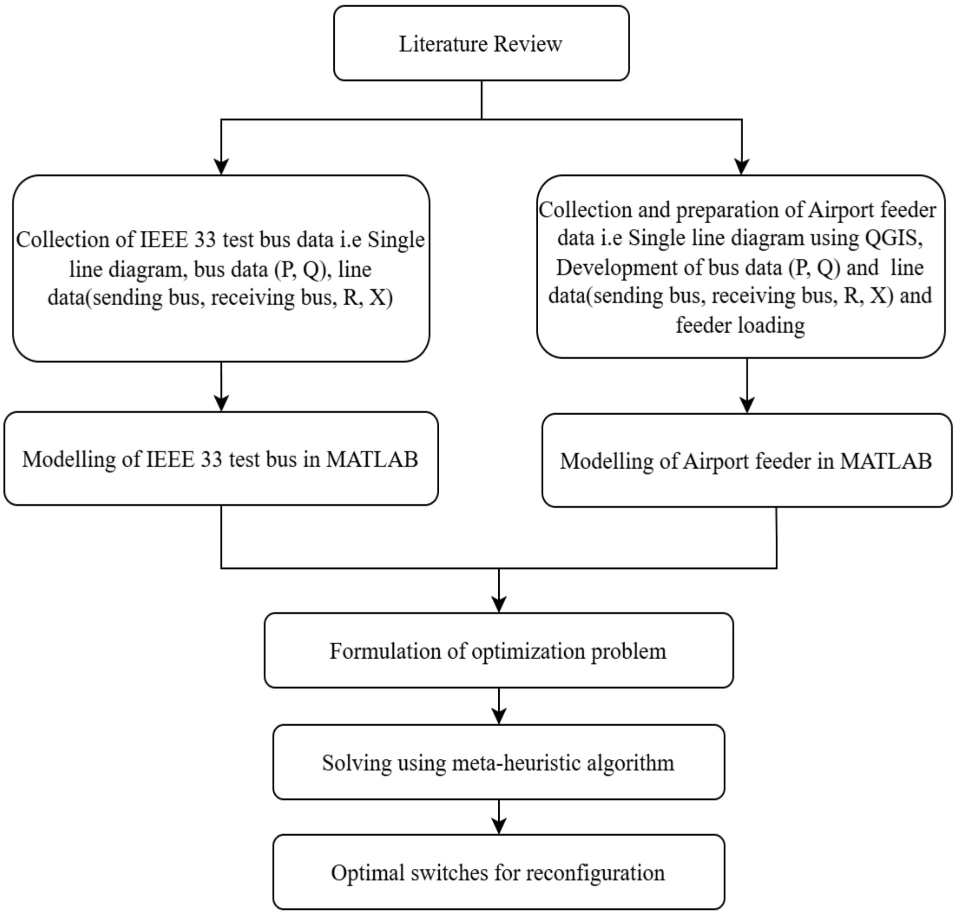

Figure 1: Overall frame work for the study

2.1. System Under Study

The overall framework of this study considers the IEEE 33-bus test system and the Pokhara Airport feeder as radial distribution networks for reconfiguration analysis. The reconfiguration problem is formulated as a constrained optimization task with the primary objective of minimizing power losses while satisfying operational constraints such as voltage limits, current limits, and radiality requirements. To determine the optimal switching configuration, five different meta-heuristic algorithms are implemented and comparatively evaluated to assess their effectiveness in improving network performance. The base-case configurations of the IEEE 33-bus system and the Pokhara Airport feeder are presented in Figure 2 and Figure 3, respectively, which serve as the reference operating conditions for subsequent reconfiguration and performance comparison.

