IJE TRANSACTIONS B: Applications Vol. 39, No. 02, (February 2026) 292-308

International Journal of Engineering

Journal Homepage: www.ije.ir

Strategic Organizing of Distributed Generation Resources to Enhance Reliability and Resilience of the Distribution System

V. Ghanbari Masir, B. Yousefi*, A. Noori, M. Rezvani

Department of Electrical Engineering, Islamic Azad University Nour Branch, Iran

PAPER INFO

Paper history:
Received 04 January 2025
Received in revised form 20 Febrruary 2025
Accepted 06 March 2025

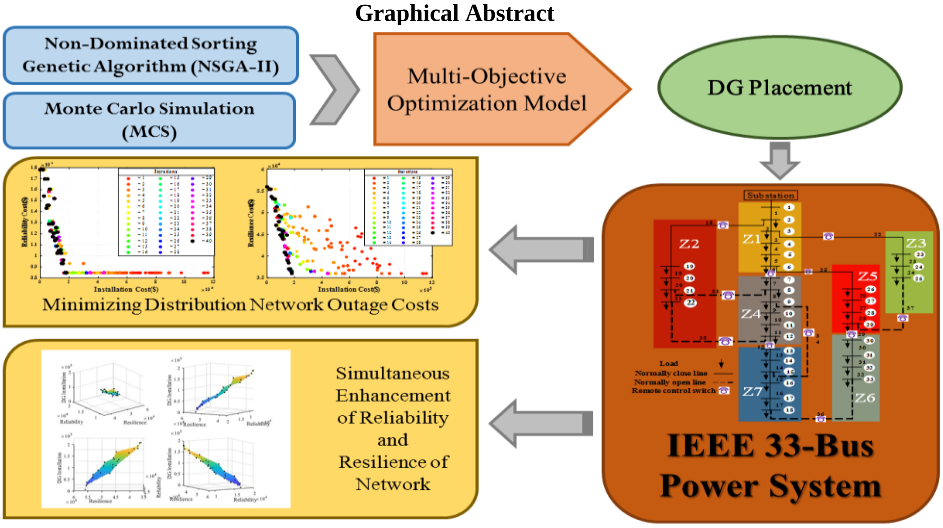
Keywords:
Reliability
Resilience
Service Restoration
Multi-Objective Optimization
Monte Carlo Simulation
Non-Dominated Sorting Genetic Algorithm

ABSTRACT

Two key research topics that aim to safeguard the system against unforeseen malfunctions or disasters and lessen their effects by reducing the resulting outages are distribution system reliability and resilience. There is a gap in the simultaneous optimization of power system resilience and reliability, particularly in distribution networks, even though are many researches devoted to their assessment and enhancement. This study proposes a new optimization paradigm for distributed generation (DG) placement-based reliability and resilience evaluation and improvement in distribution networks. Using the network's integrated remote-control switches, an optimum service restoration approach and optimal DG unit allocation are employed in this stochastic multi-objective optimization model. The methodology keeps DG investment costs low while minimizing distribution network outage costs brought on by resilience events and reliability contingencies. A mixed-integer linear programming (MILP) model that complies with network technical restrictions is used to describe the optimal service restoration issue. Two distinct scenario sets are created to represent the unpredictable nature of fault situations. Reliability and resilience scenarios are based on historical data of the network's fault rates and the failure probability functions of network components derived from Monte Carlo Simulation (MCS), respectively. A Pareto-optimal solution pool is obtained by solving the model using the non-dominated sorting genetic algorithm (NSGA-II) technique. To help the network planners choose the best option from the Pareto front, a fuzzy decision-making logic tool is then used. The suggested model is evaluated on an IEEE 33-bus system, and the simulation results demonstrate the model's efficacy.

doi: *10.5829/ije.2026.39.02b.02*

Graphical Abstract



*Corresponding Author Email: borzou.yousefi@iau.ac.ir (B. Yousefi)

Please cite this article as: Ghanbari Masir V, Yousefi B, Noori A, Rezvani M. Strategic Organizing of Distributed Generation Resources to Enhance Reliability and Resilience of the Distribution System. International Journal of Engineering, Transactions B: Applications. 2026;39(02):292-308.

NOMENCLATURE

Index and Sets

$\mathcal{L}.l$	Set and index distribution network lines.
$\mathcal{S}.s$	Set and index all contingency scenarios in the network.
$\mathcal{S}^{Rel}.\mathcal{S}^{Res}$	Sets of contingency scenarios for reliability and resilience assessment.
$\mathcal{B}.b$	Set and index network buses.
$\mathcal{Z}.z$	Set and index of network zones.
$J.j$	Set and index objective functions in fuzzy logic.

Parameters

C^{Cap}	DG installation cost per capacity unit ($/kW).
C^{Fix}	Fixed DG installation cost.
D_z	Load demand of zone z.
γ_s	Annual rate of s scenario.
$C_b^{outage}.C_z^{outage}$	Outage cost of bus b and zone z.
$A_{z.z'}$	The adjacency matrix of network zones.
$\mathcal{T}_l.\mathcal{F}_l$	Beginning and ending zones of line l, respectively.
M	A sufficiently big number.
$T_{b.s}^{Repair}.T_{z.s}^{Repair}$	Repair time of bus b and zone z in scenario s, respectively.
$V_{min}.V_{max}$	Minimum and maximum allowable voltage for network buses, respectively.
$P_b.Q_b$	Active and reactive power of load point b, respectively.
$\overline{S}_\ell^{Line}$	Apparent power capacity of line l.
$P_{b.min}^{Cap}.P_{b.max}^{Cap}$	Minimum and maximum installable active power capacity in each bus, respectively.
$\theta^{min}.\theta^{max}$	Minimum and maximum allowable power factor angle of DGs, respectively.
$R_l^{Line}.X_l^{Line}$	Per unit resistance and reactance of network line l, respectively.
P	The probability of being in, or exceeding a damage state ds.
$\bar{S}_{d.ds}$	The median value of the engineering demand parameter at which the asset reaches the threshold of the damage state ds.
β_{ds}	The standard deviation of the natural logarithm of engineering demand parameter at which the asset reaches the threshold of the damage state ds.
Φ	Standard normal cumulative distribution function.
$\alpha.\mu$	Shape parameter and scale parameter of the Weibull probability distribution function, respectively.
$a.b$	Minimum (best) and maximum (worst) values of the objective function in fuzzy logic, respectively.
v	A constant greater than 1.
u_j^d	A number between 0 and 1; 0 represents the minimum degree of importance, and 1 is the maximum degree of importance for the objective function.

Variables

$C^{Reliability}$	Outage costs due to reliability incidents
$C^{Resiliene}$	Outage costs due to resilience events
$C^{Installation}$	DG installation costs
$T_{z.s}$	Outage time of zone z in scenario s
$U_{b.s}$	Square of voltage magnitude for bus b in scenario s.
$P_{l.s}^{Line}.Q_{l.s}^{Line}$	Active and reactive power flow of line l in scenario s.
P_b^{Cap}	Installed DG capacity in bus b.
$P_b^{DG}.Q_b^{DG}$	The active and reactive output power of line l in scenario s.

Binary Variables

α_b^{DG}	1 when DG is installed in bus b.
$\beta_{s.z'.z}^{ZZ}$	1 when zone z is energized via zone $ź$.
α_b^{source}	1 when there is any power generating source in the bus b.
$\alpha_{b.s}^{status}$	1 when the DG in bus b is switched on in scenario s.
$\beta_{s.l}^{line}$	1 when line l is closed in scenario s.

1. INTRODUCTION

1. 1. Motivation Customers now anticipate a high-quality and dependable energy supply due to the growing significance of electrical energy in contemporary cultures. This means that any interruptions in the safe supply of electricity to end consumers cost the power system a lot of money. Additional work has been done to improve power systems' resilience to different types of breakdowns and forced outages to meet this issue. By lowering outage costs, these enhancements hope to offset the high long-term planning and implementation expenses (1-3).

1. 2. Literature Review Two areas of research that concentrate on power systems' capacity to handle fault eventualities in two distinct scenarios are power system resilience and reliability (4). The capacity of a system to sustain grid operation even in the case of a malfunction and guarantee a high-quality supply versus planned demand is known as reliability (5, 6). In power systems, reliability assessment is a well-known word that has been the subject of in-depth research over the last few decades. It addresses high likelihood, low consequence errors that arise during normal network operation. However, resilience is a very recent term, have been introduced by Amin (7). Nonetheless, in recent years, it has become increasingly popular among the power system community. The following is how the UK Energy Research Center defines power system resilience: An energy system's resilience is its ability to withstand disruptions and keep providing customers with reasonably priced energy services. Resilient energy systems may quickly bounce back from shocks and offer substitute ways to meet energy service demands if external conditions change. Resilience addresses occurrences with a low likelihood but significant impact (8, 9).

Reliability and resilience are two critical concepts in the context of power system performance, but they address different aspects of system robustness and performance. Reliability refers to the ability of a power system to deliver electricity consistently and without interruption under normal operating conditions (10). It focuses on the system's capability to maintain quality service despite the occurrence of faults or disturbances. Reliability is primarily concerned with high-probability, low-impact events that can be managed through preventive maintenance and fault management strategies. It involves metrics such as the System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI), which quantify the frequency and duration of outages experienced by customers (9, 11, 12). Conversely, resilience is a more recent idea that highlights the system's capacity to tolerate and bounce back from major, unforeseen disruptions or severe catastrophes. Low likelihood, high-impact events that might cause significant service interruptions are the focus of resilience (3). It focuses on the system's capacity to adapt, recover, and continue providing essential services even in degraded conditions. Key aspects of resilience include the system's ability to quickly restore operations, maintain service during disruptions, and provide alternative solutions when faced with major shocks or failures (13).

