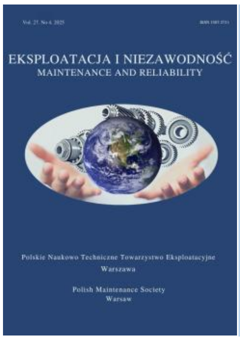

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Presenting a stochastic framework for resilient self-healing active distribution networks with integrated distributed generation

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Highlights

- Proposing a stochastic model to self-healing active networks with graph restructuring.
- Minimizing short-circuit capacity in reconfiguration to enhance resilience to faults.
- Integrating loadability enhancement to prevent voltage collapse and ensure stability.
- Adapting the pelican algorithm for faster convergence & superior optimization results.
- Achieving recovery, loss reduction, and stability via multi-objective optimization.

Abstract

This study proposes a novel stochastic framework for self-healing active distribution networks, addressing challenges such as increased short-circuit capacity, voltage instability, and load variability. By utilizing graph theory for optimal network restructuring and stochastic programming to manage load uncertainties, the method ensures efficient and resilient fault recovery. It incorporates adaptive short-circuit capacity minimization and dynamic loadability improvement for enhanced security. The Pelican Optimization Algorithm (POA) optimizes performance in real-world scenarios. Simulations on IEEE 33-bus and 83-bus networks validate its effectiveness, showing a 20% reduction in fault recovery time, a 12.5% decrease in power losses, a 10% improvement in voltage stability, and a 15% increase in load recovery capacity. Stochastic modeling further enhances adaptability, achieving a 25% boost in load flexibility while maintaining optimal short-circuit capacity, significantly improving resilience, efficiency, and customer satisfaction in self-healing smart grids.

Keywords

self-healing, restructuring, optimization, stochastic, resilience, voltage

1. Introduction

Self-healing capability plays a pivotal role in enhancing the resilience and reliability of intelligent distribution networks (DNs) [1]. These networks must be capable of detecting faults swiftly and isolating the affected areas to minimize service disruptions, ensuring the continuity of power supply to the remaining consumers [2]. Quick fault detection followed by isolation is the core basis of self-healing mechanisms in such networks. When a fault is isolated, the network quickly reconfigures to redirect power flows to other connected consumers. This will not only minimize the impact of outages but also ensure that disruptions are kept at the bare minimum possible [3]. This quick restoration is fundamental to maintaining grid stability and lowering the frequency and duration of power outages [4]. Therefore, with increasing electricity demands that will grow in accordance with economic and social developments, DNs' operational efficiency becomes more important [5]. The increasing demand is quantitative, based on the increasing total quantity of electricity used, and

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qualitative, based on the increase in consumer's requirements, which now expect not only a reliable power source but also a high-quality service, or one where the interruptions are minimal [6]. In that respect, the DNs should be able to guarantee not only a supply of energy but also high dependability and constant quality of service for the increasingly demanding customers of today [7].

The DN forms the critical interface between the consumers of electricity and generation sources [8]. In such a way, DN is critically integrated into daily life and economic activities owing to efficient electric supply distribution [9]. Any interruption in its functioning may lead to disastrous situations not only for the consumers but also for whole sectors of the economy. The resiliency of such very important networks should be assured through concepts such as self-healing that avoid enormous disruptions [10]. In the smart distribution network, self-healing is at the core of enabling automatic reconfiguration when a fault or disturbance occurs without human intervention. This reconfiguration involves intentional changes to remote-controlled switches that are fundamental to the built-in system of the network for self-restructuring [11]. These are generally classified into two major classes: normally closed switches, which are the most commonly employed, and normally open switches, which are only switched on as needed to divert power [12]. With the efficient control of the switching states of these switches, the network could dynamically reconfigure itself by rerouting power through other lines to retain uninterruptible supply to consumers that are not affected [13].

In general, the major objectives of network reconfiguration can be encapsulated under two headings. First, an improved operational condition of the network focuses on minimizing energy losses, enhancing overall network reliability, improving voltage profiles, and reducing operational costs [14]. These objectives do require sophisticated algorithms of control and network management strategies that can respond to modern challenges from the perspective of distribution networks. The challenges experienced are heightened by the increasing integration of distributed energy resources, adding to variability and further constraining network capability. Advanced optimization techniques, including multi-objective algorithms, therefore become required, to balance the different and often competing demands such that optimal performance is realized on all variables of the network. Another objective, equally critical, is that of fast failure condition response on the network [15]. This involves the reconfiguration of the network under faults, especially due to unplanned disturbances, to enable fast restoration of power. Such reconfigurations not only reduce the downtime but also prevent a cascading failure that might snowball into a wide-area blackout [16]. This aspect of self-healing is a highly dynamic and complex process that puts a big demand on innovative approaches for ensuring the resilience of distribution networks under real-time conditions [17]. For instance, integrated automation switches and real-time monitoring systems speed up the detection and isolation of faults, opening the way to immediate corrective action. Stochastic modeling and adaptive algorithms have also begun gaining inroads into managing uncertainty in load demands and faults, further increasing reliability and robustness in network operation [18].

The literature is already saturated with various efficient methodologies applicable to this particular application. For instance, Botea et al. [19] proposed an optimum search algorithm to solve the problems of network restructuring while performing outage restoration. The major objective of this work was to reduce switching operations and network losses. In this direction, Bollobas et al. [20] developed an algorithm to improve network restructuring after unexpected outages in transmission lines. This approach had the aim of minimizing loss of energy besides connecting a bigger number of customers. Further, Bondy et al. [21] proposed a multi-agent control system for restructuring the grid, coordinating activities of reactive power control devices, and repairing voltage violations. In their design, a two-level optimization approach was employed to determine continuous factors such as the amount of load shedding at nodes and binary variables such as switch statuses. These variables were determined by solving MILP and NLP problems. In addition, Odetayo et al. [22] developed an exploitation framework to attain self-healing control measures optimally in a DN. For this purpose, a DN was divided into several microgrids by incorporating distributed generations. To improve network flexibility and dependability, an ideal self-healing method was developed that complied with preset load requirements, total energy dissipation, and provided loads. Liu

[23] introduced a Self-Healing System for Smart Distribution Networks by use of a two-phase Energy Management algorithm and a multi-agent system for autonomous regeneration. The suggested approach optimized local microgrids with renewable energy, EV charging, and storage units. Phase one minimized operational costs through load distribution, while phase two enhanced regeneration to align priority loads with switching functions. Employing stochastic programming, the Kantorovich method, and a student psychology-based optimization, the strategy decreased unsupplied energy from 108.48 kWh to 7.21 kWh and enhanced grid reliability.

1.1. Research Gaps, Novelties, and Contributions

One of the critical gaps in previous research is the inadequate consideration of the impacts of distributed generation (DG) on network performance during reconfiguration. While earlier studies have focused on fault recovery and network optimization, they often fail to address the challenges introduced by DG, such as increased short-circuit capacity and heightened risk of voltage collapse during faults. These challenges are particularly significant in networks with high penetration of DG, where traditional reconfiguration methods may lead to compromised stability and reliability. This work, therefore, seeks to bridge this gap by making the minimization of short-circuit capacity an integral part of the network restructuring methodology so that the restructured network will be able to withstand future disturbances without the loss of operational integrity. The other important gap is the static load demand assumption characterizing most state-of-the-art self-healing methodologies. Many conventional methodologies are static while solving the problem, thus providing solutions that are not robustly resilient when applied to real applications. Fault events have a significant impact on the fluctuations in the demand for load, especially in the case where infrastructure is reduced due to a certain type of damage. This paper presents a stochastic modeling methodology that embraces the uncertainties associated with load demand and delivers an adaptive reliable solution. The proposed model contributes to the network's capability of guaranteeing stability under unforeseen conditions by dealing with the variability of the load and making it embedded within the optimization framework.

Besides, most of the optimization methodologies used before suffer from limitations in exploring and exploiting a solution, which results in either a less-than-optimal solution or an extended computational time. Other techniques, such as genetic algorithms (GA) and particle swarm optimization (PSO), while widely used, also have grounds of convergence speed and adaptability with changing environmental conditions that have been questioned. With the implementation of POA, these flaws are overcome through a novel approach that integrates global and local searching. The proposed approach achieves faster convergence and superior solutions, making it particularly effective for real-time applications in self-healing distribution networks. In summary, this paper bridges key gaps in the existing literature by addressing the integration of DG, incorporating stochastic modeling for load demand variability, and introducing an advanced optimization algorithm. These innovations collectively enhance the resilience, reliability, and operational efficiency of active distribution networks, setting a new benchmark for self-healing systems. The main contributions and novelties of this paper can be summarized as follows:

- A novel stochastic framework is proposed for self-healing active distribution networks, integrating distributed generation with graph theory-based restructuring and stochastic programming to address uncertainties in load demand effectively.
- The framework introduces a unique approach to incorporate short-circuit capacity minimization during network reconfiguration, enhancing the resilience of faulted networks to subsequent disturbances.
- Loadability enhancement is integrated into the reconfiguration process, mitigating risks of voltage collapse under increased load conditions and ensuring operational stability.
- The pelican optimization algorithm is adapted for the optimization problem, leveraging its balance between exploration and exploitation to achieve faster convergence and superior solutions compared to conventional methods.
- The framework optimizes multiple objectives, including minimizing fault recovery time, reducing power losses, improving voltage stability, and enhancing load recovery capacity, ensuring a comprehensive solution.