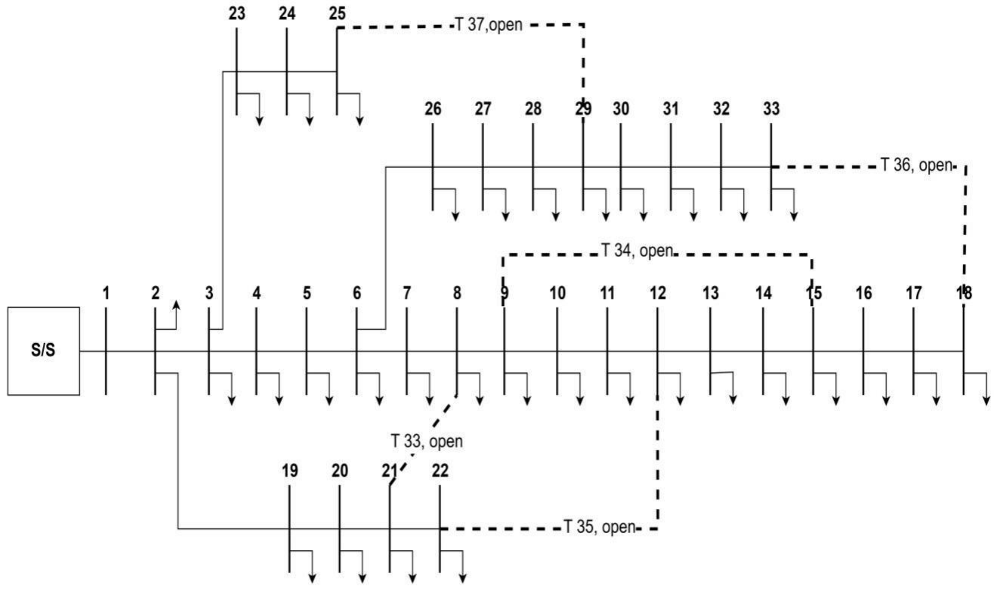

Figure 2: IEEE 33-bus

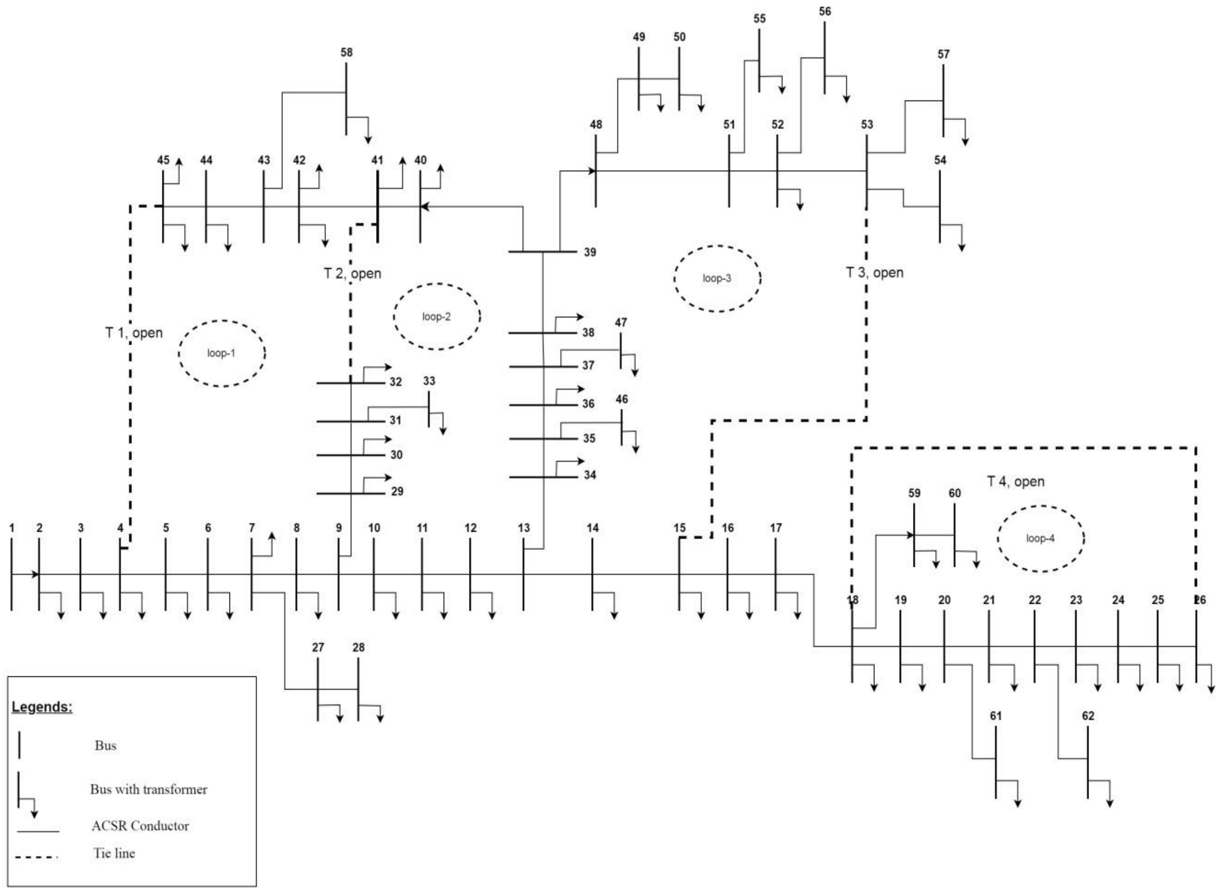

Figure 3: Airport Feeder single line diagram

The conductor used in the airport feeder are WEASEL, RABBIT and DOG whose per unit resistance, reactance and ampacity are presented in Table 1.

Table 1: Resistance, reactance and current carrying capacity of feeder conductor

Name of conductor	Resistance (Ohm/km)	Reactance (Ohm/km)	Ampacity (A)
WEASEL	0.9077	0.356	170
RABBIT	0.5426	0.340	240
DOG	0.2733	0.318	360

2.2 Case Analysis

a) Base Case: The base case represents the initial, unmodified operating condition of the radial distribution system under consideration i.e. IEEE 33-bus and airport feeder, where the network remains in its original configuration without any reconfiguration. In this state, all tie switches are kept open and the system operates with its sectionalizing switches closed. The MATLAB program gives the base case voltage profile and base case power loss.

b) Reconfigured Case: The reconfigured case involves the systematic application of metaheuristic optimization algorithms PSO, HSA, CSA, GWO and WOA to determine an optimal set of switches. The objective is to minimize a multi-objective fitness function that typically combines active power loss, reactive power loss, and Average Voltage Deviation (AVD).