In summary, while reliability aims to minimize disruptions under normal conditions, resilience prepares the system to handle and recover from severe and infrequent disturbances. Understanding the distinction between these concepts is crucial for developing comprehensive strategies to enhance power system performance and ensure both consistent service delivery and effective response to extreme events (14).

The reliability and resilience evaluation of distribution networks has drawn the attention of several power system experts and planners since distribution network defects account for over 80% of customer disruptions (2). Nevertheless, the literature lacks a paradigm that assesses and improves the distribution network's resilience and reliability at the same time (15).

Numerous studies have mostly focused on evaluating the reliability of distribution networks (16-20). By reducing the network's power outage costs, the effect of distributed renewable generating units on distribution system reliability has been assessed (21). This research takes into account wind turbines, electric storage systems, and solar units. A Markov model is used to give a stochastic model that incorporates the unpredictable character of renewable DGs. (22) presents a probabilistic analytical approach to evaluate the reliability of distribution systems with dispatchable and non-dispatchable renewable DG units using two reliability indices, SAIDI and SAIFI (15). Technical factors including DG failure, load demand, and time-dependent patterns of DG output are taken into account while restoring the DG side. To optimize the voltage profile of the distribution network and increase reliability, the best location for distributed energy resources (DERs) was examined by Mujjuni et al. (23). Yuvaraj et al. (24) suggested a renewable DG allocation planning algorithm to identify the best placements and dimensions of DG units in distribution networks for enhancing reliability and minimizing loss. Using a genetic algorithm (GA), the allocation problem is described as a mixed-integer nonlinear programming model.

Recent years have seen a surge in interest in power system research on the assessment and improvement of distribution system resilience (25-31). Additionally, by establishing several microgrids, DG resources can aid in load restoration, reducing the adverse impacts of extreme events and enhancing the resilience of distribution systems (32-35). Ma et al. (36) presented a mixed-integer second-order conic programming model for distributing dispatchable DG and forming radial microgrids in the best possible way to increase the resilience of the distribution system. After a high-impact, low probability (HILP) occurrence, the goal function reduces load outages while meeting operational limitations. A robust distribution network planning issue is put out by Panteli et al. (37), which aims to minimize system damage by coordinating the hardening and DG allocation. A two-stage robust optimization model is used to formulate the issue. This multi-stage, multi-zone uncertainty set is used to represent the unpredictability of a natural disaster. A DER-based feeder restoration technique was suggested by Home-Ortiz and Mantovani (38). Through the most efficient allocation of DERs, this method simultaneously maximizes the quantity of restored important loads and improves the restoration timeframes. By assigning DERs appropriately, this method simultaneously increases the quantity of restored important loads and improves the restoration times. The crucial restrictions of the grid are taken into account while modeling the restoration issue as a mixed-integer linear program (12, 39).

Table 1 demonstrates how our study fills a major vacuum in the literature by offering a thorough approach that, in contrast to the other references, simultaneously assesses and improves the resilience and reliability of distribution networks. Here are some highlights of this paper's noteworthy contributions and innovations:

1. 2. 1. A new planning methodology that considers resilience enhancement as well as reliability for the best DG location.

1. 2. 2. Reliability, resilience, and DG installation costs are minimized by the use of a multi-objective function optimization.

1. 2. 3. DG islanding operation, fault-isolation, and post-fault service restoration are all part of this innovative service restoration strategy that satisfies network technological limitations.

1. 2. 4. This model uses a stochastic optimization approach to describe the uncertainties of the system.

1. 2. 5. By solving the MILP model using NSGA-II, distribution system planners can select from a Pareto-optimal solution pool.

1. 2. 6. To help the decision-makers select the best option, a fuzzy decision-making technique is being used as a tool.

1. 3. Research Gaps and Contributions Despite extensive research on the reliability and resilience of power systems, significant gaps remain in integrating these aspects into a cohesive framework and evaluating their combined impact. Existing studies often treat reliability and resilience separately and lack comprehensive methods to address their interplay in practical scenarios. Some of the available research gaps are as follows:

1. 3. 1. Lack of Integrated Frameworks Although substantial research has focused on reliability and resilience individually, there is a significant gap in frameworks that address both aspects simultaneously. The existing studies often treat reliability and resilience as separate entities, neglecting their interplay in practical scenarios.

1. 3. 2. Inadequate Evaluation Methods Current methods for evaluating reliability often do not account for the complex interactions between DGs and fault conditions, especially in terms of stochastic uncertainties. Similarly, resilience studies frequently overlook the combined impacts of fault isolation, DG islanding, and post-fault restoration.

1. 3. 3. Optimization Approaches Existing optimization models tend to focus on either reliability or resilience enhancement, but few integrate both into a unified multi-objective function. There is also a lack of research on utilizing advanced decision-making tools, such as fuzzy logic, to assist in selecting optimal solutions from Pareto-optimal sets.

This paper addresses these gaps by introducing an integrated planning model that enhances both reliability and resilience, utilizing advanced optimization techniques and decision-making tools. Key contributions

TABLE 1. Comparing this paper and literature

Ref.	Focus	Problem	Approach	Contribution	Differences
(40)	Reliability Assessment	Impact of Renewable DGs on reliability	Minimization of power outage costs using a Markov model	Evaluate reliability considering the uncertain nature of renewable DGs	Focuses on reliability only, and does not integrate resilience assessment
(22)	Reliability Indices	Reliability assessment with dispatchable/non-dispatchable DG units	Probabilistic analytical method; Evaluate SAIDI and SAIFI	Considers DG failure, load demand, and time-dependent DG output patterns	Does not enhance resilience or provide a framework for both reliability and resilience
(23)	DG Placement	Optimal placement of DERs for reliability improvement	Improves voltage profile and reliability through DERs	Optimizes DG locations, and sizes	Concentrates on DG allocation lack resilience enhancement
(24)	DG Allocation Planning	Reliability improvement and loss reduction in distribution networks	Mixed-integer nonlinear programming; Genetic Algorithm	Optimum locations and sizes of DG units	Uses GA for allocation planning but does not address resilience
(30) (31) (29) (41)	Resilience Enhancement	Enhancing resilience of distribution systems	Various models to improve resilience via microgrids	Focuses on mitigating effects of extreme events using DGs	Primarily addresses resilience, not reliability simultaneously
(32) (33) (34)	Microgrid Formation	Load restoration and resilience via microgrids	Mixed-integer second-order conic programming	Improves resilience post-HILP incident	Resilience-focused, lacks integrated reliability assessment
(35)	Resilient Planning	Coordination of hardening and DG allocation for resilience	Two-stage robust optimization model with multi-stage disaster uncertainty	Coordinates DG allocation and system hardening to minimize damage	Deals with resilience planning but not combined reliability/resilience enhancement
Our Work	Reliability and Resilience	A comprehensive framework to evaluate and enhance both reliability and resilience	Integrates methods for assessment and enhancement of reliability and resilience	Addresses gap by providing a framework that combines reliability and resilience enhancement	Presents a unified approach, unlike other works that focus on either reliability or resilience separately

include a novel multi-objective optimization approach, a robust stochastic model, and innovative service restoration strategies. The main contribution of this paper is as follows:

1. 3. 4. Integrated Planning Model The new planning methodology for DG placement that is presented in this research concurrently improves the distribution network's resilience and reliability.

1. 3. 5. Multi-Objective Optimization It introduces a multi-objective function optimization approach to minimize reliability, resilience, and DG installation costs, providing a balanced solution to complex trade-offs.

1. 3. 6. Service Restoration Approach The paper proposes an innovative service restoration strategy that includes DG islanding operation, post-fault service restoration, and fault isolation while adhering to network technical constraints.

1. 3. 7. Stochastic Optimization Model The model incorporates system uncertainties using a stochastic optimization framework, enhancing the robustness of the proposed solutions.

1. 3. 8. Advanced Solution Techniques NSGA-II is employed to solve the mixed-integer linear programming (MILP) model, allowing distribution system planners to select from a Pareto-optimal solution pool.

1. 3. 9. Fuzzy Decision-Making To handle the inherent uncertainties and preferences in real-world circumstances, a fuzzy decision-making technique is used to assist decision-makers in choosing the ultimate ideal answer.

2. PROBLEM MODELING

This section presents the ideal location of dispersed energy resources in the distribution network. The allocation of resources in the network is considered to be a power system planning problem. Therefore, taking into account economic factors and analyses along with technical limitations are of high importance.

One significant element of distributed generators (DGs) on the reliability and resilience of distribution systems is their influence on the service restoration procedure. Thus, an optimal service restoration framework is presented in this paper that utilizes the actions of remote-control switches for network reconfiguration and considers the location and capacities of DGs as the decision variables. This analysis examines network reliability and resilience situations, together with their associated contingencies and cost functions, via a stochastic optimization model. Finally, the model is solved using the NSGA-II algorithm.

The following introduces network and resource restrictions and equations for the optimum service restoration problem.

2. 1. Objective Function Two perspectives should be used to assess how DG resources affect network resilience and reliability: first the resources' installation costs, and second the costs associated with customer interruptions. Calculating and contrasting these two variables may be used to do a cost-benefit analysis and determine whether or not to install the DG.

Consequently, this model takes into account three objective functions:

2. 1. 1. Reducing the financial outlay for DG resource setup and installation.

2. 1. 2. Reducing outages brought on by common network failures that result in interruptions for consumers (reliability costs).

2. 1. 3. Reducing the amount that consumers must pay in full as a result of network failures brought on by natural catastrophes and extensive network outages (resilience costs).

