Integrating artificial bee colony and cauchy algorithms for distribution network reconfiguration with soft open points

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ABSTRACT

Reconfiguring the distribution network by selecting open switch states is an effective approach to reduce power losses in the system. However, with the rise of distributed energy resources such as photovoltaic and wind turbines and dynamic loads such as electric vehicles, which introduce uncertainties, it has become necessary to integrate standard operating procedures (SOPs) to better control power flows. This study proposes an algorithm that combines the artificial bee colony (ABC) and Cauchy opposition-based learning (OBL) algorithms to solve the optimization problem of determining both the location and capacity of SOPs, alongside reconfiguring the distribution network. The primary objective is to minimize power losses while improving power quality and system reliability. The proposed methodology was validated on the IEEE 33-node and 69-node distribution networks under seven varied operational scenarios, evaluating outcomes both with and without the integration of SOPs. The findings demonstrate that installing SOPs optimally reduces power losses, enhances system reliability, and maintains voltage levels within acceptable limits. The integration of the two algorithms also accelerates the convergence process, increasing computational speed and avoiding local optimization issues. When compared with other methods, the proposed algorithm delivers similar performance but with faster computation times and fewer iterations, making it more efficient and reliable.

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1. INTRODUCTION

The rapid evolution of power distribution networks, driven by the integration of distributed energy resources (DERs) and the increasing demand for reliable and efficient energy delivery, has highlighted the limitations of traditional voltage control methods. Conventional approaches, such as switchable capacitor banks and on-load tap changers, often fail to provide the fast and accurate responses required to mitigate voltage violations and reduce power losses in dynamically changing networks [1], [2]. These limitations have spurred the exploration of advanced strategies, among which SR has emerged as a promising solution for enhancing the performance of distribution systems (DS) [3]–[6].

The process of system reconfiguration involves the deliberate adjustment of the distribution network's structure by toggling the status of switches, with the objective of achieving optimal power distribution, mitigating electrical losses, and ensuring improved voltage regulation throughout the system. However, the radial structure of distribution networks and physical construction constraints often limit the effectiveness of DS [7]. To address these challenges, power electronic devices, particularly standard operating procedures (SOPs), have been introduced as innovative tools for modernizing distribution networks. SOPs, which utilize voltage source converters (VSCs), enable real-time control of active and reactive power flows, allowing for dynamic voltage regulation and loss reduction [8], [9]. Additionally, SOPs can isolate fault-induced peak currents and mitigate voltage disturbances, thereby enhancing system reliability and operational efficiency [10].

Numerous studies have explored the integration of SOPs into distribution networks, with a primary focus on optimizing their placement and operational parameters to enhance system performance. These efforts aim to maximize efficiency, improve voltage profiles, and reduce power losses. For instance, advanced optimization techniques such as multi-objective particle swarm optimization and taxicab optimization have been employed to determine optimal set points for SOPs, demonstrating significant reductions in power losses and notable enhancements in feeder load balancing and voltage profile regulation [11]. Furthermore, genetic algorithms (GAs) have been applied to optimize SOP placement and active/reactive power settings in unbalanced distribution networks, effectively addressing uncertainties associated with distributed generation (DG) integration [12]. Additionally, mixed-integer second-order cone programming has been utilized to resolve nonlinear optimization problems, achieving minimized operational costs and identifying optimal SOP locations based on voltage violation risk and power flow indices [13].

Bi-level optimization techniques have been proposed to address the challenges of SOP planning, with GAs solving the upper-level problem of SOP placement and capacity determination, and particle swarm optimization handling the lower-level optimization of SOP functions [14]. Unique approaches, such as the integration of AC-SOP and DC-SOP for network reconfiguration, have demonstrated significant reductions in power losses [15]. The Archimedes optimization algorithm has been employed to maximize DG penetration and minimize system losses through successive SR and SOP deployments [16]. Discrete-continuous hyper-spherical search techniques have been applied to optimize radial topologies and minimize power losses in distribution systems with multiple DGs and SOPs [17]. Bi-level multi-objective optimization methods have been developed to ensure operational constraints while optimizing hosting capacity and minimizing total active losses in DSs with simultaneous SR and SOP allocation [18]. Modified particle swarm optimization techniques have been used to address the challenges of integrating SR and SOP in active DSs, focusing on reducing power losses, enhancing steady-state operation efficiency, and optimizing voltage profiles [19].

The artificial bee colony (ABC) algorithm has also been successfully applied to distribution network reconfiguration, demonstrating its effectiveness in optimizing the capacity and location of distributed energy resources while minimizing power losses [20], [21]. Despite the advantages of these methods, such as their ability to accurately determine SOP locations and capacities, reduce power losses, and optimize voltage profiles, they are not without limitations. The complexity and computational time required for these techniques, particularly in large networks, remain significant challenges. Additionally, methods like GAs are prone to falling into local optima, leading to suboptimal solutions. The reliance on precise and comprehensive input data further complicates the optimization process, as data scarcity can adversely affect the effectiveness of the solutions [11]–[19].

In light of these challenges, this paper proposes a novel approach that integrates the ABC algorithm with the Cauchy mutation operator to enhance the optimization of distribution network reconfiguration with soft open points (SOPs). The Cauchy operator, known for its ability to generate large step sizes, improves the exploration and exploitation capabilities of the ABC algorithm, enabling it to escape local optima and converge more efficiently toward global solutions. The proposed method aims to optimize network topology, minimize power losses, and improve voltage stability while considering the operational constraints of SOPs. Through comprehensive simulations and case studies, the effectiveness of the proposed approach is demonstrated, highlighting its potential for real-world applications in modern power distribution systems.

In this study, the author proposes an improved ABC algorithm by integrating it with the Cauchy opposition-based learning (OBL) algorithm in steps 1 and 2 of the traditional ABC algorithm, specifically: i) using Cauchy OBL to generate populations from the random population of ABC, and ii) using Cauchy OBL to determine the position of the food source in a multi-dimensional manner, instead of the one-dimensional approach of ABC. With the aim of reducing losses and improving voltage quality, the objective function is considered on the distribution network with SOP installation. The proposed algorithm addresses a complex optimization problem involving both discrete and continuous variables, such as the location and size of SOPs and the open/close states of switches in the reconfiguration problem, along with the technical constraints of the distribution grid. The research results are evaluated on 33-node and 69-node - IEEE under various scenarios to assess the algorithms effectiveness.