To perform load flow analysis for both the base case and reconfigured cases of the test and practical distribution systems, the Backward–Forward Sweep (BFS) load flow method is employed. The IEEE 33-bus test system and the Pokhara Airport feeder are modeled as radial distribution networks, and the BFS algorithm is used to compute bus voltages, branch currents, and real power losses under each switching configuration. The BFS method is selected due to its computational simplicity, fast convergence characteristics, and suitability for radial distribution systems where traditional Newton–Raphson methods may face convergence difficulties. In this approach, branch currents are calculated in the backward sweep using load currents, and updated bus voltages are obtained in the forward sweep, iterating until the specified convergence criterion is satisfied [20].

2.3 Formulation of the objective function

The objective of the distribution network reconfiguration problem is to simultaneously minimize active power loss, reactive power loss, and voltage deviation. A weighted-sum multi-objective function is adopted and expressed as:

$$\min\,(F) = w_{t1} f_1 + w_{t2} f_2 + w_{t3} f_3 \tag{1}$$

where w_{t1}, w_{t2}, w_{t3} are the weighting factors assigned to each objective. In this study, equal weightage is considered ($w_{t1} = w_{t2} = w_{t3} = 0.33$) to provide balanced importance to loss reduction and voltage profile improvement. Also, the f_1, f_2, and f_3 represents the index function for the active power loss, reactive power loss and the average voltage deviation index respectively.

2.3.1 Active Power Loss Index

The real power loss [1] in each branch is given by:

$$P_{loss}(i, i+1) = R_{i,i+1}.\left(I_{branch}(i, i+1)\right)^2 \tag{2}$$

The total system real power loss [1] is:

$$P_{tloss} = \sum_{i=0}^{N_{br}} P_{loss}(i, i+1) \tag{3}$$

The active power loss index [9] is defined as:

$$f_1 = \frac{P_{tloss}(reconfig)}{P_{tloss}(base)} \tag{4}$$

Where N_{br} is the total number of branches.

2.3.2 Reactive Power Loss Index

Similarly, the reactive power loss [1] in each branch is expressed as:

$$Q_{loss}(i, i+1) = X_{i,i+1}.\left(I_{branch}(i, i+1)\right)^2 \tag{5}$$

The total reactive power loss [1] is:

$$Q_{tloss} = \sum_{i=0}^{N_{br}} Q_{loss}(i, i+1) \tag{6}$$

The reactive power loss index [9] is defined as:

$$f_2 = \frac{Q_{tloss}(reconfig)}{Q_{tloss}(base)} \tag{7}$$

2.3.3 Voltage Deviation Index

The average voltage deviation index [9] is calculated as:

$$\Delta \mathrm{V}_{\mathrm{total}} = \sum_{\mathrm{i}=1}^{N_{bus}} |1 - V_i| \tag{8}$$

for $i = 1,2, \ldots N_{bus}$

The voltage deviation objective function is defined as:

$$f_3 = \frac{\Delta \mathrm{V}_{\mathrm{total}}(reconfig)}{\Delta \mathrm{V}_{\mathrm{total}}(base)} \tag{9}$$

where V_i is the voltage magnitude at bus i, and N_{bus} is the total number of buses.

2.4 Constraints

2.4.1 Bus Voltage Limits

$$V_{min} \leq V_i \leq V_{max} \tag{10}$$

Where $i = 1,2,\ldots.. N_{bus}$

where $V_{min} = 0.9$p.u. and $V_{max} = 1.0$p.u.

2.4.2 Branch Current Limits

$$\mathrm{I}_i \leq \mathrm{I}_{imax} \tag{11}$$

where I_{imax} is the thermal current limit of branch i.

2.4.3 Radial Topology Constraint

The reconfigured network must retain a radial structure with no islanding [5]:

$$N_{br} = (N_{bus} - 1) \tag{12}$$

Network connectivity and radiality are verified using a Breadth-First Search (BFS) algorithm applied to the network adjacency list.

2.4.4 Constraint Violation Penalty

To discourage infeasible solutions during optimization, a penalty-based violation factor is incorporated.

The voltage violation is computed as:

$$V_{vio} = \sum_{i=1}^{N_{bus}} \max(0, V_{min} - V_i) + \sum_{i=1}^{N_{bus}} \max(0, V_i - V_{max}) \tag{13}$$

The current violation is expressed as:

$$\mathrm{I}_{\mathrm{vio}} = \sum_{\mathrm{i}=1}^{N_{br}} \max(0, |\,\mathrm{I}_i| - \mathrm{I}_{imax}) \tag{14}$$

The total violation factor is defined as:

$$\mathrm{V_f} = \mathrm{k_f} * (\mathrm{V_{vio}} + \mathrm{I_{vio}}) \tag{15}$$

where k_f is a large penalty coefficient.

2.5 Meta-Heuristic Optimization Algorithms

2.5.1 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a population-based meta-heuristic inspired by the collective behaviour of bird flocks. In PSO, each particle represents a candidate network configuration and moves through the search space by updating its velocity and position based on its own best experience and the global best solution.