Equations 1-3 are used to define these objective functions.

$$C^{Installation} = \sum_{b\in B} \alpha_b^{DG} C^{Fix} + P_b^{Cap} C^{Cap} \tag{1}$$

$$C^{Reliability} = \sum_{s\in S^{Rel}} \sum_{z\in Z} T_{z.s} D_z \gamma_s C_z^{Outage} \tag{2}$$

$$C^{Resilience} = \sum_{s\in S^{Res}} \sum_{z\in Z} T_{z.s} D_z \gamma_s C_z^{Outage} \tag{3}$$

Equation 1 states that the cost of installing resources is made up of two parts: a fixed installation cost and a variable installation cost that varies with installed capacity. The second function of the objective Equation 2 computes the total outage costs incurred by faults with preset yearly occurrence rates and is established based on reliability scenarios. Each scenario in the reliability scenario collection consists of a single defect because it is uncommon for many faults to occur simultaneously in a reliability outage scenario. The outage costs suffered by various problems with predefined occurrence probability are added up using Equation 3, which is developed for resilience situations. It should be mentioned that no one knows the resilience scenario's yearly rate. Nonetheless, the likelihood of an event happening is established. The most likely situations are then determined using the fragility curves of the network's constituent parts. To put it another way, resilience scenarios are defined by the likelihood of each scenario occurring as an event rather than a yearly rate. It is highly feasible for many faults to occur simultaneously in resilience settings.

To optimize this model, two sets of equations—optimal service restoration constraints and network technical restrictions—are taken into account. These are explained in detail in this section.

2. 2. Service Restoration Constraints Corrective action should be taken when a network failure arises so that the network experiences the least amount of outage possible. Accordingly, each problem should be isolated in a way that interrupts the least amount of network demand feasible. As soon as the fault is fixed, the impacted zones should be restored. For this reason, the best possible service restoration plan is required. The following presents the suggested restoration model as a set of constraints.

The electrical connection between the network's zones should be taken into account first. This restriction is expressed as follows:

$$\sum_{z'\in Z}\beta_{z.z'.s}^{ZZ} = 1-\sum_{b\in z}(\alpha_b^{source}+\alpha_{b.s}^{status}) \quad (4)$$

Limitation According to Equation 4, each network zone has to either host a DG or be linked to an electrified zone to be energized. Additionally, each zone has to be connected to a single powered zone to preserve the network's radial layout.

$$\alpha_{b.s}^{status} \le \alpha_b^{DG} \quad (5)$$

According to Equation 5, a DG can only be operational in a given circumstance if it has already been installed in that bus. A connection connecting the two zones is necessary for a zone to be electrified by another, hence the zones must be close to one another.

$$\beta_{s.\acute{z}.z}=0; \quad \forall s\in S.(z.z')\in Z.A_{z.z'}=0 \quad (6)$$

Equation 6 states that at least one switchable connection connecting a bus in zone z to a bus in zone z′ is necessary for zone z to be powered by zone z′.

The switch between zones z and z′ should be closed once zone z has been powered. It is also important to consider the following restriction to avoid reciprocal energization, as only one of the two zones can be electrified by the other:

$$\beta_{s.z'.z}^{ZZ}+\beta_{s.z.z'}^{ZZ}=\beta_{s.\ell}^{line}; \forall s\in\mathcal{S}.(z.z')\in \mathcal{Z}.\ell\in\mathcal{L}.(\mathcal{F}_\ell=z.\mathcal{T}_\ell=z' or\ \mathcal{F}_\ell=z'.\mathcal{T}_\ell=z) \quad (7)$$

For lines that are not switchable inside the zones, $\beta_{l.s}^{line}$ is always 1. For lines that are switchable between the zones, $\beta_{l.s}^{line}$ might be either 0 or 1. Equation 7 states that if a line connecting two zones is open, neither zone can energize the other. The only zone that may be activated by the other is the one that is closed.

If the technical limitations are not broken, any zone with DG and the zones that are linked to it can function in island mode throughout the service restoration process. Therefore, one line of the network should be in "open" condition for each islanded zone to ensure the network's radial structure.

$$\sum_{\ell\in\mathcal{L}}\beta_{s.\ell}^{line}\le\sum_{b\in\mathcal{B}}(1-\alpha_b^{source}-\alpha_{b.s}^{status}); \quad \forall s\in\mathcal{S}.\ell\in\mathcal{L}.b\in\mathcal{B} \quad (8)$$

The power flow route is determined by Equations 4-8. The network zones' outage times are computed using the following formulas.

The zone being supplied has a longer outage period than the supplier zone since the supplier zone will be activated first, followed by the supplied zone assuming there is no issue there:

$$T_{z.s}\ge T_{z'.s}-M\times\left(1-\beta_{s.z'.z}^{ZZ}\right); \forall s\in\mathcal{S}.(z.z')\in Z \quad (9)$$

Equation 9 states that if zone z' ($\beta_{s.z.z'}^{ZZ}=1$), energizes zone z, then the zone z's outage time is larger than or equal to the zone z′'s outage time. Since remote-control switches have a very quick action time, if zone z is fault-free when zone z' is powered, the two zones' restoration times will be equal. If a zone has a problem, it cannot be restored until the issue is fixed. Put differently:

$$T_{z.s}\ge T_{z.s}^{Repair}; \quad \forall s\in\mathcal{S}.z\in Z \quad (10)$$

2. 3. Network Technical Constraints This section discusses the technological limitations that must be taken into account to guarantee the network operates and performs satisfactorily. For every situation, power flow equations, bus voltage limitations, and line power constraints must be upheld.

The following formula is taken into consideration while calculating voltage drop:

$$-M\times\left(1-\beta_{\ell.s}^{line}\right)\le \left\{U_{b.s}-U_{b'.s}-2\left(P_{\ell.s}^{line}R_\ell^{line}+Q_{\ell.s}^{line}X_\ell^{line}\right)\right\}\le M\times\left(1-\beta_{\ell.s}^{line}\right) \quad \forall s\in\mathcal{S}.\ell\in\mathcal{L}.(b.b')\in\mathcal{B}.\mathcal{F}_\ell=b.\mathcal{T}_\ell=b' \quad (11)$$

Equation 11 uses a linear approximation of the voltage-drop equation. Each bus's total power is determined by the following formulae for power flow calculations:

$$\sum_{\ell;\mathcal{F}_\ell=b}P_{\ell.s}^{line}+P_b=\sum_{\ell;\mathcal{T}_\ell=b}P_{\ell.s}^{line}+P_b^{DG}; \quad \forall s\in\mathcal{S}.b\in\mathcal{B}.b\ne substation \quad (12)$$

$$\sum_{\ell;\mathcal{F}_\ell=b}Q_{\ell.s}^{line}+Q_b=\sum_{\ell;\mathcal{T}_\ell=b}Q_{\ell.s}^{line}+Q_b^{DG}; \quad \forall s\in\mathcal{S}.b\in\mathcal{B}.b\ne substation \quad (13)$$

Equations 12 and 13 require that a bus's input and output power total zero. Bus voltage limit constraints, which establish the maximum and minimum permitted voltage magnitudes for every network bus, are a crucial component of distribution network functioning.

$$V_{min}^2 \le U_{b.s} \le V_{max}^2;\ \forall s \in \mathcal{S}.b \in \mathcal{B} \qquad (14)$$

The line thermal capacity, which establishes the maximum and lowest line capacity for electricity flow, is another technical limitation in distribution networks. Equation 15 linearizes this restriction using an octagonal approximation (16):

$$\pm P_{\ell.s}^{Line} \pm Q_{\ell.s}^{Line} \le 0.9239 \times \overline{S}_{\ell}^{Line};\quad \forall \ell \in \mathcal{L}.s \in \mathcal{S} \qquad (15)$$

DG operational restrictions must be considered in addition to network technical constraints. The DGs' active and reactive output power minimum and maximum are listed below.

$$\alpha_b^{DG} P_{min}^{Cap} \le P_b^{Cap} \le \alpha_b^{DG} P_{max}^{Cap};\ \forall\, b \in \mathcal{B} \qquad (16)$$

$$0 \le P_{b.s}^{DG} \le P_b^{Cap};\quad \forall b \in \mathcal{B}.s \in \mathcal{S} \qquad (17)$$

$$P_{b.s}^{DG} \le \alpha_{b.s}^{status} M;\quad \forall b \in \mathcal{B}.s \in \mathcal{S} \qquad (18)$$

$$P_{b.s}^{DG} \tan(\theta^{min}) \le Q_{b.s}^{DG} \le P_{b.s}^{DG} \tan(\theta^{max});\quad \forall b \in \mathcal{B}.s \in \mathcal{S} \qquad (19)$$

The suggested framework is a mixed-integer linear programming (MILP) model, which is composed of Equations 1-19.

An index that is computed in each simulation is shown to compare various case studies and to give a better understanding of the network's resilience and reliability level.

$$RI = 1 - \frac{\sum_s (\sum_z T_{s.z} D_z)\gamma_s}{(\sum_s \max_z (T_{s.z}^{Repair}) \sum_z D_z)\gamma_s} \qquad (20)$$

Since the problem occurs until all faults are fixed, Equation 20 determines the ratio of energy provided as a result of optimal service restoration to total energy that is not supplied. In other words, Equation 20 calculates the ratio of the energy given by modifying acts to the total energy that would remain unsupplied if those modifying actions were not carried out. Thus, the aforementioned index will be 0 if modifying activities are unable to restore any load, and it will be one if such actions restore all loads right after the problem or faults.

3. PROPOSED ALGORITHM

3. 1. Input Data

3. 1. 1. Test System The IEEE 33-bus system is used to test the model and confirm the suggested framework's functionality. (42) provides a full description of this system's features. The system must undergo certain changes to conduct service restoration studies. To help the current typically open lines provide reconfiguration capabilities, remote control switches have been included in various locations. The updated IEEE 33-bus system diagram is shown in Figure 1.