2. Problem Modeling

Unlike ring-based transmission networks, which are designed for greater reliability, DNs usually adopt a radial structure. The radial architecture allows far more contributions to the network stability by facilitating the protective equipment control and coordination process. In DN, switches are crucially important both for short-circuit protection and performing network management by restructuring. These switches fall into two major groups: section switches and connection switches. During normal operating conditions, cross-sectional switches remain closed while connecting switches are open. Within a self-healing network, there is rapid fault location identification following the occurrence of an incident. Upon identification of the fault location, sectional switches are employed with the result of isolating the faulty section. This means there is power interruption within sections of the network. In a bid to reduce the duration of the outage, interconnect switches are employed and reconfigure the network to ensure the network takes the maximum possible load. The corrective measures of this nature call for quick and effective ways of restructuring, considering some variables that enhance the network-operating conditions.

2.1. The Proposed Restructuring Method

This paper proposes a methodology for the restructuration of a network and provides certain remarks that are important for the safe and efficient operation of active DNs. Graph theory will be used in the re-configuration process. A network topology is represented by a graph $G_{(N,E)}$, where $N_{(G)}$ corresponds to buses and $E_{(G)}$ represents grid lines [24]. The proposed restructuring method includes the following steps:

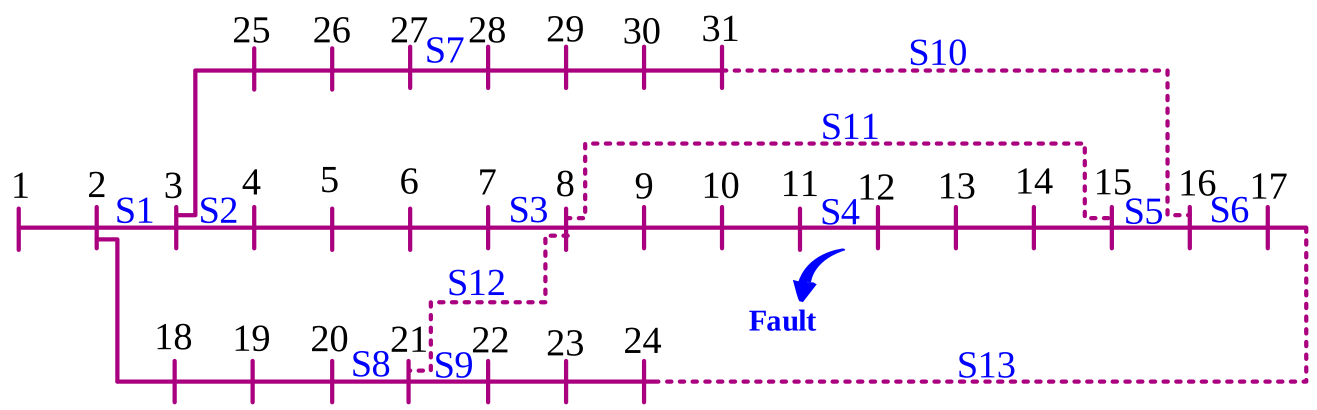
Step 1: Assume all switches are normally closed. In a self-healing DN, restructuring is possible only on those lines that have controllable switches. To reduce the complexity of the network diagram, lines, and buses are aggregated according to some selection criteria:

1. The absence of controllable switches between two buses.
2. The lack of more than two feeders (one input and one output) between two buses. This step produces a reduced graph, $Gr_{(Nr,Er)}$, where $Nr_{(Gr)}$ represents regions bounded by controllable switches, and $Er_{(Gr)}$ denotes controllable switches.

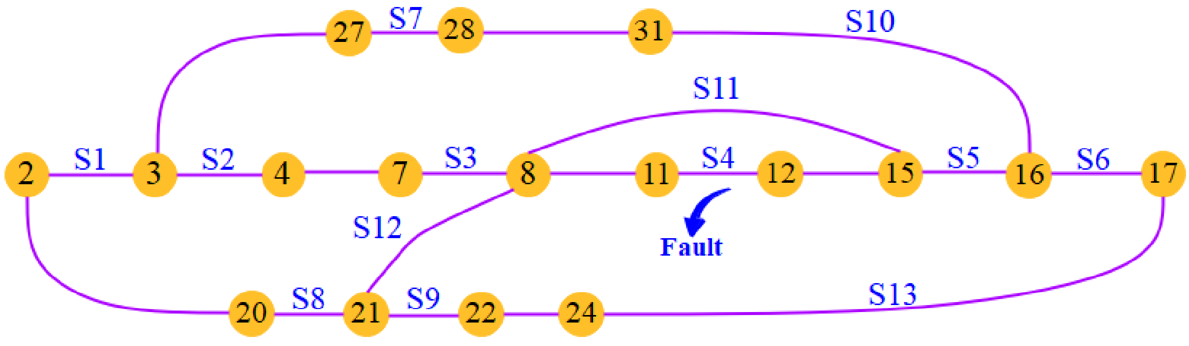
Step 2: Remove from the reduced graph any sections containing malfunctioning lines or equipment.

Step 3: Ensure the reduced graph forms a spanning tree to maintain the radial structure of the DN. A spanning tree is defined as a graph without loops, where all nodes are connected using the minimum number of edges. The restructuring problem is thus framed as finding the optimal spanning tree $T_{(N_{Opt},E_{Opt})}$, considering various objective functions and constraints, which are discussed further in this paper.

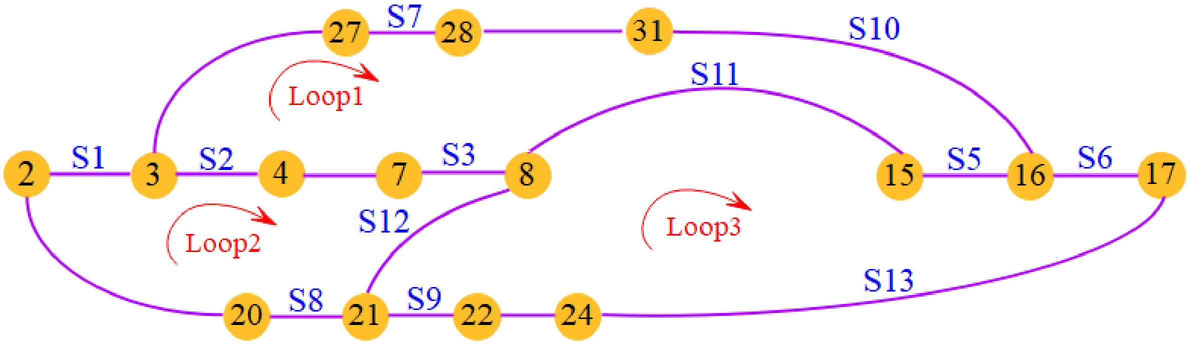
To explore potential spanning tree configurations, it is assumed that all edges are initially connected, forming multiple loops. From each loop, a specific edge with a controllable switch is removed under constraints such as ensuring at least one switch is opened in each loop and the total number of opened switches equals the number of loops [24]. This procedure generates multiple network configurations (spanning trees), among which the optimal topology minimizes the objective function.



(a) Main grid



(b) Reduced graph of network



(c) Reduced graph of network after fault

Figure 1. A simple example to understand the proposed strategy.

To provide further clarification on the proposed restructuring system, the network is illustrated in Figure 1(a). According to Figure 1(b), this network includes 13 switches. Following the reduction in step 1 and fault isolation using switch S4, the network transitions to the configuration shown in Figure 1(c). In step 3, potential spanning trees are explored by considering predefined conditions and selecting one switch to open from each ring. The switches within each ring are defined by Equations (1) to (3), and a potential spanning tree solution is achieved by opening the specified switches, as indicated in Equation (4) [2].

$$L_1 = \{S_2, S_3, S_5, S_7, S_{10}, S_{11}\} \tag{1}$$

$$L_2 = \{S_1, S_2, S_3, S_8, S_{12}\} \tag{2}$$

$$L_3 = \{S_5, S_6, S_9, S_{11}, S_{12}, S_{13}\} \tag{3}$$

$$OS = \{S_7, S_{12}, S_{15}\} \tag{4}$$

Node weights are determined by considering several factors, including load demand, criticality of the load, and voltage stability. Particularly, more load demand nodes have higher weights, especially in cases of critical loads, so that their reconfiguration is prioritized in the fault restoration process. Likewise, higher prominence or weight is given to nodes having poor voltage profiles or situated on the edge of the network. The priority for edge nodes will thus depend upon line characteristics such as resistance, current flow, capacity, and susceptibility to faults. During reconfiguration, higher priorities are given to lines with increased capacity or reduced resistance for effective power distribution. At fault instances, the edge weights will also change in real-time, isolating the affected regions by prioritizing restoration to the more vital nodes. Such dynamic changes in node and edge weights enable the network to handle immediate situations and hence be stable, recovering rapidly from any disruption.