For the i^{th} particle at iteration k, the velocity and position updates are given by [7]:

$$\mathrm{u}_\mathrm{i}^{\mathrm{k}+1} = w\mathrm{u}_\mathrm{i}^\mathrm{k} + C_1 r_1 [P_{bi}^k - \mathrm{X}_\mathrm{i}^\mathrm{k}] + C_2 r_2 [G_b^k - \mathrm{X}_\mathrm{i}^\mathrm{k}] \tag{16}$$

$$X_i^{k+1} = X_i^k + u_i^{k+1} \tag{17}$$

Where X_i Position of the i^{th}particle (candidate solution), u_iVelocity of the i^{th}particle, $w$is the inertia weight, $C_1$and $C_2$are acceleration coefficients, $r_1$and $r_2$are random numbers in $[0, 1]$, $P_i$is the personal best position, and $G$is the global best position.

Each particle is evaluated using the proposed multi-objective fitness function, and infeasible solutions are penalized using the violation factor. Radiality is ensured using BFS before fitness evaluation.

2.5.2 Harmony Search Algorithm (HSA)

The Harmony Search Algorithm (HSA) is inspired by the musical improvisation process, where each harmony represents a candidate solution. The algorithm maintains a Harmony Memory (HM) containing the best solutions found so far.

New harmonies are generated using three mechanisms: memory consideration, pitch adjustment, and random selection, governed by the Harmony Memory Considering Rate (HMCR) and Pitch Adjustment Rate (PAR). A new harmony is generated as [12]:

$$x_i' = \begin{cases} x_i \in HM, & \text{if } rand < HMCR \\ x_i \in X_i, & \text{otherwise} \end{cases} \tag{18}$$

where $rand(\,)$ is a uniformly distributed random number between 0 and 1 and x^i is the set of the possible range of values for each decision variable.

Pitch adjustment is applied with probability PAR to improve solution diversity. The newly generated harmony replaces the worst harmony in HM if it yields a better fitness value.

In this work, HSA is employed to identify optimal switching combinations while satisfying radiality and operational constraints.

2.5.3 Cuckoo Search Algorithm (CSA)

Cuckoo Search Algorithm (CSA) is inspired by the brood parasitism behaviour of cuckoo birds. Each nest represents a candidate solution, and new solutions are generated using Lévy flights to enhance global search capability.

The position update using Lévy flight is expressed as [15]:

$$X_i^{t+1} = X_i^t + \alpha \cdot \text{Levy}(\beta) \tag{19}$$

A fraction $P_a$of the worst nests is replaced by new random solutions to avoid premature convergence. The best nests are retained for the next iteration.

CSA is applied to the network reconfiguration problem by encoding switch states as nests and evaluating their fitness using the proposed objective function.

2.5.4 Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is inspired by the leadership hierarchy and hunting mechanism of grey wolves. The population is divided into alpha (α), beta (β), delta (δ), and omega (ω) wolves. The α, β, and δwolves guide the search process.

The position update of a wolf is determined based on the average influence of the three leading wolves [17]:

$$X(t+1) = \frac{\left(X_{i\alpha} + X_{i\beta} + X_{i\delta}\right)}{3} \tag{20}$$

Control parameters dynamically balance exploration and exploitation during the optimization process. In this study, GWO is used to efficiently explore the switching combinations while maintaining network radiality and operational constraints.

2.5.5 Whale Optimization Algorithm (WOA)

The Whale Optimization Algorithm (WOA) is inspired by the bubble-net feeding strategy of humpback whales. Each whale represents a candidate solution, and optimization is achieved through exploration and exploitation phases.

During exploration ($|A| > 1$), whales update their positions relative to randomly selected whales, while exploitation ($|A| < 1$) is performed using shrinking encircling and spiral updating mechanisms [18]:

$$\mathrm{X(t+1) = X_{rand} - A * D} \tag{21}$$

where $\mathrm{X_{rand}}$ is a random position vector selected from the current population, A is Coefficient vectors and D is "distance" vector used to update the whale's position. WOA is employed to determine optimal feeder reconfiguration by balancing global search and local exploitation.

2.6 Implementation of PSO, HSA, CSA, GWO, WOA and BFS for Optimal Reconfiguration

The Algorithms are implemented in MATLAB software with required codes as the flowchart shown in Figure 4.