3. 1. 2. Outage Scenarios Fault scenarios are created to put the suggested stochastic model into practice. As previously mentioned, N-1 and N-2 contingencies are commonly used as scenarios for reliability assessments. In the reliability analysis of this study, each scenario comprises only one defect since the likelihood of two or more faults happening is very small.

The 33-bus system's reliability evaluation considers yearly outage rates, repair durations, and outage costs. These are randomly generated using a uniform probability distribution function of the stated constraints ($0.001 \le \gamma_s \le 0.25$, $70 \le T_{b.s}^{Repair} \le 150$ mins, $0.25 \le C_b^{outage} \le 0.7$ \$/kWh). On the other hand, resilience scenarios include several failures throughout the system because severe occurrences have a significant impact on the network. The fragility curves of the components should be considered when estimating the effect of an incident on network equipment. These curves, which may range in structure depending on the component's location, kind, and condition, display the likelihood of a component failing based on the event's intensity. The component's failure probability is 0 when the event's intensity is extremely low, and it rises when the event's intensity is beyond the threshold value.

For the resilience evaluation, the chance of network pole failure versus wind speed ω, (43) is calculated as follows, assuming the hurricane phenomenon:

$$P_T(\omega) = \begin{cases} 0 & \omega \le \omega_{critical} \\ P_{T-hw}(\omega) & \omega_{critical} \le \omega \le \omega_{collapse} \\ 1 & \omega \ge \omega_{collapse} \end{cases} \qquad (21)$$

Additionally, the following is the likelihood that network lines may fail:

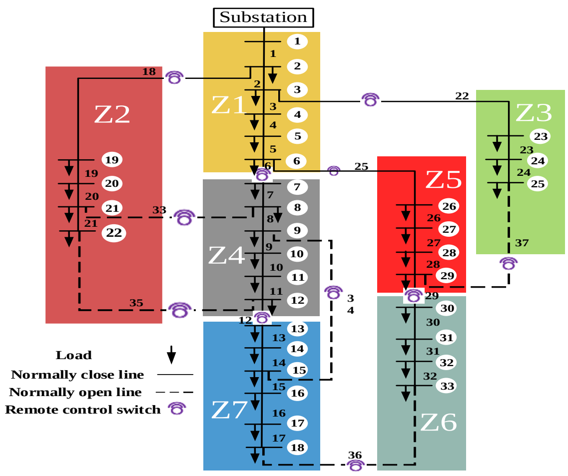


Figure 1. Modified IEEE 33-bus test system

$$P_L(\omega) = \begin{cases} \overline{P_L} & \omega \leq \omega_{critical} \\ P_{L-hw}(\omega) & \omega_{critical} \leq \omega \leq \omega_{collapse} \\ 1 & \omega \geq \omega_{collapse} \end{cases} \quad (22)$$

Using the log-normal distribution function, the failure probability is computed for wind speeds between critical and collapse speeds:

$$P = \Phi\left[\frac{1}{\beta_{ds}} \ln\left(\frac{S_d}{\bar{S}_{d.ds}}\right)\right] \quad (23)$$

The following formula is used to determine the line's failure probability when the poles are linked in series:

$$P[PoleFailure] = 1 - P[Pole\ Survival] \\ = 1 - P[(F_1 = 0) \cap (F_2 = 2) \cap \ldots (F_N = 0)] \quad (24)$$

The following is how the Weibull distribution function is used to model hurricanes:

$$f_{x_i}(x_i) = \frac{\alpha}{u}\left(\frac{x_i}{u}\right)^{\alpha-1} \exp\left[-\left(\frac{x_i}{u}\right)^{\alpha}\right] \quad (25)$$

The following formula is used to determine the likelihood of component failure concerning wind speed:

$$p_f = \int_0^{\infty} P f_{x_i}(x_i) dx_i \quad (26)$$

3. 2. Decision Criterion Unlike single-objective optimization, there are usually several Pareto optimal solutions when dealing with a multi-objective optimization problem. The Pareto front or Pareto set, which is the collection of all Pareto-efficient scenarios, provides network designers and operators with a set of feasible optimal solutions.

Decision-makers priorities determine which solutions are accessible, and engineering and economic judgments are particularly crucial during this stage. The literature offers a variety of strategies for handling these types of decision-making processes (44). Fuzzy decision-making method. Here, a final sample solution from the Pareto set is obtained using the fuzzy decision-making approach (45). Each goal function in this approach is given a continuous and diminishing membership function. Figure 2 shows an example declining membership function. The decision-maker assigns a value of 1 to the membership function, while the maximum of the objective function is assigned a value of 0. As a result, membership values for various objective function values range from 0 to 1.

Figure 2 shows the ith objective function, f_i, and its membership order, u_i^f. Using the Pareto fronts objective functions, the values of these parameters may be found. By resolving the following minimization problem, the final answer is found:

$$Min \sum_{j \in J} \left| u_j^d - u_j^f \right|^{v} \quad (27)$$

The optimal value for the jth function membership order is u_j^d. In this case, all objective functions are

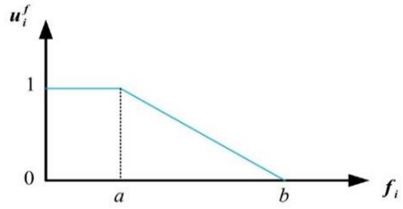


Figure 2. A decreasing membership function

considered to have $u_j^d = 1$. Consequently, Equation 28 replaces Equation 27 in the manner shown below:

$$Min \sum_{j \in J} \left| \frac{(a - f_j)}{a - b} \right|^{v} \quad (28)$$

To clarify the relationship between the different tools used in problem modeling—such as NSGA-II, Monte Carlo simulation, stochastic optimization, and fuzzy decision-making logic—I'll break down the key aspects of our proposed algorithm. Here's how these tools interact:

3. 2. 1. Monte Carlo Simulation This is used to generate outage scenarios for reliability and resilience assessments. Simulating various fault scenarios (e.g., single faults for reliability, multiple faults for resilience), helps in estimating the probability distributions of different outcomes, such as outage durations and repair times. Monte Carlo simulation helps to incorporate the inherent randomness and uncertainties in the model, providing a robust analysis of potential scenarios.

3. 2. 2. Stochastic Optimization This approach is integrated into our model to handle the uncertainties generated by Monte Carlo simulation. It involves optimizing decisions (e.g., the placement of distributed energy resources or the configuration of the network) under uncertain conditions. The stochastic nature of the problem is accounted for by considering various possible states of the system, and the optimization process aims to find solutions that perform well across these states.

3. 2. 3. NSGA-II (Non-dominated Sorting Genetic Algorithm II) This multi-objective optimization algorithm is employed to solve the optimization problem generated by the stochastic model. NSGA-II is used to generate a Pareto front of solutions that balance conflicting objectives, such as minimizing outage costs while maximizing system resilience. It provides a set of Pareto-optimal solutions, offering decision-makers a range of trade-off options.

3. 2. 4. Fuzzy Decision-Making Logic Once the Pareto front is obtained, fuzzy decision-making logic is applied to select the most suitable solution. This involves defining membership functions for each objective and then aggregating these to identify the solution that best matches the decision-maker's preferences. Fuzzy logic helps in handling the ambiguity and imprecision associated with human judgment, translating qualitative preferences into a quantitative decision-making framework.

3. 3. Effects of Forecast Errors

3. 3. 1. Forecast Errors in Objective Functions The objective functions in our model are designed to minimize three key costs: installation costs of Distributed Generation (DG) resources, customer interruption costs due to network faults, and make-whole payment costs due to natural disasters. Forecast errors can affect these objectives in various ways:

3. 3. 1. 1. Installation Costs Forecast errors in the expected capacity and cost of DG resources can lead to suboptimal investment decisions. If the forecast underestimates the required capacity or overestimates the costs, the model may either underinvest in DG resources, leading to higher interruption costs, or overinvest, which increases installation costs without proportional benefits in reliability and resilience.

3. 3. 1. 2. Reliability Costs Errors in forecasting fault occurrence rates and repair times can lead to incorrect assessments of reliability costs. An overestimate of fault frequencies may result in excessive investment in DG resources, whereas an underestimate could result in insufficient investments, leading to higher actual interruption costs.

3. 3. 1. 3. Resilience Costs Forecast errors in the likelihood of extreme events and their impact on network components can affect the resilience cost calculations. Misestimates in the severity or probability of natural disasters can lead to either over or underestimations of resilience costs, impacting the overall cost-benefit analysis.

3. 3. 2. Impact on Optimization Process Forecast errors can also influence the optimization process, especially in the context of service restoration and network technical constraints. The accuracy of fault predictions and repair times affects the formulation of constraints and network operational limits.

3. 3. 2. 1. Service Restoration Constraints Inaccurate forecasts of fault occurrences and repair durations may lead to either overly conservative or aggressive restoration strategies, impacting the efficiency and effectiveness of the restoration process.

3. 3. 2. 2. Network Technical Constraints Errors in forecasting power flow requirements and voltage limits can lead to violations of technical constraints, affecting the feasibility of the proposed solutions and the overall performance of the network.

3. 3. 3. Mitigation Strategies To address the effects of forecast errors, the following strategies can be employed:

3. 3. 3. 1. Robust Optimization Incorporate robustness into the optimization model by accounting for uncertainties in forecast parameters. This approach ensures that the proposed solutions perform well under a range of forecast scenarios.

3. 3. 3. 2. Scenario Analysis Perform sensitivity analyses and scenario planning to assess how variations in forecast parameters impact the objective functions and constraints. This can help in understanding the potential range of performance outcomes and in making informed decisions.

3. 3. 3. 3. Adaptive Mechanisms: Implement adaptive strategies that allow for adjustments based on updated forecasts and real-time data. This approach can help in mitigating the impact of forecast errors by dynamically adjusting the restoration and operational strategies.