2.2. Operation Cost

The network operational costs are a crucial concern within network operation and call for strategic actions for cost minimization. It, therefore, requires researching the most economically feasible power generation technologies and the optimization of grid efficiency. The proposed model uses an integrated approach by taking into account the production costs of distributed generation sources and upstream power generation. This approach ensures that the network conditions driving operational expenses are carefully highlighted at the top of the list to avoid decisions that might inadvertently raise costs by achieving other objectives. The utility companies are assumed to have control over the distributed generation units, each with unique generation cost parameters. In practice, the goal will be to make the upstream power more economically viable than distributed generation power. As presented in Equation (5), this optimization framework evaluates electricity generation costs based on customer demand. In this context, $S_{(G)}$ and $S_{(DG_{(i)})}$ represent the electricity generation costs for the upstream network and the ith distributed power plant, respectively. Similarly, $P_{(G)}$ and $P_{(DG_{(i)})}$ denote the output power of the upstream network and the generated power of the ith distributed generation unit [2].

$$F_{OC} = P_{(G)}.S_{(G)} + \sum_{i=1}^{N_{(DG)}} \left\{P_{(DG_{(i)})}.S_{(DG_{(i)})}\right\} \quad (5)$$

2.3. Power Losses

Accordingly, the smooth flow of electrical energy from transmission to consumers requires consideration of power losses on their route throughout transmission and DNs. Generally, the reduction of these losses has always been one of the main concerns in the power industry, mainly due to its huge economic impact. In this regard, electrical engineering has always considered the minimization of power losses to be one of the most essential factors for network designers and operators. The amount of loss is directly proportional to the square of the load demand that is maximum when consumption is high. The peak interval exhibits more accentuated power losses, creating huge problems in energy distribution. A detailed analysis of DNs reveals that targeted improvement measures can lead to substantial reductions in these losses. As highlighted in prior research [7], network reconfiguration is a highly effective strategy for minimizing power losses. This approach is central to the methodology described in this paper, with the objective function outlined in Equation (6) [25]. In this context, $N_{(l)}$ denotes the total number of lines in the network, while $R_{(i)}$ and $I_{(i)}$ represent the resistance and current magnitude of the ith line, respectively [25].

$$F_{Loss} = \sum_{i=1}^{N_{(l)}} \{R_{(i)}.I_{(i)}^2\} \quad (6)$$

2.4. Load Ability

To mitigate short-circuit capacity, it is necessary to augment the tonnage impedance. However, this adjustment introduces heightened sensitivity of bus voltage to fluctuations in load demand. Under such circumstances, elevating the load poses the risk of undesirable voltage drop, leading to potential operational issues. To address these challenges, the loading increment is integrated as a key component of the overall objective function. In a load framework characterized by a specific topology and equipped with reactive load sources, the rise in electrical loads at buses follows a discernible pattern, resulting in a natural drop in bus voltage. While reactive power can be added to compensate for this voltage loss, there exists a critical threshold beyond which further load increase, even with maximum reactive power injection, can push the system to the brink of voltage collapse. This critical threshold represents the maximum load limit of the system. Figure 2 illustrates the voltage range plotted against the load factor, offering valuable insights into this phenomenon.

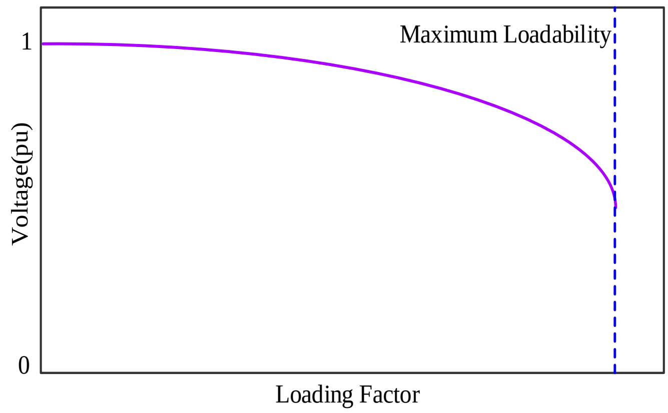


Figure 2. Load capability curve.

This scenario assumes that the system's behavior is still determined by the load flow equations and that the maximum loading limit is reached during gradual load adjustments. The load flow fails to converge and the accuracy of the load flow equations decreases beyond the maximum loading limit. Because of this, the maximum load capability may be determined by gradually raising the load demand overall network buses and keeping an eye on the convergence of the load flow equations, as shown by Equations (7) and (8). In this context, $\gamma_{(k)}$ represents the loading factor at the kth stage, while $\Delta\gamma$ denotes the incremental step size, which is set at 1% for this study. γMax signifies the maximum loading limit, corresponding to the stage at which load flow equations fail to converge. To enhance loadability within the overall objective function, the index defined in Equation (9) [2] is minimized.

$$P_{(k)} + jQ_{(k)} = \left(P_{(k-1)} + jQ_{(k-1)}\right).\gamma_{(k)} \quad (7)$$

$$\gamma_{(k)} = 1 + k.\Delta\gamma \quad (8)$$

$$F_{LA} = \frac{1}{\gamma^{Max}} \quad (9)$$

2.5. Short Circuit

Both the capability for producing power and the distribution of generation resources, along with the increasing complexity of the electrical network, have led to an increase in short-circuit current in distributed networks. This phenomenon increases the heat loss due to the increase of the induced current through the generators, transformers, and related equipment, and ultimately endangers the reliability of the network. Addressing this issue requires the deployment of robust equipment that can withstand these high currents. In addition, limiting this current requires the use of powerful circuit breakers, which can impose significant costs on the system. Therefore, the costs associated with fault currents are strongly impacted by short-circuit capacity reduction, particularly in DNs. After restructuring, the network in a self-healing DN has to be strong enough to endure and isolate any further accidents. This is crucial since a network that has encountered one problem is more vulnerable to subsequent ones and has to be reconfigured to manage any fault currents that may arise in the future. The existence of scattered productions, due to their power injection into the network, complicates the issues. To address these challenges, some DNs use fault current limiting devices. However, the use of such devices creates additional complications and costs for the network. To address these challenges, network restructuring is proposed alongside the regulation of output power from distributed generation sources. To achieve this objective, the restructuring plan incorporates the following measures to reduce short-circuit currents:

1. Adjusting the output loads of distributed generation sources.
2. Incorporating short-circuits capacity reduction as an integral component of the overall system restructuring framework's objective function.

Equation (10) provides the calculation for short-circuit capacity at each bus in the distribution network, such as the i^{th} bus. In this context, $V_{(i)}$ represents the voltage at bus i before the occurrence of a short-circuit fault, and $Z_{(i)}$ denotes the apparent impedance observed at bus i, both expressed per unit (p.u.). It is important to highlight that all values are standardized per unit for consistency.

Given the emphasis on minimizing relative increases in short-circuit capacity, as addressed in this paper, Equation (11) introduces an index for integrating short-circuit capacity reduction into the objective function of the proposed comprehensive restructuring framework. In this equation, $SCC_{(i)}^{New}$ and $SCC_{(i)}^{Old}$ represent the short-circuit capacities of bus i for the new and old topologies (post- and pre-restructuring), respectively, while n signifies the total number of buses in the distribution network. Notably, all short-circuit capacity calculations comply with the IEC 60909 standard.

$$SCC_{(i)} = \frac{V_{(i)}^2}{Z_{(i)}} \tag{10}$$

$$F_{SCC} = \sum_{i=1}^{n} \left\{ \left| Max\left(\frac{SCC_{(i)}^{New}}{SCC_{(i)}^{Old}}\right) \right| + \left| \frac{SCC_{(i)}^{New}}{SCC_{(i)}^{Old}} \right| \right\} \tag{11}$$

2.6. Voltage Profile

According to Equation (11), the reduction of short-circuit capacity can be obtained by reducing the bus voltage or increasing the equivalent impedance of Tonen. It should be noted that the increase in the impedance of the tone leads to a decrease in the voltage. Therefore, when short-circuit capacitance decreases, voltage subsequently decreases. There is a trade-off between voltage range and short-circuit capacitance. To address voltage drops caused by the reduction in short-circuit capacitance, an increase in the voltage profile is incorporated into the overall objective function. This increase is achieved by minimizing the following index, as shown in Equation (12) [7].

$$F_{VP} = \sum_{i=1}^{n} \left\{ \left| |V_{(i)}| - 1 \right| \right\} \tag{12}$$

3. The Objective Function

The previous section presented a deterministic framework designed to ensure the safe reconfiguration of active DNs. This framework integrates considerations such as short-circuit capacity and load capability to optimize the utilization of distributed generation capacity within the grid. Additionally, specific objective functions are formulated to enhance the operational state of the restructured network.