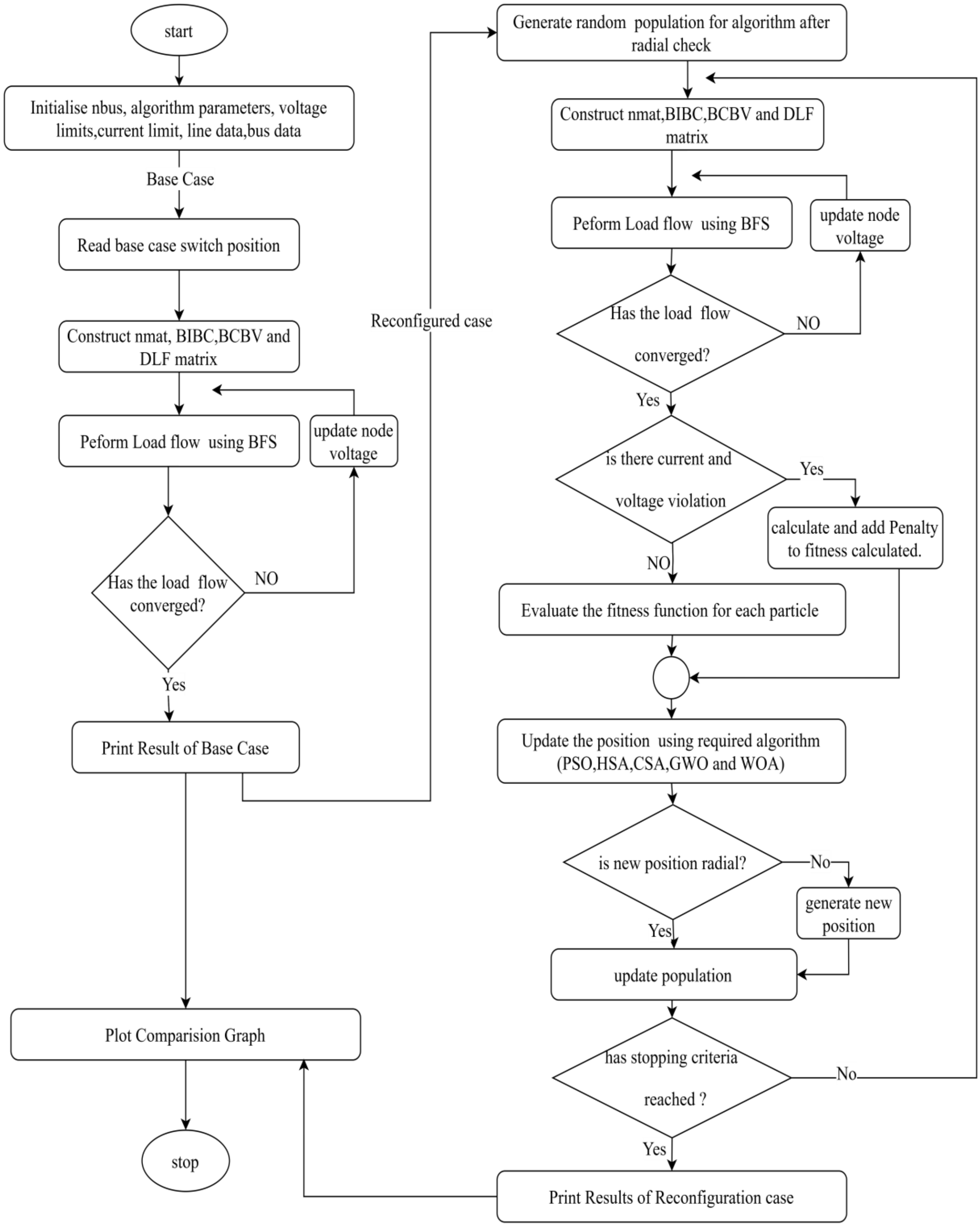

Figure 4: Overall flow chart of the code implemented and reconfiguration process

The process mentioned in the flow chart 4 can be described in the following steps:

Step 1: Initialise Parameters (input data) according to algorithms: nbus (number of buses), Switch configurations (open/closed states), algorithm parameters, Constraints: voltage limits (V_min, V_max), current limit (I_max), Network data: line resistance/reactance, bus load/generation.

Step 2: Base Case Analysis

a) Read initial switch positions (base case configuration).

b) For Each Particle: Construct matrices (nmat, BIBC, BCBV, DLF).
c) Run BFS-based load flow to compute: Voltages, currents, and power losses.
d) Check convergence: If not converged, update voltages and repeat, if converged, proceed.
e) Print and store base case results (voltages, currents, losses).
Step 3: Reconfigured Case
a) Create algorithm population of mentioned sizes of random switches ensuring radial topology.
b) For Each Particle: Construct matrices (nmat, BIBC, BCBV, DLF).
c) Run BFS-based load flow to compute: Voltages, currents, and power losses.
d) Check convergence: If not converged, update voltages and repeat, if converged, proceed.
e) Calculate fitness value according to objective function for all particle.
f) Apply penalties for violations only:
-Voltage violation: Penalize if V_i < V_min or Vi > V_max.
-Current violation: Penalize if I_i > I_max.
g) Update switch position according to algorithm.
h) Check whether the new particle/position is radial or not If configuration is radial update population, if configuration is non-radial, regenerate valid particles/switch configuration.
i) Iteration Check If max iterations have reached: exit loop, else repeat the iteration loop.
step 4. Result comparison Compare the results of Base case and reconfigure case for active power loss, reactive power loss, bus voltages and convergence.
step 5. Stop: End the algorithm.

2.7 Hardware and Software Description

The proposed algorithms and load flow analysis were developed and run in MATLAB software R2018b on a Laptop with 2.40 GHz, core i5, 4 GB RAM.

3. Results and Discussion

The IEEE 33-bus and Pokhara airport feeder RDS was used to evaluate and compare the performance of five optimization algorithms PSO, HSA, CSA, GWO and WOA for network reconfiguration. In the base configuration, for IEEE 33-bus open switches were 33, 34, 35, 36 and 37. Number of tie switches is five so the dimension of the problem becomes five. while, the open switches were 62, 63, 64, and 65 for Pokhara airport feeder. Number of tie switches is four so the dimension of the problem becomes four. Each algorithm was executed 20 independent times to assess reliability and stability. Table 2 presents the main control parameters used for each optimization algorithm.