The structure of this paper is outlined as follows: section 1 presents, Introduction problem, section 2 presents the model, constraint coditions and proposed for problem. Section 3 presents a results and discussions, and section 4 present conclusion.

2. MODEL, CONSTRAINT CODITIONS AND PROPOSED FOR PROBLEM

2.1. SOPs model

SOP are sophisticated power electronic devices that are increasingly being utilized in radial distribution networks to replace traditional sectionalizing and tie switches Figures 1 and 2. These advanced devices play a crucial role in enhancing system performance by optimizing power flow distribution, improving voltage stability, and reducing energy losses [9]. To achieve this goal, it is essential to effectively isolate faults and quickly restore the power supply during fault conditions, while also dynamically and continuously managing the active and reactive power flow between nodes or feeders during standard grid operations [10]. The core focus of this study is illustrated in Figures 1 and 2, where the basic topology of two-terminal voltage source converters is positioned at sectionalizing and tie switches. Due to their connection through a DC bus, the reactive power outputs of the two converters are independent of each other [11]. The proposed SOP configuration can be modeled using (1).

$$P_n^{SOP} + P_m^{SOP} + P_n^{SOPloss} + P_m^{SOPloss} = 0 \quad (1)$$

In this model, P_n^{SOP}, P_m^{SOP} denote the active power injected by the SOP at the nth and mth nodes, respectively, and $P_n^{SOPlosse}$, $P_m^{SOPlosse}$ take into consideration the power losses generated internally by the SOP converters at these nodes. This investigation accordingly incorporates the concept of a lossless SOP. In the context of a lossless SOP deployment, the aggregate active power injected into the mth and nth nodes sums to zero [12]. The constraints governing the SOP's active power are delineated in (2).

$$P_n^{SOP} + P_m^{SOP} = 0 \quad (2)$$

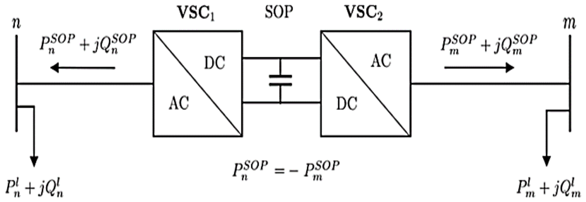

Figure 1. The placement of the SOP model at the sectionalizing switch

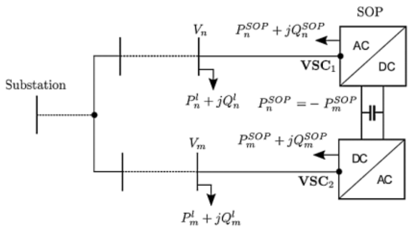

Figure 2. Integration of the SOP model at the tie-switch location

The reactive power contributions from the SOP to the distribution system network are constrained such that they do not surpass the cumulative reactive power demand of the system loads, as stipulated in (3).

$$\sum_{k=1}^{N_{SOP}} \left(Q_n^{SOP}(k) + Q_m^{SOP}(k) \right) \leq \sum_{u=1}^{N_{load}} Q_u^1 \quad \forall u \in N_{load}, \forall k \in N_{SOP} \quad (3)$$

In this context, Q_u^l indicates the reactive power demand at the nth node; while N_{load} and N_{SOP} denote the total number of loads and SOPs, respectively; Additionally, Q_n^{SOP} and Q_m^{SOP} represent the reactive power injected by the SOP at the nth and mth nodes. The capacity constraints of the SOPs are mathematically expressed in (4) and (5):

$$\sqrt{\left(P_n^{SOP}\right)^2 + \left(Q_n^{SOP}\right)^2} \leq \left(S_{rated}^{SOP}\right) \quad (4)$$

$$\sqrt{\left(P_m^{SOP}\right)^2 + \left(Q_m^{SOP}\right)^2} \leq \left(S_{rated}^{SOP}\right) \quad (5)$$

here, S_{rated}^{SOP} rated refers to the rated capacity of the SOP.

2.2. Optimization objective

This study introduces an optimized formulation designed to minimize active power losses in the distribution network, ensuring that all operational and procedural constraints remain within permissible bounds [12]. The optimized formulation is represented by (6).

$$Min_X(P_{loss}) = \sum_{d=1}^{N_{br}} \propto_d \left(\frac{P_d^2+Q_d^2}{|V_d|^2}\right) r_d \tag{6}$$

In this equation, X denotes the decision vector, which includes the status of sectionalizing and tie switches, along with the sizing and placement of SOPs; N_{br} represents the total number of branches; where $\alpha_d=1$ indicates the connection and $\alpha_d = 0$ the disconnection of the d^{th} branch; For the d_{th} branch, P_d, Q_d, and V_d correspond to the active power, reactive power, and voltage at the sending end, respectively, whereas r_d signifies the resistance of the branch. As shown in (6) is resolved by accounting for both the equality and inequality constraints related to the operational limits and SOP specifications within DS [18], [19]. The problem constraints are provided in the following manner:

The voltage magnitude at each node within the distribution system (DS) must be maintained within permissible bounds, as delineated by the inequality constraints specified in (7)

$$V_{min} \leq |V_n| \leq V_{max} \ \ with\ \forall n \in N_{node} \tag{7}$$

In this equation, V_n corresponds to the voltage level measured at node n, while V_{min} and V_{max} define the lower and upper bounds of acceptable voltage levels, set at 0.95 p.u and 1.05 p.u, respectively. Additionally, N_{node} indicates the total number of nodes in the system.

Another constraint involves the current limit of each branch, which is expressed in (8):

$$|I_d| \leq I_d^{max} \ \ with\ \forall d \in N_{br} \tag{8}$$

In this context, I_d denotes the current flowing through the dth, while I_d^{max} ignifies the maximum allowable current for that branch.