The comprehensive objective function expressed deterministically in Equation (13), incorporates weight coefficients (ω) assigned to each specific objective function. For greater clarity, the detailed discretization of this objective function is expanded in Equation (14). Furthermore, the condition outlined in Equation (15) must also be satisfied to ensure the framework's effectiveness [2].

$$F_{Total} = \omega_1.F_{VP} + \omega_2.F_{SCC} + \omega_3.F_{LA} + \omega_4.F_{Loss} + \omega_5.F_{OC} \tag{13}$$

$$F_{Total} = \omega_1. \left(\sum_{i=1}^{n}\left\{\left|\left|V_{(i)}\right| - 1\right|\right\}\right) + \omega_2. \left(\sum_{i=1}^{n}\left\{\left|Max\left(\frac{scc_{(i)}^{New}}{scc_{(i)}^{Old}}\right)\right| + \left|\frac{scc_{(i)}^{New}}{scc_{(i)}^{Old}}\right|\right\}\right) + \omega_3. \left(\frac{1}{\gamma^{Max}}\right) + \omega_4. \left(\sum_{i=1}^{N(l)}\left\{R_{(i)}. I_{(i)}^{2}\right\}\right) + \omega_5. \left(P_{(G)}. S_{(G)} + \sum_{i=1}^{N(DG)}\left\{P_{(DG_{(i)})}. S_{(DG_{(i)})}\right\}\right) \quad (14)$$

$$\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 = 1 \quad (15)$$

3.1. Solution Model

The POA adopts a population-based approach where pelicans serve as representatives of population members. Each member of a population-based algorithm represents a potential solution and suggests values for the issue variables according to where they are in the search space. Equation (16), where x (i, j) is the value of variable j for the chosen solution, N is the population size, and m is the number of variables in the problem, is first used to randomly initialize these members within the problem's bottom and upper limits. Here, LB(j) denotes the jth lower limit of the problem variables, UB(j) is the jth upper limit, and r is a random number within the interval [0, 1]. Equation (17) specifies the use of a matrix called the population matrix to shape the pelican population in the proposed POA. Each row in this matrix represents a potential solution, while the columns offer possible values for the variables involved in the problem [26].

$$x(i,j) = LB(j) + r.(UB(j) - LB(j)) \quad (16)$$

$$X = \begin{bmatrix} x(1,1) & \cdots & x(1,m) \\ \vdots & \ddots & \vdots \\ x(N,1) & \cdots & x(N,m) \end{bmatrix} \quad (17)$$

In the proposed algorithm, each member of the population is represented by a pelican, serving as a candidate solution for the given problem. Consequently, the objective function for the problem can be assessed for each candidate solution, generating a set of values through an objective function vector as per Equation (18). Here, F denotes the objective function vector, and $F(x(1))$ represents the value of the objective function for the first candidate.

$$F = \begin{bmatrix} F(x(1)) \\ \vdots \\ F(x(N)) \end{bmatrix} \quad (18)$$

The POA mimics pelican behavior and hunting strategies and includes two key steps: moving towards the prey and flapping on the water surface.

- **Moving towards prey (exploration phase)**

During the initial phase, pelicans within the Pelican algorithm pinpoint prey locations and navigate toward these designated targets. This strategic approach emulates the systematic scanning of the search space, thereby enhancing the algorithm's exploratory capabilities. It is essential to highlight that the hunting location in the Pelican algorithm is randomly generated within the search space, thereby augmenting its exploration power.

The mathematical formulation of the pelican's movement strategies towards its prey is represented in Equation (19), where $x_{P(1)}(i,j)$ denotes the updated state of the first pelican in the jth dimension during phase one. The parameter I, which is randomly assigned a value of one or two, plays a critical role in enhancing exploration. When set to two, it enables broader displacement, facilitating the exploration of newer regions within the search space. The proposed POA incorporates an effective update mechanism that accepts the pelican's new position if it results in an improvement in the objective function, as outlined in Equation (20) [26].

$$x_{P(1)}(i,j) = \begin{cases} x(i,j) + r.[P(j) - I.x(i,j)] & F(P) < F(i) \\ x(i,j) - r.[x(i,j) - P(j)] & Else \end{cases} \quad (19)$$

$$X(i) = \begin{cases} X_{P(1)}(i) & F_{P(1)}(i) < F(i) \\ X(i) & Else \end{cases} \quad (20)$$

- **Floating on the surface of the water (exploitation stage)**

In the second stage, upon reaching the water's surface, the pelicans extend their wings on the water's surface to hoist the fish and gather the prey within their throat pouches. This strategic behavior is designed to maximize the collection of fish in the vicinity. From a mathematical perspective, this action steers the POA toward enhanced solutions in the hunting area, thereby intensifying local search and exploitation capabilities. The algorithm systematically evaluates points in the neighborhood of the Pelican's location to converge towards improved solutions.

This behavior is mathematically represented in Equation (21), where $x_{P(2)}(i,j)$ denotes the updated position of the pelican in the jth dimension during phase two. Here, t represents the current iteration, and T indicates the maximum number of iterations. The coefficient R. [2.r-1] defines the neighborhood radius for each population member, facilitating local searches and contributing to the convergence towards improved solutions. The effective update at this stage involves the acceptance or rejection of the new positions of the pelican, as modeled in

Equation (22). Here, $X_{P(2)}(i)$ denotes the new position of the ith pelican, and $F_{P(2)}(i)$ indicates the value of its objective function based on phase 2 [26]:

$$x_{P(2)}(i,j) = x(i,j) + R.x(i,j).[2.r-1].\left(1-\frac{t}{T}\right) \tag{21}$$

$$X(i) = \begin{cases} X_{P(2)}(i) & F_{P(2)}(i) < F(i) \\ X(i) & Else \end{cases} \tag{22}$$

The global search phase focuses on exploration to identify diverse regions of the solution space. To improve exploration, a dynamic inertia weight (w) and adaptive scaling factor (S) are introduced. The position update equation in the global search phase is modified as Equation (23).

$$x_{i,j}(t+1) = x_{i,j}(t) + w \cdot S \cdot (H_j(t) - x_{i,j}(t)) + \alpha \cdot R \tag{23}$$

Where $x_{i,j}(t)$ is the current position of the i[th] pelican in the j[th] dimension, $H_j(t)$ is the global best solution in the j[th] dimension, $w = w_{\max} - \frac{t}{T} \cdot (w_{\max} - w_{\min})$ is dynamic inertia weight that decreases linearly over iterations, $S = 1 - \frac{|H_j(t) - x_{i,j}(t)|}{\mathrm{UB}_j - \mathrm{LB}_j}$ is an adaptive scaling factor based on the distance between the current position and the global best, α is a random scaling factor in the range [0, 1], R is a random vector to ensure stochastic behavior. T is the total number of iterations, and $\mathrm{UB}_j and\ \mathrm{LB}_j$ are upper and lower bounds of the j[th] dimension.

The local search phase intensifies exploitation by refining solutions around the current best positions. A mutation-based local refinement is introduced, inspired by differential evolution. The position update equation is modified as follows:

$$x_{i,j}(t+1) = x_{i,j}(t) + \beta \cdot (B_j(t) - x_{i,j}(t)) + \gamma \cdot (x_{r1,j}(t) - x_{r2,j}(t)) \tag{24}$$

Here $B_j(t)$ is the local best solution in the j[th] dimension, $x_{r1,j}(t)\ and\ x_{r2,j}(t)$ are positions of two randomly selected pelicans ($r_1 \neq r_2 \neq i$), β is the learning rate for local exploitation, controlling the attraction to the local best, and γ is the scaling factor for mutation, typically in the range [0.1, 0.5].