Table 2: Parameters used for different optimization algorithms for IEEE 33-bus

Algorithm	Parameters	Value IEEE 33-bus	Algorithm	Parameters	Value IEEE 33-bus
PSO	w_{max}	0.8	**CSA**	Pa	0.25
	w_{min}	0.4		Alpha	0.1
	C_1	2.5		Beta	1.5
	C_2	1.5		Number of Nests	150
	Number of Population	150		Number of Iterations	100
	Number of Iterations	100	**GWO**	Number of Wolves	150
HSA	HMS	150		Number of Iterations	100
	HMCR	0.8	**WOA**	Number of Whales	150
	PAR	0.3		Number of Iterations	100
	Number of Iterations	10000			
	Bandwidth	1			

Each algorithm was run 20 independent times and best convergence value of the algorithms among 20 runs is presented in Figure 5 and Figure 6 for IEEE 33-bus and Pokhara airport feeder respectively.

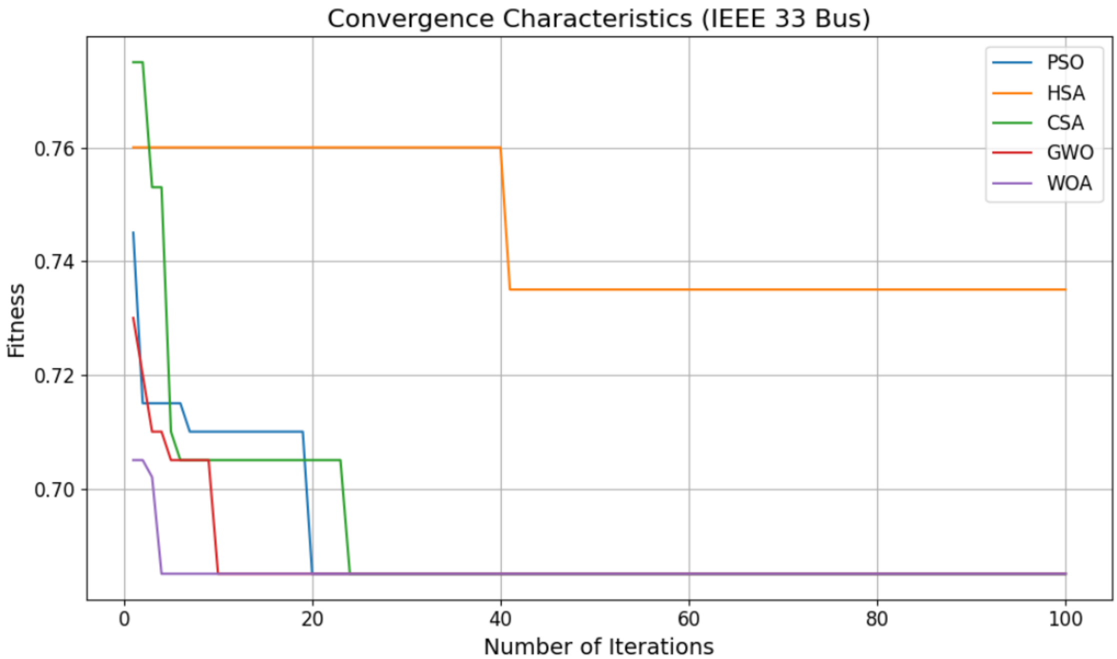

Figure 5: Convergence Characteristics (IEEE 33Bus)