The guarantee of uninterrupted connectivity and power delivery to all loads from the primary substation amidst network reconfiguration, preserving the radial configuration of the distribution system is imperative. Consequently, the proposed objective function incorporates an equality constraint that encapsulates the necessity of maintaining radiality. This constraint is outlined in (9).

$$N_{br} = N_{node} - 1 \tag{9}$$

The constraints pertaining to SOP are articulated through (2) to (5), in addition to being formalized in (10) and (11).

$$Q_{min}^{SOP-n} \leq Q_n^{SOP} \leq Q_{max}^{SOP-n} \tag{10}$$

$$Q_{min}^{SOP-m} \leq Q_m^{SOP} \leq Q_{max}^{SOP-m} \tag{11}$$

here, Q_{min}^{SOP-n} and Q_{max}^{SOP-n} denote the lower and upper limits of the reactive power constraints imposed by the SOP injected into the n^{th} node, respectively; Q_{min}^{SOP-m} and Q_{max}^{SOP-m} indicate the minimum and maximum limits of the reactive power constraints imposed by the SOP injected into the mth node, respectively; while and represent the reactive power injections from the SOP at the m^{th} node, respectively; and Q_m^{SOP} and Q_m^{SOP} represent the reactive power injected by the SOP at the n^{th} and m^{th} nodes, respectively.

2.3. Combine artificial bee conoly algorith with the cauchy OBL algorithm to problem fomulation

The initial population's characteristics significantly impact both the global convergence speed and the overall effectiveness of the optimization algorithm. A diverse initial population can greatly enhance algorithms optimization performance. However, in the basic ABC algorithm, the initial population is generated randomly, which does not ensure sufficient diversity, potentially leading to suboptimal performance during the search process. Additionally, the neighborhood search phase also affects the algorithms convergence speed, as ineffective search strategies may cause the algorithm to get stuck in local optima.

To overcome these limitations and improve the performance of the ABC algorithm, we propose integrating the Cauchy OBL algorithm with the ABC algorithm to optimize the initialization process and speed up convergence. Specifically, our proposed method operates as follows:

– Population initialization: the Cauchy OLB algorithm is used to generate superior individuals from the random initialization of the ABC algorithm. This helps enhance the diversity of the population from the

start, rather than relying solely on random individuals, thereby improving the optimization capability of the algorithm.
- Searching for better food sources: by using Cauchy OLB to improve the initial population, the algorithm can quickly identify better food sources (solutions) in the search space. This is achieved through operations based on (18), helping the algorithm move closer to the global optimum.With this approach, we expect that the improved algorithm will converge faster and achieve better optimal results compared to the basic ABC algorithm.

2.3.1. Overview of artificial bee conlony algorithm

The ABC algorithm, pioneered by Fuad *et al.* [20], is a metaheuristic optimization technique modeled after the efficient foraging patterns and collaborative behavior exhibited by honeybee colonies in nature. This algorithm categorizes bees into three distinct roles: employed bees, onlooker bees, and scout bees. The colony is bifurcated into two groups: the first comprises employed bees, while the second consists of onlooker bees. When a food source is exhausted, employed bees adaptively transform into scout bees to explore new regions. In the ABC framework, each food source symbolizes a candidate solution to the optimization problem, with the nectar quantity reflecting the fitness value of the solution. It is important to note that the quantity of employed bees matches the number of food sources, which directly aligns with the number of candidate solutions being assessed during each iteration. The stages of ABC are repeated until a stopping criterion is met.
- Initialization phase [22]

The algorithm commences with the initialization of key parameters, including the maximum cycle number (MCN) and the limit for abandoning food sources. Representing the dimensionality of the problem as D, an initial population of food sources, denoted as x, is randomly generated within the predefined solution space, expressed as follows: $x = \{x_1, x_2, \ldots, x_{SN}\}$. Each food source x_i corresponds to a potential solution of the optimization problem and is represented as $x_i = \{x_{i1}, x_{i2}, \ldots, x_{iD}\}$ for i ranging from 1 to SN. The initialization process includes assigning values to x_i.

$$x_{id} = x_{id,min} + rand(0,1)(x_{id,max} - x_{id,min}) \text{ with } (d = 1,2\ldots,D) \tag{12}$$

In this contex, $x_{id,max}$ and $x_{id,min}$ represent the upper and lower bounds of the search space, respectively, while *rand(0,1)* denotes a randomly generated number within the interval (0,1). The concentration and fitness level of the food source are then determined (13).

$$f_{it}(x_i) = \begin{cases} 1 + f(x_i) & f(x_i) \geq 0 \\ \frac{1}{1+|f(x_i)|} & f(x_i) \leq 0 \end{cases} \tag{13}$$

In this equation, $f(x_i)$ represents the objective function value, while $f_{it}(x_i)$ corresponds to the food concentration of the i^{th} food source.
- Employed bee phase [20]

Guide the bees to explore the nearby food sources, and the algorithm for generating new food sources is $v_i = \{v_{i1}, v_{i2}, \ldots, v_{iD}\}$

$$v_{id} = \begin{cases} x_{id} + r_{id}(x_{id} - x_{qd}) & if\ d = d_{rand} \\ x_{id} & if\ d \neq d_{rand} \end{cases} \tag{14}$$

here, q is a randomly selected number within the range [1, SN] where $q \neq i$ distinct food source, different from the i^{th} one is chosen from the total SN food sources. Additionally, d_{rand} is a random integer between [1, D], and $r_{id} \in$ - [1,1] is a random number that determines the search scope.

After the neighborhood search, the selection follows the "greed principle. If the new food source has a higher concentration, it replaces the old one; if not, the old source is retained. This approach directs the optimization process towards more promising areas, maximizing food concentration.
- Onlooker bee phase [22]

$$P(x_i) = \frac{f_{it}(x_i)}{\sum_{i=1}^{SN} f_{it}(x_i)} \tag{15}$$

Similarly, the follower bee performs a local search around the selected food source utilizing (14) and applies a greedy selection mechanism. If the nectar quality of the newly discovered source surpasses that of the original source identified by the lead bee, the old source is updated, and a role transition occurs. Otherwise, the initial selection is retained without modification.