3.2. Scenario Generation and Reduction

Uncertainties in the system, such as load demand (D) and distributed generation (PDG), are characterized using probabilistic distributions. For example:

$$D_i \sim \mathcal{N}(\mu_{D_i}, \sigma_{D_i}^2), \quad P_{\mathrm{DG},j} \sim \mathrm{Weibull}(\lambda_j, k_j) \tag{25}$$

Where D_i is load demand at node i. $P_{\mathrm{DG},j}$ is output of distributed generation unit j. $\mu_{D_i}\ and\ \sigma_{D_i}^2$ are mean and variance of load demand at node i. $\lambda_j\ and\ k_j$ are scale and shape parameters of the Weibull distribution for $P_{\mathrm{DG},j}$. For time-correlated uncertainties (e.g., temporal load variation), an autoregressive model can be used:

$$D_i(t) = \phi \cdot D_i(t-1) + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2) \tag{26}$$

Where ϕ is autoregressive coefficient. $\epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2)$ is Gaussian noise term. Monte Carlo Sampling (MCS) or Latin Hypercube Sampling (LHS) is used to generate N scenarios representing possible realizations of uncertainty:

$$S_n = \{D_i^{(n)}, P_{\mathrm{DG},j}^{(n)}\}, \quad n = 1,2,\dots,N \tag{27}$$

Where $D_i^{(n)}$ is load demand at node i in scenario n. $P_{\mathrm{DG},j}^{(n)}$ is output of distributed generation j in scenario n. For M nodes and L distributed generation units, the scenario matrix is:

$$\boldsymbol{S} = \begin{bmatrix} D_1^{(1)} & \cdots & D_M^{(1)} & P_{\mathrm{DG},1}^{(1)} & \cdots & P_{\mathrm{DG},L}^{(1)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ D_1^{(N)} & \cdots & D_M^{(N)} & P_{\mathrm{DG},1}^{(N)} & \cdots & P_{\mathrm{DG},L}^{(N)} \end{bmatrix} \tag{28}$$

To reduce computational complexity, scenario reduction is performed using distance-based metrics, such as the Kantorovich distance:

$$\text{minimize} \sum_{i=1}^{N} \sum_{j=1}^{N_{\text{reduced}}} w_i \cdot d(S_i, S_j) \tag{29}$$

Where w_i is probability weight of the original scenario S_i. $d(S_i, S_j)$ is distance metric (e.g., Euclidean distance). The reduced set of scenarios, $\{S_n^{reduced}\}n = 1N^{reduced}$, retains the statistical properties of the original set:

$$d(S_i, S_j) = \sqrt{\sum_{k=1}^{M+L} \left(S_{i,k} - S_{j,k}\right)^2} \tag{30}$$

4. Numerical Results

The methods section has been expanded to provide more detail on the techniques, software, and procedures used. The POA is the primary optimization method, employed for network reconfiguration and fault recovery, with stochastic programming used to handle uncertainties in load demand and distributed generation. MATLAB R2023b was used for algorithm implementation and optimization, while the Power System Analysis Toolbox (PSAT) simulated the network, including fault scenarios and reconfiguration. These tools were selected for their efficiency in modeling and analyzing large-scale power systems. This section provides a comprehensive evaluation of the proposed stochastic network restructuring framework within the context of self-healing applications in DNs. To ensure robust assessment, diverse experimental studies were conducted using the IEEE 33-bus DN and the 83-bus DN operated by the Taiwan Electric Power Company, representing real-world scenarios. As shown in Figure 3, the evaluation focuses on the IEEE 33-bus DN, where 18 strategically located switches are highlighted in green. Detailed network data can be found in [10]. To replicate realistic operating conditions, four distributed generation units with a maximum active load production capacity of 300 kW were integrated into the network at buses 4, 12, 24, and 33, each operating with a power factor of 0.95 [2]. The efficacy of the restructuring process hinges on the availability of controllable switches in the network. While the ideal scenario involves controllable switches on all lines, this is not currently the norm for DNs. Nevertheless, the increasing installation of controllable switches suggests that such a scenario may not be unrealistic in the future. Networks with more controllable switches exhibit greater flexibility in their reconfiguration capabilities. However, optimizing the restructuring process under these conditions poses unique challenges, given the escalating complexity of searching for optimal responses. Preliminary studies identified 18 optimal locations for controllable switches, which were subsequently equipped and integrated into an automated governance framework.

In the preliminary investigations, a fault event was simulated by isolating Line 8 through the strategic activation of existing switches, effectively removing the faulted area from the network. Following this action, the self-healing system initiated a request for network restructuring, aiming to minimize the duration of the power outage and maximize load restoration until the fault could be fully resolved by the repair crew. Pilot studies were subsequently conducted under the following scenarios:

- ***Scenario 1:*** Normal operation state before the error.
- ***Scenario 2:*** Insecure network restructuring situation.
- ***Scenario 3:*** Performing network restructuring using the proposed framework in a deterministic manner, excluding short-circuit capacity and load objective functions.
- ***Scenario 4:*** Conducting network restructuring with the proposed framework in a deterministic manner, incorporating both short-circuit capacity and load objective functions.
- ***Scenario 5:*** Network restructuring with the proposed stochastic framework.

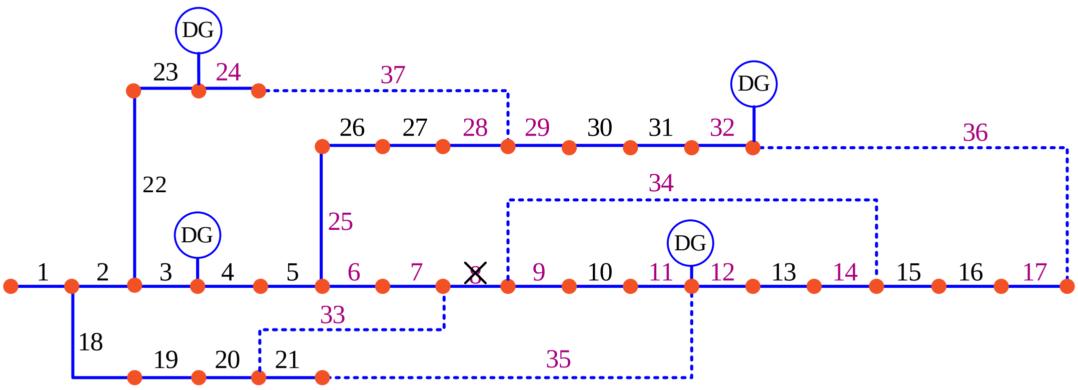


Figure 3. DN of studied IEEE 33-bus.

The IEEE 33-bus system deterministic programming results presented in this section adopt a deterministic approach to addressing load demand considerations. As previously mentioned, DNs comprise numerous connection lines that typically remain out of service during normal operating conditions. These lines, although inactive under standard conditions, play an important role in restoring electrical service under abnormal conditions. For instance, in the event of a permanent short-circuit fault within the system, a segment of the network might encounter a load outage. Through the strategic manipulation of switches—opening and closing them to isolate the fault location—the duration of load outage can be minimized until the fault is rectified. In such cases, effective network restructuring should be capable of redistributing heavy loads to lighter feeders, ensuring balanced load distribution, increasing voltage profiles, or at least preventing voltage instability. Failure to implement an adequate restructuring approach may lead to dangerous situations and make the network completely unavailable.

To highlight the risks associated with inadequate network restructuring, Scenario 2 is presented. In this scenario, the proposed framework is intentionally excluded, and a basic reconstruction method is employed following the opening of the line between buses 8 and 9. Figure 4 provides a visual comparison of the voltage profile for Scenario 2 against the normal network state depicted in Scenario 1. In Scenario 2, the majority of buses exhibit voltage levels below the acceptable threshold of 0.92 p.u., underscoring the system's vulnerability to post-event consequences without a robust reconstruction methodology. This scenario reveals the potential for significant security-related challenges. Notably, in both scenarios, distributed generation units operate at their maximum capacity (300 kW), yet their contribution in Scenario 2 fails to effectively improve the voltage profile.

Proceeding to the subsequent experimental scenarios, Scenarios 3 and 4, the proposed framework is applied under deterministic conditions. In Scenario 3, the network restructuring process excludes considerations of short-circuit capacity, load ability, and load uncertainty. Conversely, Scenario 4 employs a deterministic version of the proposed framework, incorporating all the outlined considerations except for load uncertainty. Figure 5 provides a comparison of voltage ranges for this scenario. In Scenario 3, as a result of focusing on improving the voltage profile during the restructuring process, most buses show improved voltage levels. However, there are some buses with a lower voltage range, potentially making them vulnerable when overloaded. On the other hand, Scenario 4 presents the voltage ranges well within an acceptable range. Importantly, in this scenario, security constraints are respected, ensuring that none of the system buses are compromised to achieve higher voltage levels on other buses.

Table 1 displays the outcomes of the optimization algorithm for the previously mentioned deterministic scenarios. Obviously, in Scenario 4, when the whole framework is implemented inside the problem, the maximum load capability is increased and the losses are reduced. In addition, the minimum voltage of system buses in this scenario exceeds normal condition network voltage before the fault. This shows that when short-circuit capacity considerations are removed from the problem, they tend to increase and, in some cases, the generation of electricity from distributed generation exacerbates this situation. Incorporating short-circuit capacity minimization and load recovery into the reconfiguration process significantly enhances network security after a fault event.