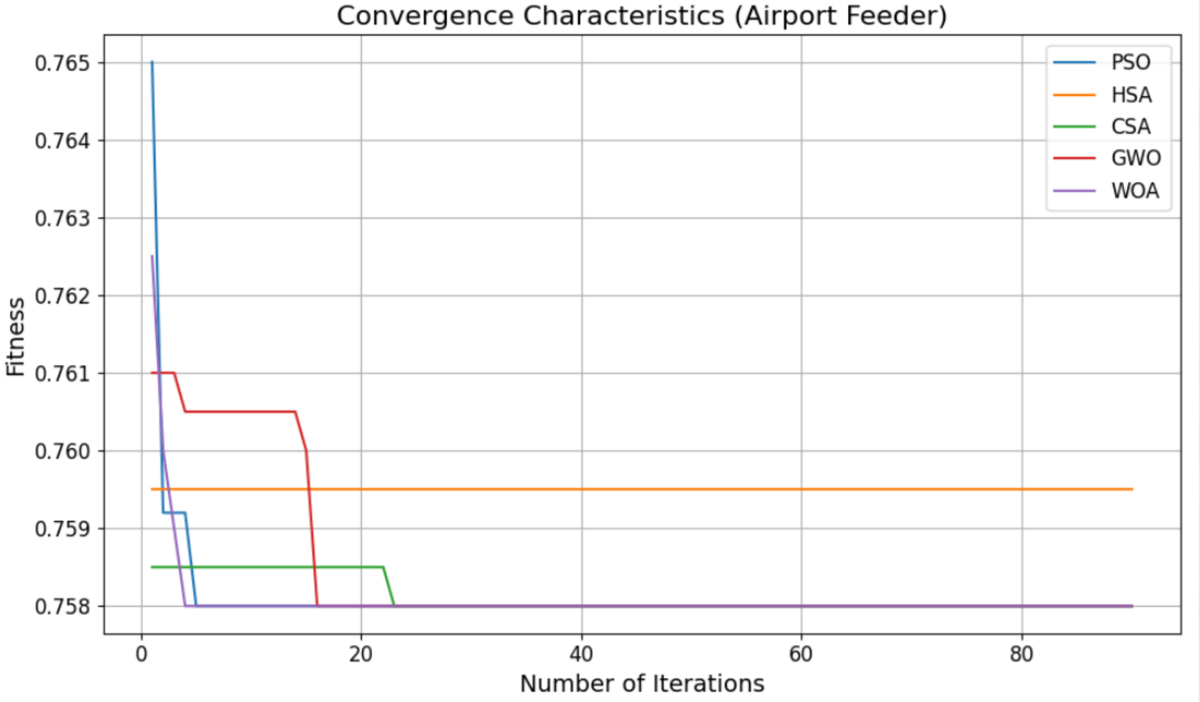

Figure 6: Convergence Characteristics (Airport Feeder)

For the IEEE 33-bus system, all five algorithms (PSO, HSA, CSA, GWO and WOA) converged to the same optimal fitness value of 0.6849. The convergence to the optimum occurred at the 21st iteration for PSO, 467th for HSA, 25th for CSA, 10th for GWO and 5th for WOA. Across 20 independent runs, PSO reached the optimum solution 9 times, HSA 10 times, CSA 11 times, GWO 8 times and WOA 10 times, indicating that CSA exhibited the highest success rate among the tested algorithms for this network.

Similarly, for the Pokhara airport feeder, all five algorithms converged to the same optimal fitness value of 0.7579. The convergence iterations were the 6th for PSO, 640th for HSA, 24th for CSA, 15th for GWO and 5th for WOA. Over 20 independent runs, PSO achieved the optimal solution 13 times, HSA 20 times, CSA 19 times, GWO 20 times and WOA 20 times, demonstrating superior consistency of HSA, GWO and WOA for the real-world distribution system.

The performance of the different metaheuristic algorithms on the IEEE 33-bus system and the Pokhara airport feeder was further evaluated through statistical analysis over 20 independent runs. The results were highly competitive, as summarized in Table 3 and Table 4 which present the best, worst, mean and standard deviation (SD) values of the fitness function for each algorithm. A smaller SD indicates that the obtained solutions are closely clustered around the mean value, reflecting higher robustness and solution stability.

For the IEEE 33-bus system, the base-case active power loss was 202.6771 kW, which was reduced to 144.578 kW after network reconfiguration, corresponding to a 28.67% reduction. Similarly, the reactive power loss decreased from 135.1409 kVAR to 100.5318 kVAR, achieving a 25.61% reduction. The average voltage deviation (AVD) was also improved from 0.051544 p.u. in the base case to 0.031871 p.u. after reconfiguration. The optimal open switch combination identified by the applied algorithms was [9, 14, 28, 32, 33].

Table 3: Comparison of optimization algorithms for IEEE 33-bus system (20 runs)

Items		**Base case**	**Reconfigured Case (IEEE 33-Bus)**				
			PSO	**HSA**	**CSA**	**GWO**	**WOA**
Open/Tie switches(for best fitness)		33,34,35,36,37	9,14,28,32,33	9,14,28,32,33	9,14,28,32,33	9,14,28,32,33	9,14,28,32,33
Fitness (For 20 runs)	Best Switch		0.6849	0.6849	0.6849	0.6849	0.6849
	Worst Switch		0.7041	0.6928	0.6935	0.6964	0.6996
	Average		0.6903	0.6886	0.6882	0.6903	0.6894
	SD		0.0056	0.0038	0.0037	0.0047	0.0049
Active Power(kW)	Best Switch	202.6771	144.578	144.578	144.578	144.578	144.578
Reactive power(kVAR)	Best Switch	135.1409	100.5318	100.5318	100.5318	100.5318	100.5318
AVD	Best Switch	0.051544	0.031871	0.031871	0.031871	0.031871	0.031871
Active Power Loss Reduction (%)	Best Switch		28.67%	28.67%	28.67%	28.67%	28.67%
Reactive Power Loss Reduction (%)	Best Switch		25.61%	25.61%	25.61%	25.61%	25.61%
AVD Reduction (%)	Best Switch		38.17%	38.17%	38.17%	38.17%	38.17%
Time For Convergence(sec)	Best Switch		12.2724	2.1704	10.1669	3.8471	3.7312
	Average		33.0158	23.4513	21.6995	21.3767	23.862
	SD		17.7872	8.6152	8.4059	12.4087	17.7497
convergence @iteration	Best Switch		21	467	25	10	5
	Average		57.95	6437	58.95	45.6	44.85
Frequency of Best Switch Occurrence	Times		9	10	11	8	10
	Percentage		45.0%	50.0%	55.0%	40.0%	50.0%

For the Pokhara airport feeder, the base-case active power loss of 226.3445 kW was reduced to 174.8185 kW following reconfiguration, representing a 22.76% reduction. The reactive power loss decreased from 260.5359 kVAR to 194.6124 kVAR, yielding a 25.30% reduction. In addition, the AVD improved from 0.055189 p.u. to 0.042897 p.u. after reconfiguration. The optimal open switch combination obtained for the airport feeder was [23, 30, 37, 64].