– Scout bee phase [22]

If the food source's quality shows no improvement over successive iterations following the greedy selection, it is deemed a local optimum and abandoned. The worker bee then transitions to a scout bee, initiating a global search using (12) to identify a new solution. Once a new food source is found, the scout bee reverts to its worker role, ensuring continued exploration and avoidance of stagnation in the optimization process.

The algorithm logs the best food source found and checks the termination condition. The actions of employed, observer, and scout bees continue until the termination condition is met, typically either satisfying the allowable error value or reaching zero cycles.

2.3.2. Improved ABC combined Cauchy OBL to problem formulation

The performance of the ABC algorithm is influenced by two main factors: the computational time and the proximity of each individual in the initial population to the optimal solution [23], [24]. If the initial individuals are closer to the optimal value, the population typically converges more quickly during the optimization process. To enhance this behavior, the proposed algorithm introduces two key improvements through the integration of the Cauchy OBL algorithm, further boosting convergence efficiency.

- Using Cauchy to generate individuals from the initial individuals of the ABC algorithm.
- Using Cauchy OBL to calculate the nearest food sources to the newly selected group of individuals.

H.R. Tizhoosh initially suggested OBL in 2005. In OBL [25], $\overline{x_i}(t) = (\overline{x_1}, \overline{x_2}, \ldots, \overline{x_D})$, reversed solution for each individual x_i, use the following formula to calculate:

$$\overline{x_i}(t) = x_{idmax} + x_{idmin} - x_i \tag{16}$$

Cauchy reverse education between the individual range's midpoint and reverse point—also known as the Cauchy reverse point—a point is produced at random [26], noted as x_i^f.

$$x_i^f = rand\left(\frac{x_{idmax}+x_{idmin}}{2}, \overline{x_i}\right) \tag{17}$$

The following actions are taken to start the Cauchy OBL process:

1. To generate the first set of answers uniformly and randomly, use (12).
2. Use (16) and (17) to get this initial population's Cauchy-inverse. After that, the original set and this inverse group are combined to create a whole new population.
3. Assess everyone's fitness within this expanded population. Sort them according to their fitness scores in a descending manner. Choose the top half of this sorted group, which consists of the people who are more fit, to create the refined starting population for the other operations.

The steps for implementing Cauchy reverse learning in the employed phase are as follows:

1. Apply (14) to conduct a neighborhood search, leading to the creation of potential solution candidates.
2. Generate the Cauchy inverse of these candidate solutions using (16) and (17).
3. Implement a greedy selection mechanism between the original and inverse candidate solutions. This process selects the most favorable solution, thereby enhancing the algorithm's capability for global exploration and optimization.

In the ABC algorithm combined with Cauchy OBL, candidate solutions are typically selected randomly from the initial population. However, in this study, the ABC-Cauchy OBL approach strategically selects the initial individuals, as illustrated in Figure 3.

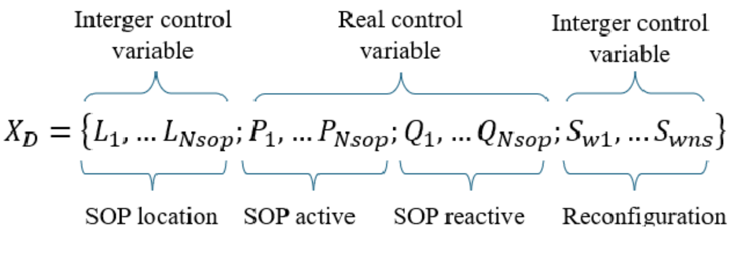

Figure 3. The original individual IABC's structure

This selection process involves two distinct components: integer control variables representing the rervice restoration problem, and real-valued control variables corresponding to the SOP size constraints. We address each part of this structure independently to avoid selecting non-discrete numbers that fall outside the permissible range when updating the designated stream locations. In this architecture, every constituent element including network reconfiguration, active and reactive power injection through SOP, and SOP positioning employs distinct crossover and mutation mechanisms to enable the creation of innovative solutions.

2.3.3. Multidimensional update

In the multidimensional phase of the ABC algorithm, the standard single-dimensional position update is typically applied. This research incorporates a multi-dimensional update mechanism within the improved ABC (IABC) algorithm. Rather than relying on the traditional single-dimensional update process, the IABC algorithm adopts a multi-dimensional position update strategy, leveraging the integration of the Cauchy OBL algorithm [23], [24]. To accelerate the convergence speed by utilizing the improvements of the Cauchy OBL algorithm to find better solutions, (14) in the basic ABC algorithm is replaced by (18):

$$v_{id} = \begin{cases} x_{id} + r_{id}\left(x_{id} - x_{qd}\right) + cl(g_d - x_{id})\ if\ rand\ < C_R, d = d_{max} \\ x_{id} \qquad\qquad\qquad if\ otherwise \end{cases} \tag{18}$$

In this model, the term *cl* is part of the set parameters and is referred to as the balance operator. This operator is crucial for achieving equilibrium between the exploration and exploitation capabilities during the search for candidate solutions. In the context of this study, the balance operator's value is set at 2. Additionally, *CR* represents the probability of selection, with its value ranging between 0 and 1. In this specific case, C_R is assigned a value of 0.3. Furthermore, g_d denotes the global optimum of the d dimension across all currently explored solutions. The proposed algorithm is presented in Figure 4.