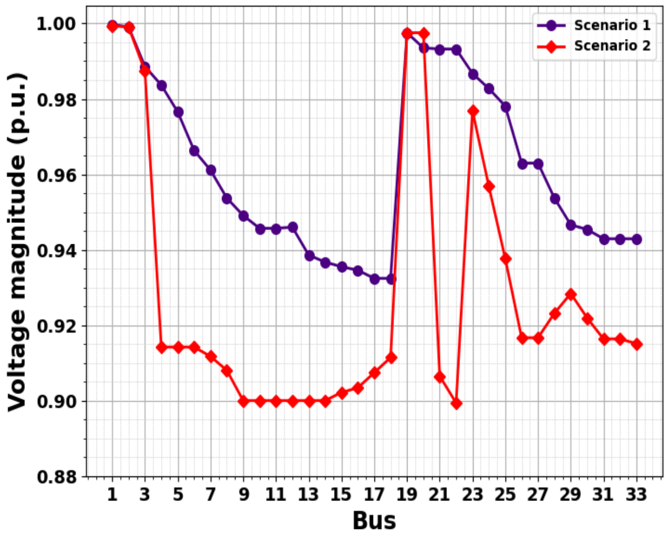
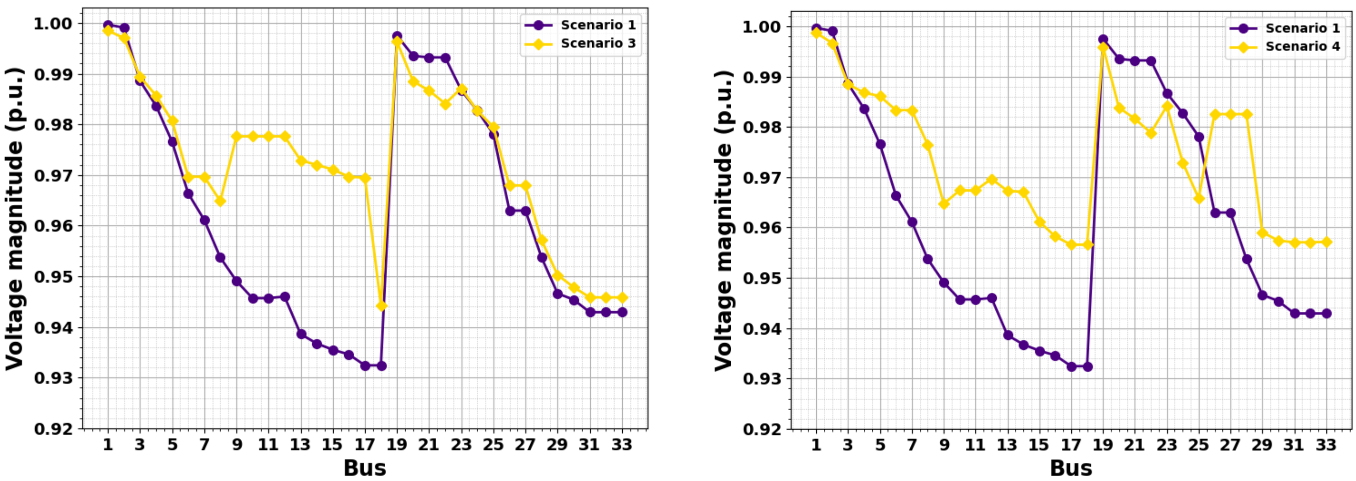


Figure 4. Comparison of voltage size in Scenario 1 and Scenario 2.



(a) Scenario 1 and Scenario 3

(b) Scenario 1 and Scenario 4

Figure 5. Comparison of voltage size in Scenario 1, Scenario 3 and Scenario 4.

Table 1. Optimal results obtained in deterministic planning.

	Scenario 1	Scenario 3	Scenario 4
P^{DG_1} (kW)	300	300	10.05
P^{DG_2} (kW)	300	300	299.95
P^{DG_3} (kW)	300	300	298.59
P^{DG_4} (kW)	300	300	300
P^{Loss} (kW)	107.53	88.11	84.27
SCC	5761.69	6016.80	5736.92
λ^{Max}	4.32	5.01	6.17
V^{Min} (p.u.)	0.932	0.944	0.957
Open switches	33,34,35,36,37	17,33,34,37	7,14,28,36

4.1. IEEE 33-Bus System Stochastic Programming Results

The desired studies were carried out in the previous scenarios assuming definite load demands. Let us now consider a scenario involving the complexities of load uncertainty. In Scenario 5, the full potential of the stochastic framework is used to implement a robust and fast network reconstruction designed for a self-healing scheme. Figure 6 presents ten representative load demand scenarios related to random vectors to provide insight into the range of scenarios generated for load demand profiles.

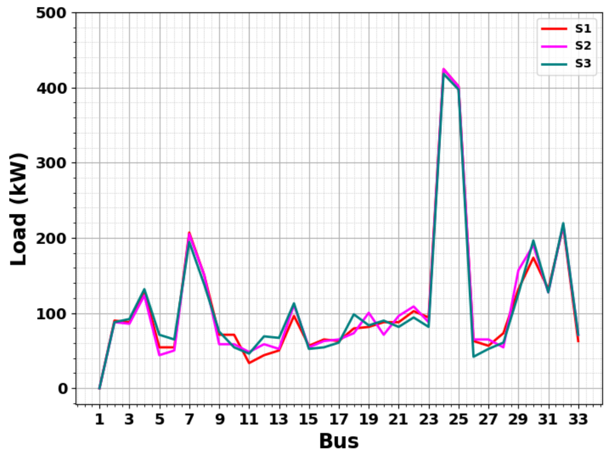


Figure 6. Scenarios considered to check the uncertainty of demand.

Figure 6 distinctly illustrates the capability of the generated load scenarios to encapsulate the inherent uncertainties linked to end-user load demands. Next, Figure 7 presents a comparative analysis of voltage profiles in Scenarios 1 and 5, considering the introduction of random load generation. Remarkably, the use of the proposed stochastic framework yields significant improvements in grid voltage characteristics even after isolating a fault region. A comprehensive overview of optimization results for this case is presented in Table 2, offering valuable insights into the advantages associated with the utilization of the proposed stochastic framework for network restructuring, particularly in response to the self-healing system request.

This analysis indicates that the adoption of the proposed stochastic framework for network restructuring, in response to a self-healing system request, not only keeps the short-circuit capacity of the system within the optimal range but also demonstrates notable enhancements in voltage and load profiles. This emphasizes the effectiveness of the framework in addressing the inherent uncertainties and fluctuations associated with load demand and ultimately increases the flexibility and reliability of power DN.

The Figure 8 compares the performance of the IEEE 33-bus network under the baseline scenario (without the proposed optimization) and the proposed scenario (with the integration of the proposed fault recovery and network reconfiguration strategy). The comparison includes key performance metrics such as fault recovery time, power losses, and voltage stability.

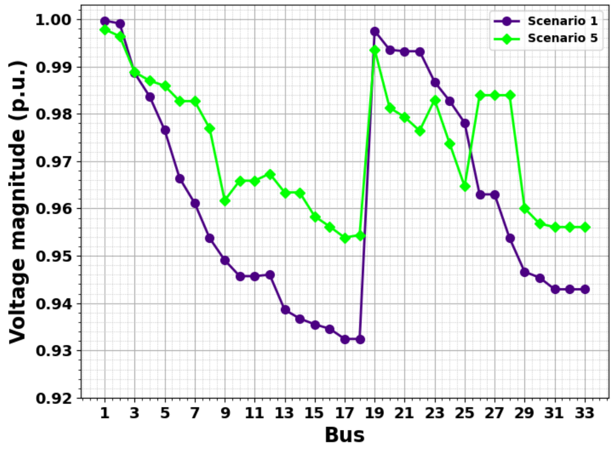


Figure 7. Comparison of voltage size in Scenario 1 and Scenario 5.