Table 4: Comparison of optimization algorithms for airport feeder (20 runs)

Items		Base case	Reconfigured Case (airport feeder)				
			PSO	HSA	CSA	GWO	WOA
Open/Tie switches (for best fitness)		62,63,64,65	23,30,37,64	23,30,37,64	23,30,37,64	23,30,37,64	23,30,37,64
Fitness (For 20 runs)	Best Switch		0.7579	0.7579	0.7579	0.7579	0.7579
	Worst Switch		0.7583	-	0.7581	-	-
	Average		0.758	0.7579	0.7579	0.7579	0.7579
	SD		0.0001	0.00	0.00004	0.00	0.00
Active Power (kW)	Best Switch	226.3445	174.8185	174.8185	174.8185	174.8185	174.8185
Reactive Power (kVAR)	Best Switch	260.5359	194.6124	194.6124	194.6124	194.6124	194.6124
AVD	Best Switch	0.055189	0.042897	0.042897	0.042897	0.042897	0.042897
Active Power Loss Reduction (%)	Best Switch		22.76%	22.76%	22.76%	22.76%	22.76%
Reactive Power Loss Reduction (%)	Best Switch		25.30%	25.30%	25.30%	25.30%	25.30%
AVD Reduction (%)	Best Switch		22.27%	22.27%	22.27%	22.27%	22.27%
Time For Convergence(sec)	Best Switch		12.878	8.2565	27.4632	35.48	8.9884
	Average		84.7622	27.1281	54.4742	175.0843	60.706
	SD		50.0041	17.6763	19.7276	49.6374	38.096
convergence @iteration	Best Switch		6	640	24	15	5
	Average		42	2361.15	53.85	74.2	27.8
Frequency of Best Switch Occurrence	Times		13	20	19	20	20
	Percentage		65.0%	100.0%	95.0%	100.0%	100.0%

4. Conclusions

Five different metaheuristic optimization techniques were successfully applied for the optimal reconfiguration of distribution networks to minimize active power loss, reactive power loss, and average voltage deviation. The effectiveness of the proposed approach was validated using the IEEE 33-bus system and the real-world 11 kV Airport feeder of the Pokhara Distribution Centre.

The proposed methodology was first validated on the IEEE 33-bus system. All five algorithms PSO, HSA, CSA, GWO and WOA converged to the same optimal configuration [9, 14, 28, 32, 33] with a fitness value of 0.6849. Active power loss was reduced from 202.6771 kW to 144.578 kW (28.67%), reactive power loss from 135.1409 kVAR to 100.5318 kVAR (25.61%) and AVD from 0.051544 p.u. to 0.031871 p.u. (38.17%). Over 20 independent runs, all algorithms consistently reached the optimum solution. The standard deviations of fitness values were 0.0056 (PSO), 0.0038 (HSA), 0.0037 (CSA), 0.0047 (GWO) and 0.0049 (WOA). The average convergence times were 33.0158 s (PSO), 23.4513 s (HSA), 21.6995 s (CSA), 21.3767 s (GWO) and 23.862 s (WOA), with best convergence times ranging from 2.1704 s (HSA) to 12.2724 s (PSO). CSA and HSA showed higher stability based on convergence time deviation. The frequency of best switch occurrence was 45% (PSO), 50% (HSA), 55% (CSA), 40% (GWO) and 50% (WOA), indicating superior consistency of CSA for the IEEE 33-bus network.

The approach was then applied to the NEA airport feeder, Pokhara. All algorithms converged to the same optimal configuration [23, 30, 37, 64] with a fitness value of 0.7579. Active power loss decreased from 226.3445 kW to 174.8185 kW (22.76%), reactive power loss from 260.5359 kVAR to 194.6124 kVAR (25.30%) and AVD from 0.055189 p.u. to 0.042897 p.u. (22.27%). In 20 independent runs, all algorithms achieved the optimum solution. The fitness value standard deviations were 0.0001 (PSO), 0.00 (HSA), 0.00004 (CSA), 0.00 (GWO) and 0.00 (WOA). Average convergence times were 84.7622 s (PSO), 27.1281 s (HSA), 54.4742 s (CSA), 175.0843 s (GWO) and 60.706 s (WOA), with best convergence times ranging from 8.2565 s (HSA) to 35.48 s (GWO). CSA and HSA again demonstrated higher stability. The frequency of best switch occurrence was 65% (PSO), 100% (HSA), 95% (CSA), 100% (GWO) and 100% (WOA), confirming the strong consistency of HSA, GWO and WOA for the airport feeder.

Limitation and future recommendation

Despite the promising results obtained, this study has several limitations. The analysis is limited to specific test systems, namely the IEEE 33-bus radial distribution system and a single real-world 11 kV Airport feeder. The study considers steady-state operating conditions with static load data and does not account for time-varying or dynamic load behavior. In addition, the optimization focuses primarily on minimizing active power loss, reactive power loss, and average voltage deviation, while other important factors such as reliability indices, switching operation costs, and protection coordination are not considered.

Future research can extend this work by considering dynamic and time-varying load conditions to better represent real-world operating scenarios. The study can also be expanded to include additional objectives such as reliability improvement, cost of switching operations, and integration of distributed energy resources (DERs) like solar and wind generation.

Conflicts of Interest Statement

The authors declare no conflicts of interest for this study.

Data Availability Statement

The data supporting the findings of this study are presented in the manuscript. Additional data will be provided upon request.

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