In summary, while forecast errors can impact the performance of the proposed method, incorporating robust optimization techniques, scenario analysis, and adaptive mechanisms can help mitigate these effects and enhance the overall reliability and resilience of the network.

3. 4. Numerical Results Four case studies are used to apply the suggested methodology on a 33-bus system:

3. 4. 1. Base Case the network's reaction in the absence of DG installation.

In this scenario, the goal functions are optimized separately to determine the network's minimal reliability and resilience costs, and optimal service restoration is carried out in the absence of DG resources. The following values are achieved for reliability:

$C^{Reliability} = 17812\$. \quad RI = 0.73$

A fault in zone 1 results in the highest reliability cost. Since the substation is the only source of supply for the network, any problem in Zone 1 renders all other network zones without power until the issue is fixed. The following outcomes occur when minimizing resilience costs is the goal:

$C^{Resilience} = 55921\$. \quad RI = 0.181$

3. 4. 2. Reliability Optimum Case DG location with the goals of installation costs and reliability.

In this instance, the goal is to reduce reliability for installation costs only, rather than reliability and resilience costs at the same time. It should be mentioned that installation expenses are extremely expensive when reliability costs are the only factor taken into account. Thus, for a two-objective optimization problem, the NSGA_II method is used. A fuzzy solution is then obtained by applying the fuzzy logic to the Pareto front. In this instance, the following values are obtained:

$C^{Reliability} = 12237\$. \quad RI = 0.808$

$C^{Resilience} = 51298\$. \quad RI = 0.259$

$C^{Installation} = 70450\$$

Reliability and resilience costs, as well as the indices that go along with them, are greater than in the simultaneous case, even if installation costs have decreased.

3. 4. 3. Resilience Optimum Case The goals of DG deployment are installation costs and robustness.

In this instance, minimizing installation costs and resilience is the main goal. In this instance, the following values are obtained:

$C^{Reliability} = 16040\$. \quad RI = 0.804$

$C^{Resilience} = 47089\$. \quad RI = 0.259$

$C^{Installation} = 65750\$$

It's also clear that installation costs are lower, but the costs of resilience and reliability are greater than in the simultaneous scenario. Table 2 gives a synopsis of the case studies. It highlights the significance of the optimization technique and shows the costs that each case study produced.

In addition to providing distinct DG placement options, taking reliability and resilience costs into account at the same time as objectives also produces better outcomes than standalone optimization. The clear decrease in reliability and resilience outage costs, particularly over the long run, justifies the installation cost rise, despite the noticeable increase.

3. 4. 4. Simultaneous Reliability and Resilience Enhancement Reliability, resilience, and installation costs are the goals of DG placement.

TABLE 2. Summary of the case studies (Reliability=REL, Resilience=RES)

	Costs ($)			% Cost reduction	
Case	**Installation**	**REL**	**RES**	**REL**	**RES**
Base	0	17812	55921	0	0
REL	70450	12237	51298	31.3%	8.2%
RES	65750	16040	47089	9.9%	15.8%
Simultaneous	126700	10460	40830	41.3%	27.0%

The NSGA-II parameters in this instance are taken to be those listed in Table 3. Solution number "8" is selected as the best option by using the fuzzy decision-making approach on the problem's Pareto solution set. This solution yields the following values:

$C^{Reliability} = 10460\$. \quad RI = 0.839$

$C^{Resilience} = 40830\$. \quad RI = 0.408$

$C^{Installation} = 126700\$$

The data from Table 4 has been used to run the simulations.

4. SIMULATIONS AND ANALYSIS OF THE RESULTS

The simulations were conducted on an HP laptop with Windows 7 and 4GB of RAM. While this system was sufficient for the 33-bus network analyzed, larger networks would likely require more advanced computing resources due to increased execution times and memory demands. To improve scalability, future work could explore the use of more powerful hardware, parallel processing techniques, or algorithmic optimizations to handle larger networks efficiently. Figure 3 displays the likelihood of a hurricane at various speeds by taking into account $u = 21.8$ and $\alpha = 1.77$ in Equation 25. Equation 26 yields the probability $p_f = 0.0183$ for network cables and $p_f = 0.00078$ for poles based on the previously indicated values. The diagrams of Equation 26 is shown in Figure 4 assuming that $\beta_{ds} = 0.21$ and $\ln\left(\frac{S_d}{\bar{S}_{d.ds}}\right) = 4.4$ for poles and $\beta_{ds} = 0.16$ and $\ln\left(\frac{S_d}{\bar{S}_{d.ds}}\right) = 3.93$ for network cables.

TABLE 3. Values of NSGA-II parameters

Members of the initial population	40
Iterations	40
Crossover percentage	80%
Mutation percentage	2%
Mutation impact rate	1%

TABLE 4. Assumed values of parameters in model simulations

Parameter	**Value**	**Unit**
Bus voltage limits	0/9≤ ,≤ 1/1	pu
Voltage at slack bus	=1	pu
DG capacity limits	1≤ ,≤ 50	MW
DG operating power factor limit	0.9	-
Customers' outage cost limits	0.25-0.75	$/kWh
DG installation fixed cost	1000	$
DG installation variable cost	50	$/kW

The decision to exclude the return period from our analysis was made to maintain a focused approach to evaluating the general effectiveness of DG placement for resilience enhancement under various scenarios. Our study aimed to explore the immediate impact of DG installation on reliability and resilience without delving into region-specific probabilistic factors such as hurricane return periods. While the return period is indeed a critical factor in long-term resilience planning, our objective was to provide a broader, more generalized framework that could be applicable across different regions, regardless of their specific natural disaster profiles. By doing so, we aimed to offer a foundation that can be adapted to various regional contexts by incorporating additional factors such as return periods in future, more targeted studies. Furthermore, the economic optimization in our study is primarily centered on balancing installation costs with immediate resilience and reliability improvements. The inclusion of return periods would require a more complex probabilistic analysis that could potentially obscure the primary objectives of our research. However, we acknowledge that incorporating return periods could enhance the economic assessment, and we suggest this as a key area for future research. In future work, we plan to extend our model to include region-specific probabilistic factors such as hurricane return periods. This will allow for a more comprehensive economic analysis that can better inform decision-making in regions where the frequency and intensity of hurricanes significantly impact resilience planning. The number of poles in each line is calculated by using the network line length data and assuming that there is a pole every 50 meters. Based on the failure probabilities of the network's poles and cables, the failure probability of every bus is determined by 500 iterations of Monte Carlo simulation as shown in Figure 5.

MCS may also be used to determine which buses have a malfunction in each storm scenario and how long it will take to fix it. The resilience scenarios are produced by taking into account 20 situations with equal probabilities, as shown in Figure 6.

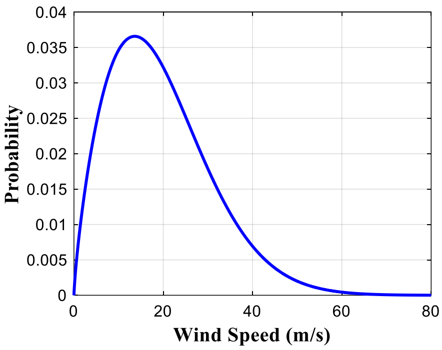


Figure 3. The diagram of hurricanes whith different wind speeds

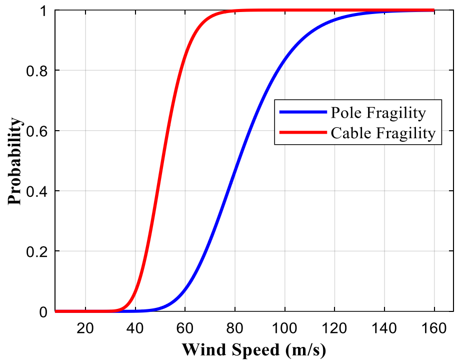


Figure 4. The fragility curves of network poles and lines

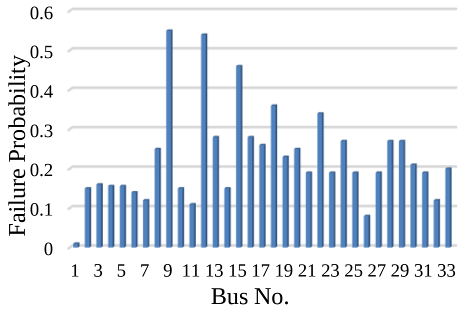


Figure 5. The failure probability of network buses obtained from MCS

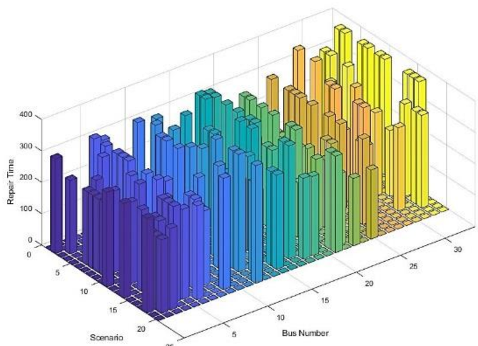


Figure 6. Faults and repair times of each resilience scenario obtained from MCS

The two-dimensional images of the Pareto front in each NSGA-II algorithm iteration are displayed in Figures 7 and 8. In the last iteration, it is evident that the fronts are convergent to the final Pareto front (black points).

There are 29 members of the last Pareto front. It indicates that 29 members out of the entire population are non-dominated problem solvers. Depending on the decision-maker's goals, any one of these methods may be the best way to solve the issue. The base-case study's ideal solutions are found in Figures 7 and 8 when the DG installation cost is $0. Figure 9 shows the Pareto front in three dimensions. Figures 10 and 11 indicate the estimated outage duration of each bus as a result of resilience events and reliability faults for both the base-case and optimum fuzzy logic solutions (solution number 8). The projected outage time of network buses is significantly impacted by DG location. This effect is more noticeable in the network's reliability. Additionally, DG location has a bigger effect on the network's terminating zones, which lose power due to any breakdown in their upstream zones. Figure 12 shows the 33-bus system's resilience curve for various repair techniques. It demonstrates how network resilience has been significantly increased by the fuzzy approach.