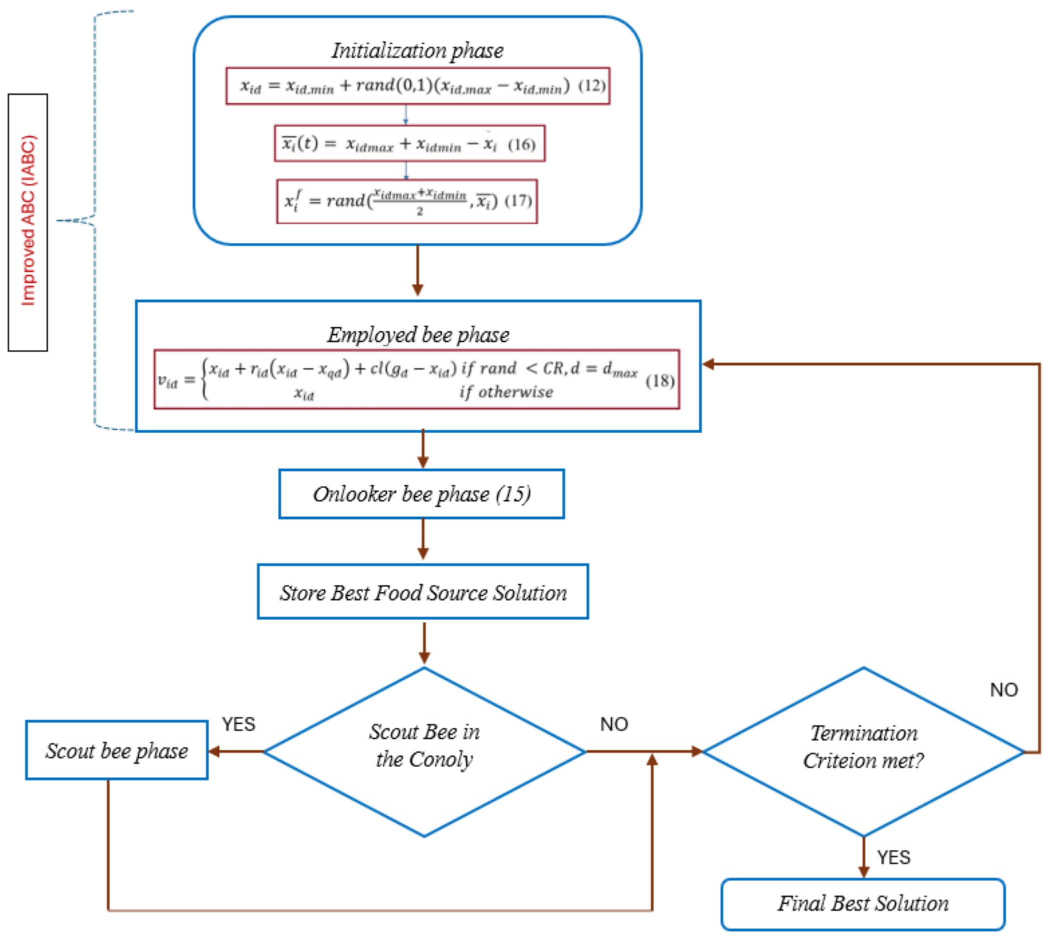

Figure 4. Flowchart proposed improved ABC (IABC) algorithm

3. RESULTS AND DISCUSSION

This research implements an enhanced ladder-iterative power flow methodology [25], [27] to analyze the performance of the introduced cost function (6) operational constraints, and system characteristics subsequent to SR and the incorporation of SOPs. The simulations were performed using MATLAB 2019R on a computing system equipped with a 240W power supply unit (PSU), an Intel Core i7 3770 processor, 16 GB of RAM, and a GeForce GT 1030 graphics processing unit. The efficacy of the proposed approach was assessed across eight distinct scenarios.

The proposed Improved ABC algorithm is applied to two standard distribution networks: the IEEE 33-node and 69-node systems. This work investigates the operational benefits of IABC in addressing SR and optimizing SOP placement across eight scenarios [28]–[31]. Each scenario explores different combinations concerning the practical implementation of tie and sectionalizing switches solutions for SR and SOP integration. While the study allows for the installation of up to two SOPs, the proposed method is scalable and can accommodate any number of SOPs. To demonstrate the superiority of IABC, simulation results for Case 7 are compared with those obtained using the ABC and Cauchy Algorithms, highlighting IABC's ability to enhance voltage profiles and reduce system losses. The IABC algorithm is configured with an initial population size of 80 and a maximum iteration limit of 300, which are consistently applied across all scenarios.

- Base case: power flow simulation conducted in the absence of SOPs or SR deployment.
- Case 1: an optimal scenario leveraging maximum solar radiation efficiency, excluding the integration of SOPs.
- Case 2: a single idealized implementation of a SOP without employing SR.
- Case 3: a singular optimal deployment of a SOP exclusively at tie switches, without incorporating SR.
- Case 4: two optimally positioned SOP installations, independent of SR.
- Case 5: two optimal SOP installations feasible solely at tie switches, without the application of SR.
- Case 6: concurrent execution of an optimized SR alongside a single SOP installation, utilizing the proposed methodology.
- Case 7: implementation of optimal simultaneous SR and two SOP installations using the provided technique.

This section elucidates the methodology and showcases the most effective modeling results obtained for the IEEE 33-Node and 69-Node test cases.

3.1. Results from the IEEE 33-node simulation

The IEEE 33-bus test system is initially set up with 33 nodes, 37 branches, 32 sectionalizing switches that are typically closed, and 5 tie switches (T33 to T37) that are normally open, functioning at a base voltage of 12.6 kV (or 1 p.u.), as shown in Figure 5. The system exhibits a base active power loss of 202.67 kW, with total real and reactive power loads of 3.72 MW and 2.3 MVAR, respectively [31], [32]. The voltage magnitude at all buses is constrained within the range of 0.95 to 1.05 p.u., while the active and reactive power injection limits for the SOPs are defined within the range of 0 to 2.5 MW and 0 to 2.5 MVAR.

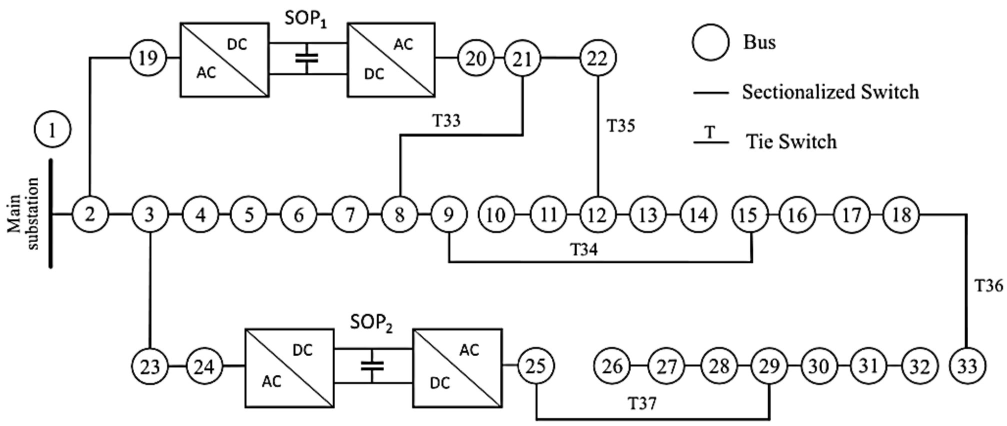

Figure 5. Optimal system reconfiguration and SOP placement in the IEEE 33-node test system

The effectiveness of the IABC method in addressing SOP placement and system reconfiguration problems is demonstrated through seven different cases, as listed in Table 1 for the IEEE – 33 node.