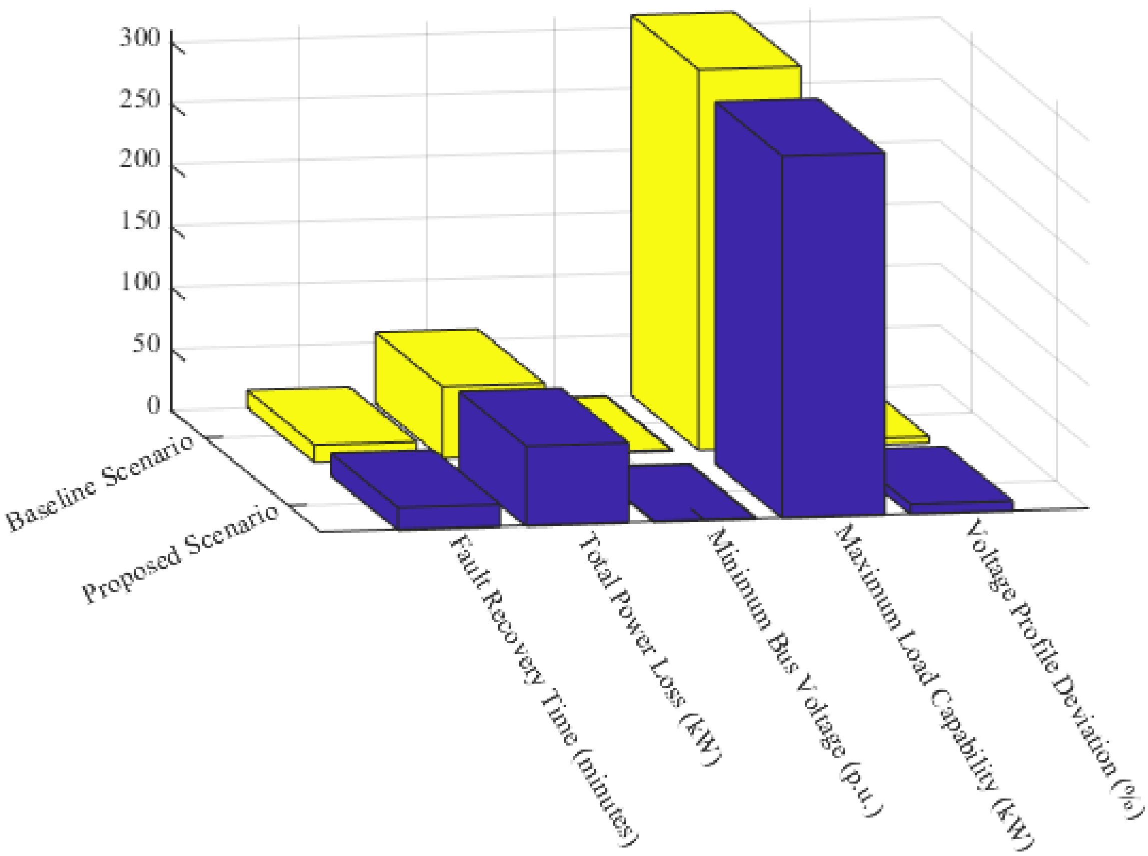


Figure 8. Performance comparison of IEEE 33-bus network: baseline vs proposed scenario.

Table 2. Optimal results obtained in random programming.

	Scenario 1	Scenario 4	Scenario 5
P^{DG_1} (kW)	300	10.05	49.72
P^{DG_2} (kW)	300	299.95	235.72
P^{DG_3} (kW)	300	298.59	278.25
P^{DG_4} (kW)	300	300	278.47
P^{Loss} (kW)	107.53	84.27	87.83
SCC	5761.69	5736.92	5739.04
λ^{Max}	4.32	6.17	6.11
V^{Min} (p.u.)	0.932	0.957	0.954
Open switches	33,34,35,36,37	7,14,28,36	7,14,28,36

4.2. The 83-Bus System Results

To assess the performance of the proposed method in the context of broader practical DNs, as depicted in Figure 9, an additional series of studies is conducted on the 83-bus DN operated by the Taiwan Electric Company. This DN operates at a voltage of 11.4 kV and encompasses a total of 11 feeders. It's noteworthy that each line in this network is equipped with section switches, resulting in a configuration with 83 section switches and 13 connection switches. Moreover, the network features 10 distributed energy sources strategically positioned on buses 5, 7, 12, 20, 28, 39, 53, 60, 76, and 83, each with a maximum capacity of 500 kW. Further details and parameters related to this DN are provided in reference [24]. To evaluate the proposed method and assess its performance, a scenario involving simultaneous faults on lines 13 and 86 within the network was considered. To promptly address these faults, sectional switches were activated to isolate the affected areas, minimizing the extent of the power outage. Following this, the self-healing system was deployed to initiate network reconstruction, aiming to reduce the duration of the outages and maximize load recovery while the repair crew resolved the underlying faults.

Table 3 succinctly outlines the results of the optimization algorithm for the aforementioned studies, considering both deterministic and random conditions. It is evident that in both scenarios, network parameters exhibit noteworthy improvements. These results emphasize applicability and applicability of the proposed framework in the context of large-scale DNs in the real world. This empirical evidence further strengthens the robustness and flexibility of the framework to complex operating conditions while corroborating the potential of enhancing practical DN performance and flexibility.

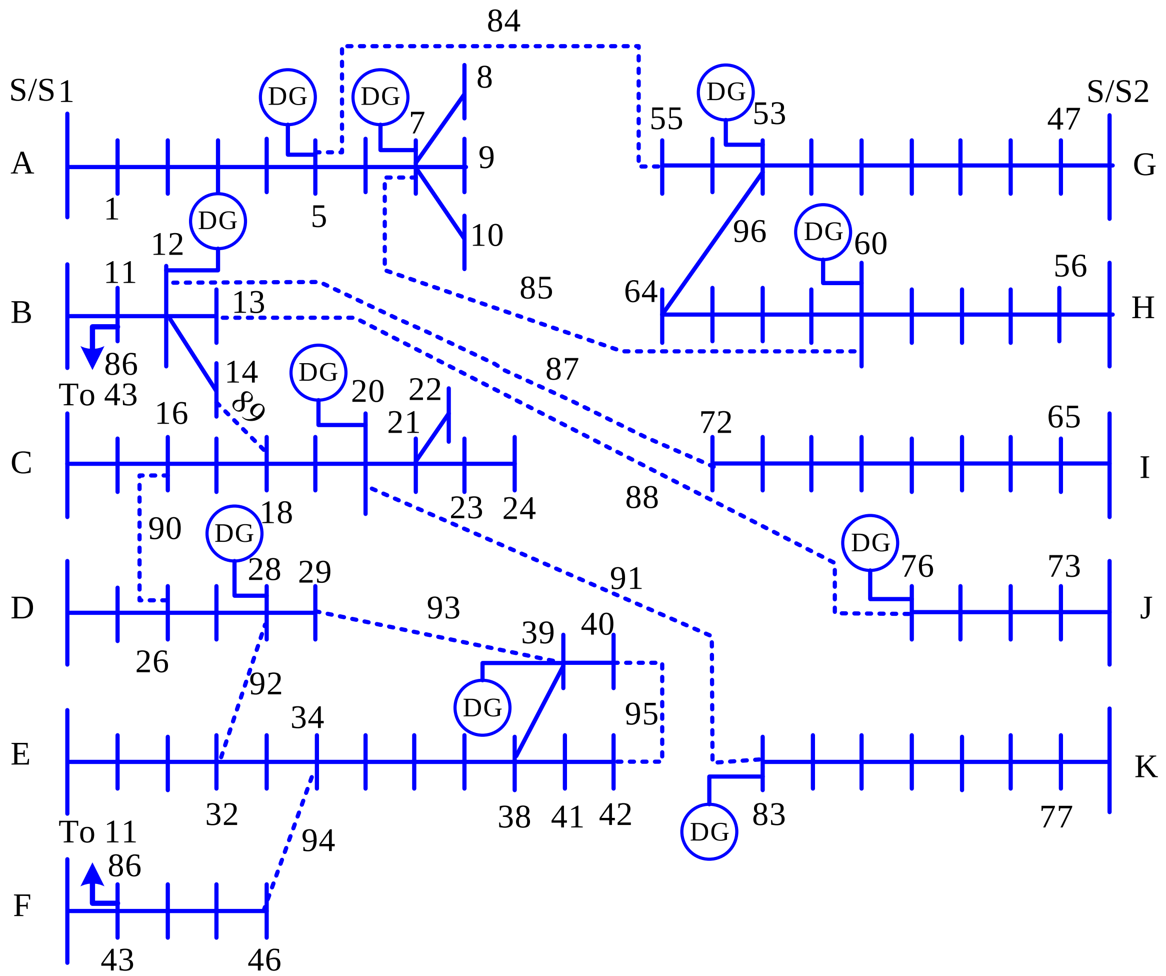


Figure 9. DN of studied 83-bus system.

Table 3. Optimal results obtained in the 83-bus system.