5. DISCUSSION AND SUMMARY

The numerical analysis conducted on the 33-bus system across four distinct scenarios provides valuable insights into the effectiveness of different Distributed Generation

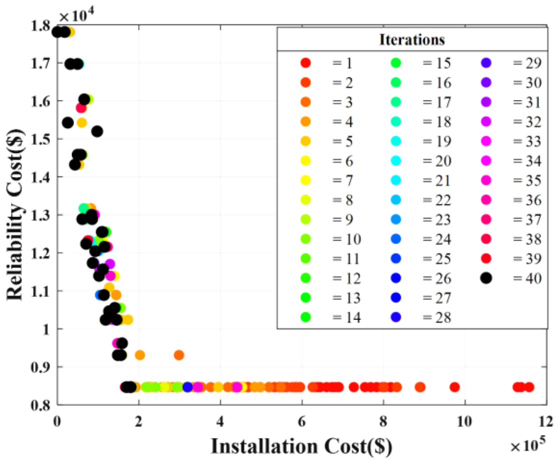


Figure 7. 2-D view of the Pareto fronts (reliability vs. installation)

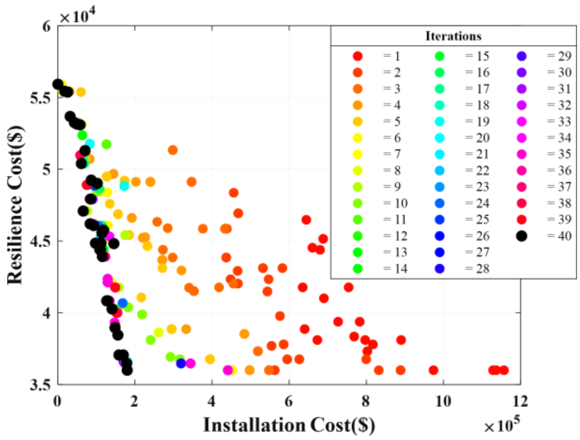


Figure 8. 2-D view of the Pareto fronts (resilience vs. installation)

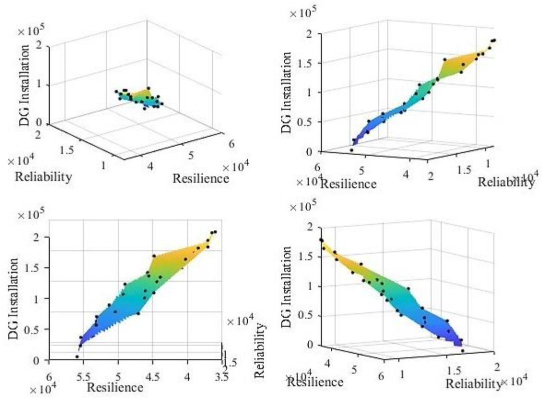


Figure 9. 3-D view from different angles of the final Pareto front and the surface fitted to it

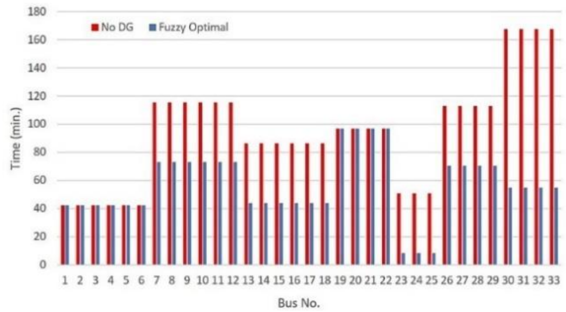


Figure 10. Expected outage time of each bus due to reliability faults

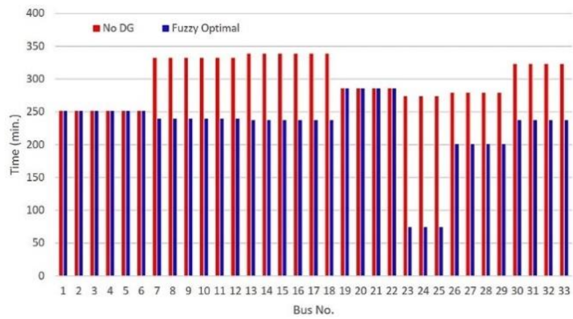


Figure 11. Expected outage time of each bus in case of the resilience event

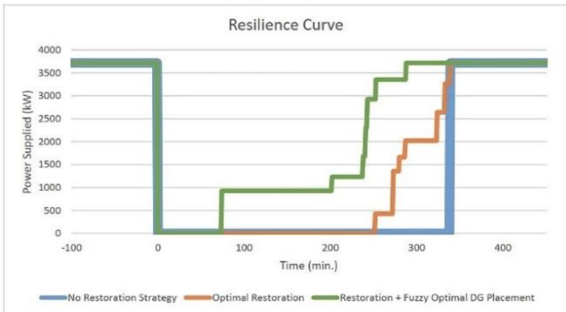


Figure 12. The resilience curve of the 33-bus system for different restoration strategies

(DG) placement strategies in optimizing network reliability and resilience. The key findings from each scenario are summarized as follows:

5. 1. Base Case (No DG Installed)
5. 1. 1. Reliability Cost: $17,812
5. 1. 2. Resilience Cost: $55,921
5. 1. 3. Key Observation: The absence of DG resources leads to the highest reliability and resilience costs. This is particularly evident when faults occur in critical zones (e.g. zone 1), where the entire network is affected due to the lack of alternate supply sources.

5. 2. Reliability Optimum Case
5. 2. 1. Reliability Cost: $12,237 (31.3% reduction)
5. 2. 2. Resilience Cost: $51,298 (8.2% reduction)
5. 2. 3. Installation Cost: $70,450
5. 2. 4. Key Observation Focusing solely on optimizing reliability results in a notable reduction in reliability costs. However, resilience costs remain relatively high, indicating that this approach is less effective in enhancing overall network resilience.

5. 3. Resilience Optimum Case
5. 3. 1. Reliability Cost: $16,040 (9.9% reduction)
5. 3. 2. Resilience Cost: $47,089 (15.8% reduction)
5. 3. 3. Installation Cost: $65,750
5. 3. 4. Key Observation Prioritizing resilience in DG placement reduces resilience costs more significantly than the reliability-only approach. However, reliability costs are higher compared to the simultaneous optimization strategy, highlighting the trade-off between reliability and resilience.

5. 4. Simultaneous Reliability and Resilience Enhancement
5. 4. 1. Reliability Cost: $10,460 (41.3% reduction)
5. 4. 2. Resilience Cost: $40,830 (27.0% reduction)
5. 4. 3. Installation Cost: $126,700
5. 4. 4. Key Observation Simultaneous optimization of reliability and resilience yields the best overall performance, with the lowest reliability and resilience costs. Although this approach involves the highest installation cost, the long-term benefits in terms of reduced outage costs justify the investment.
The general insight of the results is as follows:

5. 5. Impact of DG Placement The introduction of DG significantly reduces both reliability and resilience costs, particularly when optimized simultaneously. This approach not only provides a balanced improvement in both metrics but also enhances the network's ability to withstand and recover from faults.

5. 6. Pareto Optimization The NSGA-II algorithm effectively identifies optimal solutions that balance installation costs with reliability and resilience objectives. The fuzzy decision-making approach further refines these solutions, ensuring that the selected DG placement strategy offers the best trade-off between competing objectives.

5. 7. Resilience Curve Analysis The resilience curve of the 33-bus system indicates a marked improvement in network resilience when the fuzzy logic solution is applied. This demonstrates the critical role of strategic DG placement in enhancing the overall robustness of the distribution network.

5. 8. Optimization Trade-offs The simultaneous optimization of reliability and resilience resulted in the best overall performance, with the highest reduction in both reliability and resilience costs. However, it required the highest installation investment.

5. 9. Monte Carlo Simulation The failure probabilities of network buses, calculated via Monte Carlo Simulation, showed that DG placement significantly influenced the overall network resilience, reducing outage times and enhancing fault recovery.

In summary, the simultaneous optimization of reliability and resilience through strategic DG placement provides the most comprehensive improvement in network performance, justifying the higher installation costs with long-term benefits in reduced outage durations and enhanced resilience.

6. CONCLUSION

With the main objective of concurrently improving the resilience and reliability of distribution networks, this research presented a thorough and innovative method for the optimum distribution of DG resources. In a multi-objective stochastic optimization framework, the suggested model incorporates the reduction of DG installation costs, resilience, and reliability. The NSGA-II method is used to solve the optimum service restoration issue, which is defined as a Mixed-Integer Linear Programming (MILP) problem. To choose the best option from the Pareto set, a fuzzy decision-making logic is used, guaranteeing a fair trade-off between conflicting goals.

The outcomes of the simulation demonstrate how crucial simultaneous optimization is for resilience and reliability. When there is no DG installed in the base case, the reliability cost was calculated at $17,812, and the resilience cost at $55,921. However, when both reliability and resilience were optimized together, these costs were significantly reduced to $10,460 and $40,830, respectively. This simultaneous optimization not only improved the network's performance but also provided a more balanced approach, as evidenced by the reduction in costs and enhanced indices (RI) for both reliability (RI = 0.839) and resilience (RI = 0.408). Moreover, the study demonstrated that focusing on only one objective (either reliability or resilience) leads to suboptimal results. For instance, in the reliability-optimal case, while the reliability cost was reduced to $12,237, the resilience cost remained relatively high at $51,298. Similarly, in the resilience-optimal case, the resilience cost was reduced to $47,089, but the reliability cost increased to $16,040. These findings underscore the value of a simultaneous optimization approach that considers both objectives to achieve a more robust and cost-effective distribution network.