Table 1. Comparative analysis of IEEE 33-node system with and without SOP

Case	Number of SOP	Location SOP (node-node)	Opened/closed switch	Optimal SOP P (MW)	Optimal SOP Q (MVAr)	P_{losse} (kW)	Compare with the base case	V_{min}/ V_{max} (pu)
Base	-	-	-			202.67		0.913 0.997
Case 1	-	-	Open: 7; 9; 14; 32 Close: 33; 34; 35; 36			140.14	30.9%	0.941 /0.998
Case 2	1	5-6	Open: 5 Close: 33	-1.384/1.384	-1.380/1.380	114.21	43.6%	0.952 0.998
Case 3	1	8-21	-	1.101/-1.101	1.371/0.332	120.11	40.7%	0.946 0.998
Case 4	2	5-6 30-31	Open: 5; 30 Close: 33; 36	- 1.562/1.562, 0.590/0.590	0.341/0.501, 0.510/0.429	93.28	54.0%	0.960 0.998
Case 5	2	25-29 12-22	-	- 0.421/0.421 0.744/-0.744	0.501/0.499 0.499/0.142	94.62	53.3%	0.956 0.998
Case 6	1	24-25	Open: 7; 9; 14; 17; 24 Close: 33; 34; 35; 36; 37	- 0.971/0.971	0.382/1.142	91.38	54.7%	0.963 0.998
Case 7	2	24-25 19-20	Open: 9; 14; 19; 24; 32 Close: 9; 14; 19; 24; 32	- 0.821/0.821 1.351/1.351	-0.821/0.821 1.346/1.346	74.51	62.3%	0.967 0.998

Table 1 and Figure 6 present the detailed results of the study. Among the evaluated cases, Case 7 emerges as the most effective solution for distribution network reconfiguration and SOP placement, achieving a loss reduction rate of 62.3%, reducing total losses to 74.51 kW, and improving the voltage profile with a V_{min}/V_{max} index of 0.967/0.998. These results highlight the significant potential of Case 7 for optimizing network performance, making it the priority solution for implementation.

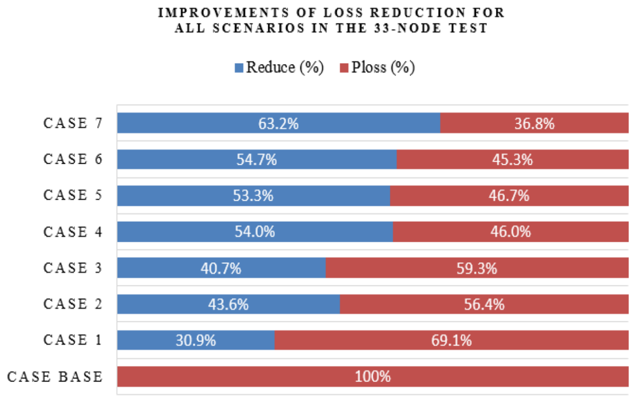

Figure 6. Compare the loss reduction rate of the cases with the base case

However, Case 6 also demonstrates strong performance and can be considered a viable alternative in specific scenarios. Case 6 achieves a loss reduction rate of 54.7%, reduces losses to 91.38 kW, and maintains a V_{min}/V_{max} index of 0.963/0.998. While slightly less effective than Case 7, Case 6 remains a practical option, particularly in situations where the implementation of Case 7 may face constraints.

Other solutions, such as Case 4, Case 5, Case 2, and Case 3, also offer varying degrees of improvement and can be applied depending on the specific conditions and requirements of the distribution network. These cases provide flexibility for system operators to tailor solutions to unique operational challenges. For instance, Case 4 and Case 5 may be suitable for networks with moderate reconfiguration needs, while Case 2 and Case 3 could be applied in scenarios with limited resources or simpler network configurations.

In cases where more complex solutions are not feasible, Case 1 serves as a baseline option. Although it offers the least improvement compared to other cases, it can still be utilized as a fallback solution when operational or financial constraints prevent the implementation of more advanced strategies.

Ultimately, the choice of the optimal solution should be guided by a comprehensive evaluation of factors such as cost, feasibility, and operational requirements. System operators must carefully balance these considerations to select the most appropriate reconfiguration and SOP placement strategy for their specific distribution network.

Figure 7 presents the voltage variations at the nodes in the 33-node grid across different scenarios, from Case Base to Case 7, compared to the lower voltage limit (Vmin = 0.95). In Case Base, some nodes (particularly from 19 to 23) have voltages below the limit, indicating voltage drop issues. However, from Case 1 to Case 7, the improvement measures gradually raise the voltage levels, with Case 7 achieving the best results, ensuring that most nodes have voltages above the minimum limit. This demonstrates that the improvement methods have significantly mitigated the voltage drop issues in the system.