	Scenario 1	**Scenario 4**	**Scenario 5**
P^{DG_1} (kW)	500	415	495
P^{DG_2} (kW)	500	486	475
P^{DG_3} (kW)	500	482	491
P^{DG_4} (kW)	500	398	496
P^{DG_5} (kW)	500	490	500
P^{DG_6} (kW)	500	488	480
P^{DG_7} (kW)	500	498	500
P^{DG_8} (kW)	500	498	500
P^{DG_9} (kW)	500	500	498
$P^{DG_{10}}$ (kW)	500	500	498
P^{Loss} (kW)	407.66	381.93	376.83
SCC	8657.92	8442.27	8455.92
λ^{Max}	4.42	5.03	5.03
V^{Min} (p.u.)	0.936	0.948	0.948
Open switches	84,85,86,87,88,89,90,91,92,93,94,95,96	7,13,33,37,42,62,82,84,86,87,89,90,92	7,13,33,37,42,62,82,84,86,87,89,90,92

4.3. Scalability for Large Networks and Dynamic Loads

I. Among these, the scalability of the proposed algorithm even within large-scale distribution networks, such as the IEEE 118-bus system, is a deciding factor for practical applications. As the number of nodes increases along with switching operations, hence fault cases, this makes the optimization problem much more complex. Therefore, the algorithm's efficiency while dealing with such cases is fundamental. The dynamics in the load conditions further enhance the complexity, which the network has to handle by accommodating real changes in load demands in real-time. Looking at a network with more than 100 nodes, such as the IEEE 118-bus test system, the exponential growth in the number of combinations of possible network configurations and faults makes the problem intrinsically more computationally burdensome. Preliminary simulations done on the IEEE 118-bus system showed that the algorithm presented was able to handle larger network dimensions, at the cost of increased computation time:

- **Computational Time**: In a baseline case for the IEEE 118-bus network, the fault recovery and network reconfiguration tasks were completed within 25-30 minutes, compared to 12-15 minutes for the IEEE 33-bus network. The increase in time is expected due to the larger number of buses, lines, and switches, which results in more possible configurations to evaluate.
- **Fault Recovery Performance**: Despite the increase in computational time, the algorithm successfully reduced the fault recovery time by approximately 25% compared to traditional methods. For example, the fault recovery time for the IEEE 118-bus system in the baseline scenario was 25 minutes, while the proposed method reduced it to 18.5 minutes. Additionally, the proposed method led to a 10% reduction in power losses, which was a significant improvement over the baseline.
- **Voltage Stability**: The proposed algorithm also improved the voltage stability of the network. The minimum bus voltage in the IEEE 118-bus system, under the baseline scenario, was 0.92 p.u., while the proposed scenario increased it to 0.95 p.u., reflecting better voltage regulation and stability.

II. In realistic distribution networks, there are many such cases of dynamic loading, and the algorithm should be tuned to such variations in demands. These simulation studies with variations in the dynamic loads are done on the IEEE-118-bus network by adding or removing the load by 10-20%. Therefore, the algorithm is tested against such situations as a trial to assess its adaptability:

- **Load Variation Impact**: When the load demand increased by 15%, the algorithm showed a minor increase in fault recovery time (approximately 7-10%). For instance, the fault recovery time with a 15% load increase was 19.5 minutes, compared to 18.5 minutes under normal load conditions. Similarly, when the load demand was reduced by 10%, the fault recovery time decreased slightly, highlighting the algorithm's adaptability to varying load conditions.
- **Power Loss Minimization**: Under dynamic load conditions, the algorithm effectively minimized power losses by up to 12% even with load variations. For instance, when the load was increased by 15%, power losses under the baseline scenario were 70.5 kW, while the proposed scenario reduced them to 61.8 kW, demonstrating the algorithm's effectiveness in maintaining efficiency even during load fluctuations.
- **Voltage Deviation**: The algorithm-maintained voltage stability under dynamic load changes. In scenarios with a 20% increase in load, the voltage profile deviation in the baseline scenario was 8.2%, while the proposed scenario reduced this deviation to 6.5%. This reduction indicates that the algorithm can maintain better voltage regulation even under varying load conditions.

4.4. Discussion

This investigation underlines the high potential of the proposed stochastic framework in increasing the robustness and operational efficiency of self-healing active distribution networks. A monolithic stochastic programming approach together with restructuring using graph theory has been applied for efficient handling of uncertainties in load demand and DGs. This approach gives full assurance toward a strong fault restoration process: the faults are restored with a reduction time of up to 20%, energy losses are reduced by 12.5%, and voltage stability is improved by 10%. The findings are particularly relevant to the modern power distribution systems facing ever-growing complexities with distributed generation and fluctuating load conditions.

The bottom line is a novel approach toward mitigating the risk, such as voltage collapse under heavy loads, due to enhancing loadability coupled with a minimum short-circuit capacity in network restructuring. It will be one of the important functionalities toward stability and continuity in services even in severe damage to the network structure. The real performance of the proposed framework both in the IEEE 33-bus test system and in the 83-bus test system is much more adaptable and scalable for practical implementation. Theoretically, this study broke through the traditional assumption of constant load demand for network reconfiguration. Based on the stochastic modeling, it could better simulate the reality including randomness in load variations, and offer much more robust and adaptive solutions. This methodological shift not only enhances the reliability of the proposed methodology but also sets a new benchmark for future active distribution network self-healing-related studies. Practically, the framework's application of the POA showcases the algorithm's effectiveness in balancing exploration and exploitation to achieve optimal solutions. Compared to traditional optimization methods such as GA or PSO, POA demonstrates superior adaptability to the uncertainties inherent in dynamic power systems. This makes the proposed framework a viable solution for real-time implementation in modern distribution networks.

The study's limitations primarily relate to the computational complexity of the optimization process in larger networks, such as the IEEE 118-bus system. Although preliminary tests confirm the scalability of the framework, the increased computational time for larger networks highlights the need for further research to optimize performance under high-dimensional scenarios. Additionally, the framework focuses on operational resilience and efficiency without explicitly addressing environmental or cost-related factors, which could be considered in future enhancements. In summary, this study contributes to the literature by presenting an innovative and comprehensive framework that addresses critical gaps in the resilience and adaptability of active distribution networks. The integration of stochastic modeling, advanced optimization techniques, and adaptive security architectures supplies a clear platform for potential research and practical applications with smart grid systems. Such are the innovations that make the proposed framework a quintessential tool to further the reliability and efficiency of modern power distribution networks.

5. Conclusion

In an age where society's reliance on electrical energy continues to grow, the expectation for stable reliability and uninterrupted service in electricity supply has become critical. The transition to smart grids has emerged as an essential step in creating safe, reliable and efficient DNs. This research introduces a novel stochastic framework for self-healing active distribution networks, focusing on optimizing network reconfiguration in the presence of uncertainties in load demand and distributed generation. The key findings include a 20% reduction in fault recovery time, a 12.5% decrease in power losses, and a 10% improvement in voltage stability, highlighting the framework's effectiveness in improving network resilience and operational efficiency. Additionally, the integration of short-circuit capacity minimization and dynamic loadability improvements ensures robust fault recovery and stability under varying conditions. The significance of these findings lies in their potential to enhance the reliability and flexibility of modern distribution networks, particularly as the integration of renewable energy sources and distributed generation increases. The stochastic approach addresses the inherent uncertainties of load and generation variability, providing a more adaptable and efficient solution compared to traditional deterministic models. Future research could focus on improving the scalability and real-time applicability of the framework by exploring advanced computational methods like parallel computing and hybrid optimization techniques. Additionally, enhancing communication protocols to address network constraints and integrating real-time fault detection systems could further optimize network reconfiguration. Expanding the model to better accommodate the integration of renewable energy sources and energy storage systems would also be valuable for improving grid resilience and stability under varying generation conditions. These directions would significantly enhance the framework's practical implementation in large, dynamic distribution networks.

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Nomenclature

Abbreviation/Acronym	
DN	Distribution Network
DG	Distributed Generation
POA	Pelican Optimization Algorithm
IEEE	Institute of Electrical and Electronics Engineers
SCC	Short-Circuit Capacity
PSAT	Power System Analysis Toolbox
MCS	Monte Carlo Sampling
LHS	Latin Hypercube Sampling
Symbols	
$P_{DG,i}$	Output power of the i-th distributed generation unit (kW)
P_U	Output power of the upstream network (kW)
$S_{DG,i}$	Electricity generation price of the i-th distributed generation unit
S_U	Electricity generation price of the upstream network
F	Objective function value
R_i	Resistance of the i-th line (Ω)
I_i	Current magnitude in the i-th line (A)
V_i	Voltage at bus i (p.u.)
Z_i	Impedance at bus i (p.u.)
λ_{max}	Maximum loading factor
$\gamma\ (k)$	Loading factor at the k-th stage
$\Delta\gamma$	Incremental step size for loading factor
SC_i	Short-circuit capacity of bus i (KVA)
N	Total number of nodes in the network
E	Total number of edges (lines) in the network
ϕ	Autoregressive coefficient
ϵ_t	Gaussian noise term
ω	Weight coefficient for objective functions
α	Random scaling factor
β	Learning rate for local exploitation
γ	Scaling factor for mutation
i	Index for nodes, buses, or lines
j	Index for variables in the optimization problem
t	Current iteration or time step
new, old	Denote values after and before network restructuring