Furthermore, the effectiveness of the proposed method is evident in its ability to address the complexities of real-world distribution networks. The model's application to a 33-bus system showed that DG placement has a substantial impact on reducing outage times, particularly in areas furthest from the supply source. The Monte Carlo Simulation results and fragility curves further validate the model's ability to predict and mitigate the effects of natural disasters, such as hurricanes, on network resilience. In conclusion, the proposed approach represents a significant advancement in the field of distribution network optimization. By addressing both reliability and resilience in a unified framework, it offers a more holistic solution to the challenges faced by modern power systems. The reduction in both outage costs and the enhancement of network resilience demonstrate the practical benefits of this approach, making it a valuable tool for utilities seeking to improve the performance and reliability of their networks.

6. 1. Limitations And Future Works The proposed model, while effective in optimizing DG placement for reliability and resilience, has certain limitations that need to be addressed. This section discusses these limitations and explores potential future applications and improvements for the model.

6. 1. 1. Limitations

6. 1. 1. 1. Simplified Network Modeling The proposed model assumes a simplified representation of the distribution network, which may not fully capture the complexities of real-world systems. For instance, the model might not consider the impact of diverse load profiles, varying demand patterns, or complex fault dynamics, which could influence the outcomes of DG placement strategies.

6. 1. 1. 2. Static Resilience and Reliability Metrics The resilience and reliability metrics used in the model are based on static scenarios and predefined parameters. This approach may overlook the dynamic nature of network conditions, such as changing environmental factors, load variations, or evolving grid configurations over time.

6. 1. 1. 3. Assumption of Uniform DG Performance The model assumes that all DG units operate under uniform performance characteristics, which may not be the case in practical scenarios. Variations in DG technologies, maintenance schedules, and operational constraints can lead to differences in actual performance, affecting the overall network reliability and resilience.

6. 1. 1. 4. Limited Consideration of Economic Factors While the model incorporates installation and outage costs, it does not fully account for other economic factors such as long-term maintenance costs, potential market fluctuations in energy prices, or regulatory changes. These factors could significantly influence the cost-effectiveness of DG placement strategies.

6. 1. 2. Future Applications

6. 1. 2. 1. Dynamic Network Resilience Modeling Future work can extend the model to incorporate dynamic resilience metrics that adapt to changing network conditions in real time. This could involve integrating advanced monitoring and control systems that allow for more responsive DG placement strategies based on real-time data.

6. 1. 2. 2. Incorporation of Diverse Load Profiles and Demand Response Expanding the model to include diverse load profiles and demand response mechanisms could provide a more accurate representation of network behavior. This would enable the optimization of DG placement under more realistic operating conditions, considering fluctuations in demand and customer participation.

6. 1. 2. 3. Integration with Smart Grid Technologies The proposed model can be enhanced by integrating it with smart grid technologies, such as advanced metering infrastructure and automated fault detection and response systems. This integration would allow for more efficient management of DG resources and improve the network's ability to respond to faults and disturbances.

6. 1. 2. 4. Application to Multi-Objective Optimization with Uncertainty Future research could explore the application of the model in a multi-objective optimization framework that explicitly considers uncertainty in network parameters, DG performance, and external factors like weather conditions. This approach would provide more robust and resilient solutions for DG placement under uncertain conditions.

6. 1. 2. 5. Economic and Regulatory Scenario Analysis The model could be applied to analyze different economic and regulatory scenarios, assessing the impact of various policy changes or market developments on DG placement strategies. This would help in understanding the long-term viability and adaptability of the proposed solutions in a changing regulatory landscape.

In summary, while the proposed model provides a robust framework for optimizing DG placement concerning reliability and resilience, its applicability could be further enhanced by addressing the identified limitations and exploring new avenues for future research.

7. REFERENCES

1. Wang Y, Fu W, Zhang X, Zhen Z, Wang F. Dynamic directed graph convolution network based ultra-short-term forecasting method of distributed photovoltaic power to enhance the resilience and flexibility of distribution network. IET Generation, Transmission & Distribution. 2024;18(2):337-52. https://doi.org/10.1049/gtd2.12963 https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/gtd2.12963
2. Paul S, Poudyal A, Poudel S, Dubey A, Wang Z. Resilience assessment and planning in power distribution systems: Past and future considerations. Renewable and Sustainable Energy Reviews. 2024;189:113991. https://doi.org/10.1016/j.rser.2023.113991 https://www.sciencedirect.com/science/article/pii/S1364032123008493
3. Dwivedi D, Mitikiri SB, Babu KVSM, Yemula PK, Srinivas VL, Chakraborty P, et al. Technological advancements and innovations in enhancing resilience of electrical distribution systems. International Journal of Critical Infrastructure Protection. 2024;46:100696. https://doi.org/10.1016/j.ijcip.2024.100696 https://www.sciencedirect.com/science/article/pii/S1874548224000374
4. Ghorbani E, Hajiabadi ME, Samadi M, Lotfi H. Providing a preventive maintenance strategy for enhancing distribution network resilience based on cost–benefit analysis. Electrical Engineering. 2023;105(2):979-91. 10.1007/s00202-022-01710-5 https://doi.org/10.1007/s00202-022-01710-5
5. Brown RE. Electric power distribution reliability: CRC press; 2017.
6. Osborn J, Kawann C. Reliability of the US electric system--Recent trends and current issues. 2002. https://escholarship.org/uc/item/88x3635h
7. Amin M, editor Challenges in reliability, security, efficiency, and resilience of energy infrastructure: Toward smart self-healing electric power grid. 2008 IEEE Power and Energy Society General Meeting - Conversion and Delivery of Electrical Energy in the 21st Century; 2008 20-24 July 2008. 10.1109/PES.2008.4596791
8. Chaudry M, Ekins P, Ramachandran K, Shakoor A, Skea J, Strbac G, et al. Building a resilient UK energy system. 2011. https://nora.nerc.ac.uk/id/eprint/16648/1/UKERC_energy_2050_resilience_Res_Report_2011.pdf.
9. Babaei MJ, Rezvani M, Shirazi AN, Yousefi B. A Distributed Finite Time Based Secondary Average Controller for Voltage/Frequency Regulation and Active/Reactive Power Sharing of AC Microgrids. International Journal of Engineering. 2025;38(1):1-11. 10.5829/ije.2025.38.01a.01 https://www.ije.ir/article_193432_affdcc04fd4febaadd291bb92e41026d.pdf
10. Oboudi MH, Mohammadi M. Two-Stage Seismic Resilience Enhancement of Electrical Distribution Systems. Reliability Engineering & System Safety. 2024;241:109635. https://doi.org/10.1016/j.ress.2023.109635 https://www.sciencedirect.com/science/article/pii/S0951832023005495
11. Tang L, Han Y, Zalhaf AS, Zhou S, Yang P, Wang C, et al. Resilience enhancement of active distribution networks under extreme disaster scenarios: A comprehensive overview of fault location strategies. Renewable and Sustainable Energy Reviews. 2024;189:113898. https://doi.org/10.1016/j.rser.2023.113898 https://www.sciencedirect.com/science/article/pii/S1364032123007566
12. Behzadi M, Amirahmadi M, Tolou Askari M, Babaeinik M. Identification of Combined Power Quality Disturbances in the Presence of Distributed Generations using Variational Mode Decomposition and K-nearest Neighbors Classifier. International Journal of Engineering. 2022;35(4):657-74. 10.5829/ije.2022.35.04A.05 https://www.ije.ir/article_142219_92cc56ed1dfc38a33a0a90cfb09c00f9.pdf
13. Najjarpour M, Tousi B, Ebadi Zahedan A. Improving Reliability of Active Distribution Networks Using Probabilistic Assessment of Renewable Resource Units. International Journal of Engineering. 2024;37(9):1780-9. 10.5829/ije.2024.37.09c.08 https://www.ije.ir/article_193445_215f5d1a3e9545fa9aca2981d1f145ed.pdf
14. Jalilpoor K, Oshnoei A, Mohammadi-Ivatloo B, Anvari-Moghaddam A. Network hardening and optimal placement of microgrids to improve transmission system resilience: A two-stage linear program. Reliability Engineering & System Safety. 2022;224:108536. https://doi.org/10.1016/j.ress.2022.108536
15. Choobdari M, Samiei Moghaddam M, Davarzani R, Azarfar A, Hoseinpour H. Robust distribution networks reconfiguration considering the improvement of network resilience considering renewable energy resources. Scientific Reports. 2024;14(1):23041. 10.1038/s41598-024-73928-1 https://doi.org/10.1038/s41598-024-73928-1
16. Ahmadi H, Martı JR. Linear current flow equations with application to distribution systems reconfiguration. IEEE Transactions on Power Systems. 2014;30(4):2073-80. https://doi.org/10.1109/TPWRS.2014.2360363
17. Gholami M, Abbaspour A, Fattaheian-Dehkordi S, Lehtonen M, Moeini-Aghtaie M, Fotuhi M. Optimal allocation of PMUs in active distribution network considering reliability of state estimation results. IET Generation, Transmission & Distribution. 2020;14(18):3641-51.
18. Kahouli O, Alsaif H, Bouteraa Y, Ben Ali N, Chaabene M. Power system reconfiguration in distribution network for improving reliability using genetic algorithm and particle swarm optimization. Applied Sciences. 2021;11(7):3092. https://doi.org/10.3390/app11073092
19. Li Z, Wu W, Zhang B, Tai X. Feeder-corridor-based distribution network planning model with explicit reliability constraints. IET Generation, Transmission & Distribution. 2020;14(22):5310-8.
20. Li Z, Wu W, Zhang B, Tai X. Analytical reliability assessment method for complex distribution networks considering post-fault network reconfiguration. IEEE Transactions on Power Systems.