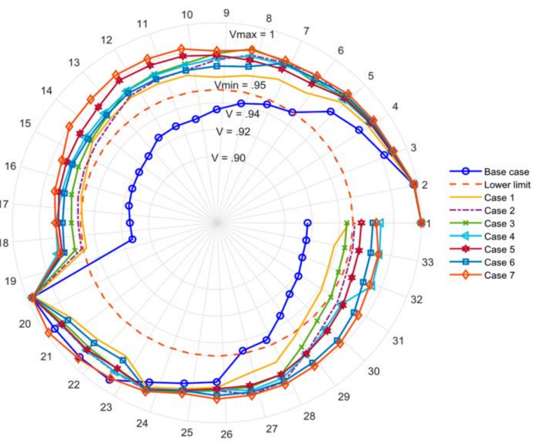

Figure 7. Voltage characteristic graph of nodes in different cases – 33 Nodes

3.2. Results from the IEEE 69-node simulation

The IEEE 69-bus test system is initially configured with 69 nodes, 73 branches, 68 sectionalizing switches that are normally closed, and 5 tie switches (T69 to T73) that are normally open, operating at a base voltage of 12.6 kV (or 1 p.u.), as depicted in Figure 8 [29], [30]. The system accommodates a total active power load of 3.80 MW and a reactive power load of 2.70 MVAR, with an initial active power loss of 224.69 kW. The operational constraints for the SOPs include active and reactive power injection limits of 0 to 2.5 MW and 0 to 2.5 MVAR, respectively. Furthermore, the voltage magnitude at each bus is regulated within the permissible range of 0.95 to 1.05 p.u.

The Table 2 and Figure 9 present the results obtained, Case 7 should be considered a priority for implementing distribution network reconfiguration and SOP placement (79.9% loss reduction, losses reduced to 40.75 kW, V_{min}/V_{max} of 0.985/1.000). Case 4 and Case 5 are also highly effective (both with 77.2% loss reduction, losses reduced to 46.21 kW, V_{min}/V_{max} of 0.979/1.000). Case 6 is a good option (76.2% loss reduction, losses reduced to 47.17 kW, V_{min}/V_{max} of 0.981/1.000). Cases 2 and 3 offer significant loss reduction (both 72.9%, losses reduced to 61.13 kW, V_{min}/V_{max} of 0.971/1.000). Case 1, with a 56.1% loss reduction, losses reduced to 98.95 kW, and V_{min}/V_{max} of 0.943/1.000, can be used when more complex solutions are not feasible. The choice of the optimal solution should consider factors such as cost, feasibility, and operational requirements of the distribution network.

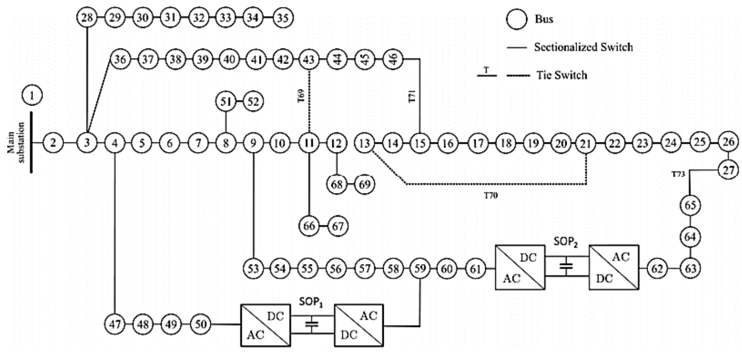

Figure 8. Optimal system reconfiguration and SOP placement in the IEEE 69-node test system

Table 2. Comparative analysis of IEEE 69-node system with and without SOP

Case	Number of SOP	Location SOP (node-node)	Opened/closed switch	Optimal SOP P (MW)	Optimal SOP Q (MVAr)	Plosse (kW)	Compare with the base case	V_{min}/ V_{max} (pu)
	-	-	-	-	-	225.26		0.909 1.00
Case 1	-	-	OS: 14;57;61 CS: 71;72;73	-	-	98.95	56.1%	0.943 1.000
Case 2	1	50–59		-1.551/1.551	0.551/1.391	61.13	72.9%	0.971 1.000
Case 3	1	50–59	-	-1.551/1.551	0.551/1.391	61.13	72.9%	0.971 1.000
Case 4	2	15–46 50-59	-	-1.593/1.593 0.452/- 0.452	0.551/1.391 0.362/0.096	46.21	77.2%	0.979 1.000
Case 5	2	15–46 50-59	-	-1.593/1.593 0.451/-0.451	0.551/1.391 0.362/0.096	46.21	77.2%	0.979 1.000
Case 6	1	50-59	OS: 12; 64 CS: 71; 73	-1.551/1.551	0.558/1.271	47.17	76.2%	0.981 1.000
Case 7	2	61-62 50-59	OS: 12; 61 CS: 71; 73	-1.471/1.471 0.183/0.183	0.555/0.227 0.856/0.415	40.75	79.9%	0.985/ 1.000

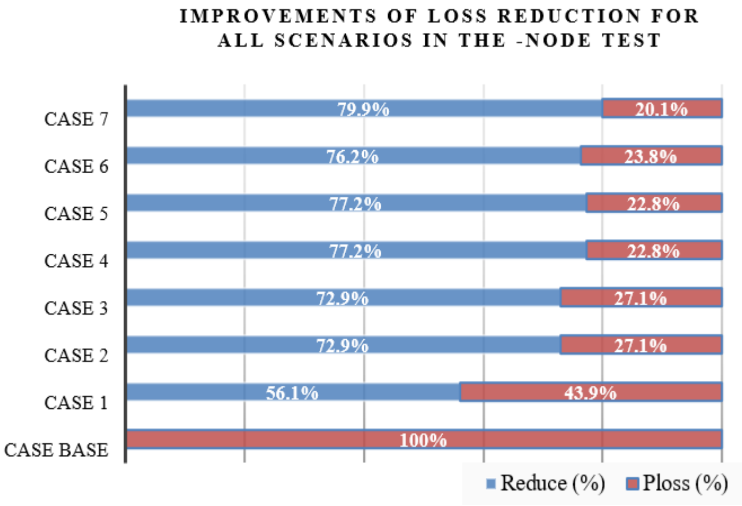

Figure 9. The IEEE 69-node's ideal SR and two SOP positions

Figure 10 presents the voltage variations at the nodes in the 69-node grid across different scenarios, ranging from the base case to Case 7, compared to the minimum voltage limit (V_{min} = 0.95 p.u.). In the base case, a significant number of nodes, particularly those between node 48 and node 66, exhibit voltages below the allowable limit, resulting in severe voltage drop issues. This voltage drop is primarily attributed to the high load concentration and insufficient reactive power support in these areas, which are common challenges in radial distribution networks.

As the system transitions from Case 1 to Case 7, a gradual improvement in voltage profiles is observed. This improvement is achieved through the implementation of various optimization strategies, including network reconfiguration and the integration of static synchronous compensators. Among all cases, Case 7 demonstrates the most significant enhancement, ensuring that all nodes maintain voltages above or near the minimum limit of 0.95 p.u. Specifically, in Case 7, the voltage at critical nodes (e.g., nodes 48–66) increases to values close to 1.0 p.u., effectively mitigating the voltage drop issues observed in the base case.

The results highlight the effectiveness of the proposed improvement methods in addressing voltage instability and enhancing the overall stability and reliability of the power system. By optimizing the network configuration and leveraging SOPs, the system not only meets the voltage requirements but also reduces active power losses and improves power quality. These outcomes underscore the importance of advanced optimization techniques in modern distribution networks, particularly in scenarios with high penetration of distributed energy resources and variable load conditions.

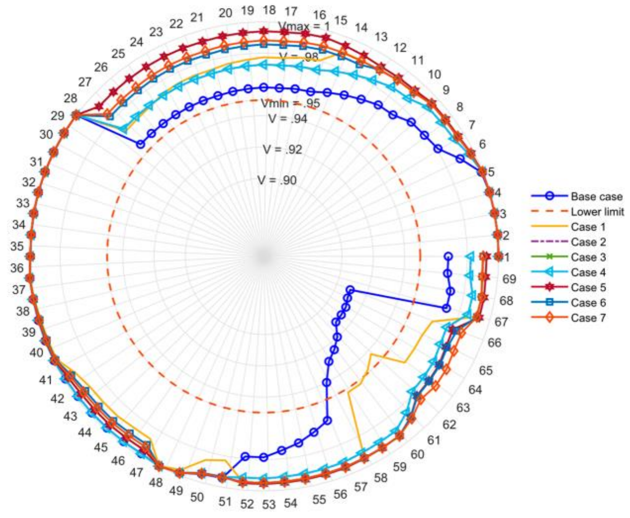

Figure 10. Voltage characteristic graph of nodes in different cases – 69 nodes

3.3. Compare IABC algorithm with other algorithms

Table 3 summarizes the results of the proposed IABC algorithm's comparison with the GA and WCA algorithms for Case 6, in the IEEE 33 node and 69 node distribution network, the IABC method demonstrates the best performance with the lowest power loss (91.31 kW) and the fewest iterations (117), while maintaining a stable V_{min}/V_{max} index (0.963/0.998). Compared to GA (93.02 kW, 172 iterations) and WCA (92.24 kW, 122 iterations), IABC is superior in reducing losses and convergence speed. Similarly, in the 69-node network, IABC has the lowest power loss (47.17 kW) and the fewest iterations (79), with a V_{min}/V_{max} index of 0.981/1.000. WCA is also effective but not as much as IABC (47.89 kW, 81 iterations), while GA has higher losses and more iterations (49.66 kW, 204 iterations). IABC proves its ability to reduce losses and improve computational speed compared to other methods.

Table 3. Comparative analysis of case 6 results for IEEE 33- and 69-node distribution networks

Method	Location SOP (node-node)	Opened closed	P_{losse} (kW)	Number of iterations	V_{min}/ V_{max} (pu)
Compared result case 6 for distribution network – **IEEE 33 nodes**					
GA [25]	24-25	Oen: 17;24; 7; 9;14 Close 33;34;35;36;37	93.02	172	0.963 0.998
WCA [33]	24-25	Oen: 17;24; 7; 9;14 Close 33;34;35;36;37	92.24	122	0.963 0.998
IABC	24-25	Oen: 17;24; 7; 9;14 Close 33;34;35;36;37	**91.31**	**117**	**0.963** **0.998**
Compared result case 6 for distribution network – **IEEE 69 nodes**					
GA [25]	50-59	Open: 12; 64 Close: 71; 73	49.66	204	0.982 1.000
WCA [33]	50-59	Open: 12; 64 Close: 71; 73	47.89	81	0.981 1.000
IABC	50-59	Open: 12; 61 Close: 71; 73	**47.17**	**79**	**0.981** **1.000**

4. CONCLUSION

This paper proposes a method to determine the optimal location and capacity of SOPs in the multi-objective DRN problem, based on a combination of the ABC with Cauchy OBL. The objective function aims to reduce power losses and improve voltage quality. The proposed algorithm is applied to the IEEE 33-node and 69-node distribution networks. The results of simulations, carried out under eight distinct scenarios, reveal varying levels of loss reduction and voltage enhancement, influenced by the positioning and capacity of the SOPs. For the 33-node network, scenario 7 is identified as the optimal case, achieving a loss reduction rate of 62.3% and voltage improvement (V_{min}/V_{max} of 0.967/0.998). Similarly, for the 69-node network, scenario 7 is also found to be optimal, with a loss reduction rate of 79.9% and voltage improvement (Vmin/Vmax of 0.985/1.000). Comparative analysis with the GA and water cycle algorithm (WCA) shows that the Improved

ABC method requires fewer iterations to achieve convergence. These consistent results highlight the effectiveness of the IABC-based method in determining the optimal location and capacity of SOPs for distribution network reconfiguration, with the primary goal of reducing power losses. The findings of this paper can serve as a valuable reference to support decision-making in various operational scenarios. This study demonstrates that combining the strengths of artificial intelligence algorithms can significantly improve computational efficiency for multi-objective problems and large solution spaces. Future research could expand on this work by incorporating additional objectives, such as system reliability, power supply costs, or considering uncertainties related to distributed generation (e.g., photovoltaic and wind turbine and electric vehicle loads.

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Nguyen Quynh Anh			✓	✓		✓		✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are openly available in [R. D. Zimmerman *et al.*, "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," IEEE Transactions on Power Systems, vol. 26, no. 1, pp. 12-19, Feb. 2011, doi: 10.1109/TPWRS.2010.2051168]. Moreover, the sample grid data employed are from open-source repositories and have been widely adopted in several previous studies, including those in references [31] and [32].

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