2019;35(2):1457-67. https://doi.org/10.1109/TPWRS.2019.2936543

21. Hamidan M-A, Borousan F. Optimal planning of distributed generation and battery energy storage systems simultaneously in distribution networks for loss reduction and reliability improvement. Journal of Energy Storage. 2022;46:103844. https://doi.org/10.1016/j.est.2021.103844
22. Alanazi M, Alanazi A, Akbari MA, Deriche M, Memon ZA. A non-simulation-based linear model for analytical reliability evaluation of radial distribution systems considering renewable DGs. Applied Energy. 2023;342:121153. https://doi.org/10.1016/j.apenergy.2023.121153
23. Agajie TF, Khan B, Guerrero JM, prakash Mahela O. Reliability enhancement and voltage profile improvement of distribution network using optimal capacity allocation and placement of distributed energy resources. Computers & Electrical Engineering. 2021;93:107295. https://doi.org/10.1016/j.compeleceng.2021.107295
24. Saini DK, Sharma M. Techno-economic hardening strategies to enhance distribution system resilience against earthquake. Reliability Engineering & System Safety. 2021;213:107682. https://doi.org/10.1016/j.ress.2021.107682
25. Calcara L, Di Pietro A, Giovinazzi S, Pollino M, Pompili M, editors. Towards the resilience assessment of electric distribution system to earthquakes and adverse meteorological conditions. 2018 AEIT International Annual Conference; 2018: IEEE. https://doi.org/10.23919/AEIT.2018.8577308
26. Gautam P, Piya P, Karki R. Resilience assessment of distribution systems integrated with distributed energy resources. IEEE Transactions on Sustainable Energy. 2020;12(1):338-48. https://doi.org/10.1109/TSTE.2020.2994174
27. Ma S, Arif A, Wang Z, editors. Resilience assessment of self-healing distribution systems under extreme weather events. 2019 IEEE Power & Energy Society General Meeting (PESGM); 2019: IEEE. https://doi.org/10.1109/PESGM40551.2019.8974122
28. Panteli M, Trakas DN, Mancarella P, Hatziargyriou ND. Power systems resilience assessment: Hardening and smart operational enhancement strategies. Proceedings of the IEEE. 2017;105(7):1202-13. https://doi.org/10.1109/JPROC.2017.2691357
29. Tari AN, Sepasian MS, Kenari MT. Resilience assessment and improvement of distribution networks against extreme weather events. International Journal of Electrical Power & Energy Systems. 2021;125:106414. https://doi.org/10.1016/j.ijepes.2020.106414
30. Shittu E, Tibrewala A, Kalla S, Wang X. Meta-analysis of the strategies for self-healing and resilience in power systems. Advances in Applied Energy. 2021;4:100036. https://doi.org/10.1016/j.adapen.2021.100036
31. Yang B, Ge S, Liu H, Li J, Zhang S. Resilience assessment methodologies and enhancement strategies of multi-energy cyber-physical systems of the distribution network. IET Energy Systems Integration. 2022;4(2):171-91. https://doi.org/10.1049/esi2.12067
32. Hemmati M, Mohammadi-Ivatloo B, Abapour M, Anvari-Moghaddam A. Optimal chance-constrained scheduling of reconfigurable microgrids considering islanding operation constraints. IEEE Systems Journal. 2020;14(4):5340-9. https://doi.org/10.1109/JSYST.2020.2964637
33. Prabawa P, Choi D-H. Multi-agent framework for service restoration in distribution systems with distributed generators and static/mobile energy storage systems. IEEE Access. 2020;8:51736-52. https://doi.org/10.1109/ACCESS.2020.2980544
34. Mujjuni F, Betts TR, Blanchard RE. Evaluation of power systems resilience to extreme weather events: A review of methods and assumptions. IEEE Access. 2023;11:87279-96. https://doi.org/10.1109/ACCESS.2023.3304643
35. Yuvaraj T, Devabalaji K, Suresh T, Prabaharan N, Ueda S, Senjyu T. Enhancing Indian Practical Distribution System Resilience Through Microgrid Formation and Integration of Distributed Energy Resources Considering Battery Electric Vehicle. IEEE Access. 2023;11:133521-39. https://doi.org/10.1109/ACCESS.2023.3336858
36. Home-Ortiz JM, Mantovani JRS, editors. Resilience enhancing through microgrids formation and distributed generation allocation. 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe); 2020: Ieee. https://doi.org/10.1109/ISGT-Europe47291.2020.9248811
37. Dehghani NL, Zhang C, Shafieezadeh A. Evolutionary optimization for resilience-based planning for power distribution networks. Nature-Inspired Computing Paradigms in Systems: Elsevier; 2021. p. 47-61.
38. Momen H, Abessi A, Jadid S. Using EVs as distributed energy resources for critical load restoration in resilient power distribution systems. IET Generation, Transmission & Distribution. 2020;14(18):3750-61. https://doi.org/10.1049/iet-gtd.2019.1561
39. Nabian Dehaghani M, Biglarahmadi M, Mousazadeh Mousavi SY, Abdolahi M. A Distributed Cooperative Secondary Control Scheme for Obtaining Power and Voltage References of Distributed Generations in Islanded DC Microgrids. International Journal of Engineering. 2024;37(2):341-51. 10.5829/ije.2024.37.02b.10 https://www.ije.ir/article_179088_e3e852b8903b1300329cbd35584f2192.pdf
40. Liu Z, Tang P, Hou K, Zhu L, Zhao J, Jia H, et al. A Lagrange-multiplier-based reliability assessment for power systems considering topology and injection uncertainties. IEEE transactions on power systems. 2023;39(1):1178-89. https://doi.org/10.1109/TPWRS.2023.3258319
41. Zhang G, Zhang F, Wang X, Zhang X. Fast resilience assessment of distribution systems with a non-simulation-based method. IEEE Transactions on Power Delivery. 2021;37(2):1088-99. https://doi.org/10.1109/TPWRD.2021.3077239
42. Arunjothi R, Meena K. Optimizing capacitor size and placement in radial distribution networks for maximum efficiency. Systems and Soft Computing. 2024;6:200111. https://doi.org/10.1016/j.sasc.2024.200111
43. Panteli M, Pickering C, Wilkinson S, Dawson R, Mancarella P. Power system resilience to extreme weather: Fragility modeling, probabilistic impact assessment, and adaptation measures. IEEE Transactions on Power Systems. 2016;32(5):3747-57. https://doi.org/10.1109/TPWRS.2016.2641463
44. Deb K. Multi-objective optimisation using evolutionary algorithms: an introduction. Multi-objective evolutionary optimisation for product design and manufacturing: Springer; 2011. p. 3-34.
45. Sakawa M, Yano H. An interactive fuzzy satisficing method for multiobjective nonlinear programming problems with fuzzy parameters. Fuzzy sets and systems. 1989;30(3):221-38.

Persian Abstract

چکیده

قابلیت اطمینان و تاب آوری سیستم قدرت دو موضوع مهم مطالعاتی هستند که هدف آنها تقویت کردن سیستم در مواجهه با خطاها یا رویدادهای احتمالی و کاهش اثرات آنها با به حداقل رساندن قطعی‌های ناشی از آن است. اگرچه مطالعات زیادی با تمرکز بر ارزیابی و بهبود قابلیت اطمینان و تاب آوری سیستم قدرت انجام شده است، اما شکافی در بهینه‌سازی همزمان این مفاهیم به ویژه در شبکه‌های توزیع وجود دارد. در این مقاله، یک چارچوب بهینه‌سازی جدید برای ارزیابی و افزایش قابلیت اطمینان و تاب آوری شبکه‌ی توزیع از طریق قرار دادن تولید پراکنده (DG) پیشنهاد شده‌است. در این راستا، یک مدل بهینه‌سازی چندهدفه‌ی تصادفی معرفی شده است که از تخصیص بهینه‌ی واحدهای DG همراه با استراتژی بازیابی خدمات بهینه با استفاده از سوئیچ‌های کنترل از راه دور تعبیه‌شده در شبکه استفاده می‌کند. این مدل هزینه‌های قطع شبکه‌ی توزیع را به دلیل احتمالات قابل اطمینان و رویدادهای تاب آوری به حداقل می‌رساند و در عین حال هزینه‌های سرمایه‌گذاری DG را حداقل می‌کند. مشکل بازیابی خدمات بهینه به عنوان یک مدل‌برنامه‌ریزی خطی اعداد مختلط (MILP) فرموله شده است که محدودیت‌های فنی شبکه را برآورده می‌کند. به منظور دریافت ماهیت نامشخص احتمالات خطا، دو مجموعه سناریوی مختلف تولید می‌شوند. داده‌های تاریخی نرخ خطای شبکه، و توابع احتمال خرابی اجزای شبکه به دست آمده از شبیه سازی مونت کارلو (MCS) به ترتیب برای سناریوهای قابلیت اطمینان و تاب آوری استفاده می‌شوند. رویکرد الگوریتم ژنتیک مرتب‌سازی غیرمسلط (NSGA-II) برای حل مدلی که یک مخزن راه‌حل بهینه پارتو ارائه می‌کند، اعمال می‌شود. سپس یک ابزار منطقی تصمیم‌گیری فازی برای کمک به برنامه‌ریزان شبکه در انتخاب راه حل نهایی از مدل پارتو استفاده می‌شود. مدل پیشنهادی بر روی سیستم IEEE 33-bus تست شده و نتایج شبیه‌سازی کارایی مدل را نشان می‌دهد.