Strategic Investments for Enhancing Power System Resilience through Zonal Microgrids

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Abstract

The existing power system is confronted with a myriad of challenges and encompassing issues such as ageing infrastructure, dynamic shifts in energy demand patterns and disturbances induced by climate change. Given the pivotal role played by the power sector in contemporary society by providing essential services and supporting economic activities, ensuring the resilience of power systems is a top priority for governments, utilities and other stakeholders like consumers. The extant power grid characterized by its aging components, requires a complete overhaul to enhance its resilience in the wake of increasing weather-induced power disruptions attributed to climate change. However, outright replacement of the existing is presently deemed economically impractical, entailing significant costs and negative social impacts. Instead, a more pragmatic strategy to augment the overall system resilience involves identifying and reinforcing critical sectors of the grid at a reasonable cost and with reasonable disruptions. This paper explores the concept of smart investment as a strategic framework to enhance power system resilience. We propose a vulnerability assessment framework, where N-1 contingency criteria are used to identify the most vulnerable lines to help determine the critical areas to be prioritized for resilience improvement investments. After identification of the critical areas, a resilience enhancement strategy which involves partitioning of the existing distribution network in zonal microgrids and optimally sizing and placing DERs in the individual microgrids is implemented. A real-life existing distribution network is used as a case study for the proposed framework to prove its effectiveness. OpenDSS a power system distribution network simulator is paired with MATLAB in implementing the proposed strategies which resulted in a significant improvement in the resilience of the systems, measured in terms of unserved loads.

Keywords: Energy Resilience, Renewable Energy, Microgrid, Criticality assessment, N-1 contingency criteria

1. Introduction

The importance of the power system to modern society cannot be overstated, it provides a critical infrastructure that supports various sectors, including transportation, healthcare, communication, and industry. However, power systems are vulnerable to a multitude of threats and challenges, such as extreme weather events, cyberattacks, and ageing infrastructure. Weather-related power outages are on the rise in the United States and the rest of the world as a result of climate change and global warming. In 2021, more than 40% of Americans lived in counties hit by weather-related disasters [1]. In Louisiana, lightning, storms, and floods are three main sources of perturbations in the power grid, leading to an average outage duration of about 20 hours in a year affecting about 500,000 people annually [2]. Recent weather-related power outages include Hurricane Ida in 2021 which caused large-scale blackouts in Louisiana and seven other states resulting in 1.2 million consumers without power [3], the Texas freeze in 2021 with approximately 10 million people in Texas going several days without power [4], 1.5 million customers in Puerto Rico were left without electricity for up to 120 days due to Hurricane Maria in 2017 [5] and the 2019 California power shutoffs to preempt the spread of wildfires that affect about 2.5 million consumers [6]. Apart from the inconvenience and financial losses suffered by consumers as a result of these weather-related outages, an enormous amount of money is spent in relation to the reconstruction of these power grids. It is estimated that between \$18 billion and \$70 billion are spent annually to bring the respective power grids back into operation in the United States [5]. For example, up to \$65 billion was spent on reconstruction in the aftermath of Hurricane Sandy in 2012 which resulted in over 8 million users without power [7] and the state of Texas spent approximately \$130 billion following the Texas freeze [4]. According to the National Oceanic and Atmospheric Administration (NOAA), 22 weather-related disasters cost the United States \$95 billion in 2020 which was a new record in terms of the number of disasters and imposed cost to the nation's economy [2]. The United States government in 2022 introduced the Inflation Reduction Act (IRA) which is considered the most significant climate legislation in United States history. The IRA's \$370 billion in climate and clean energy investments could help cut U.S. greenhouse emissions roughly 40% by 2030 [8]. As part of the broader goal, the Department of Energy has an initiative to build a better grid to support resilience, reliability, and decarbonization [9].

Power system resilience has been a topic of interest recently due to the surge of climate-related natural disasters with their effects on power systems and the introduction of IRA has added to that interest the need for efficient ways of investing in the existing grid to enhance its resilience. The existing power grid is outdated and has some parts that are outworn making it less resilient but a total replacement is not feasible due to prohibitively high economic constraints, disruptions to social and economic activities, and time limitations. A more pragmatic option is to target areas within the power grid that are critical to the enhancement of resilience and investment. Critical components are those whose failure or loss could lead to system-wide failure [10]. In the context of resilience enhancement, we refer to the components that, when disrupted, could have a high negative impact on the service. Identifying critical components of a power system and investing to reinforce them to make them more efficient and eliminate the impact of losing them is very essential in bolstering the overall system resilience. This approach of targeted investments is less cost intensive with no disruption to the daily lives of consumers and no major time constraints. The first step of this approach of targeted investment is the identification of critical components like lines and nodes within a power system.

Different methods and approaches have been explored in the literature to identify critical components of power networks, among these methods is the use of cascading failure models to identify critical parts of power networks. In [10] different types of threats are modelled to identify critical nodes whose failure is likely to have effects on the whole system. Lines and branches that are likely to propagate cascading failures are identified in [11] by using fault chain models. Optimization algorithms are used together with cascading failure modelling to identify critical nodes in [12] and [13]. Studies in[10] - [13] only determine the criticality of the components based on the destructiveness caused by those components without considering the cost or impact of the effects. [14] and [15] include the cost of cascading failure modelling to detect critical components but no remedies are proposed to deal with the resulting failure.

Another methodology implemented in identifying critical components is the use of graph theory where power networks are represented in the form of graphs or complex networks consisting of nodes and links and different metrics of centrality used to identify critical components. In [16], [17] and [18] the between centrality metric was used to determine critical transmission lines and nodes within a complex power network. Closeness, another complex network centrality-based metric was employed in [19] to propose methods of identifying critical lines and weak nodes. [20] also uses Markov criticality to identify critical links or lines in complex power networks. More than one centrality metric of complex networks can be combined to detect critical components, for instance, three metrics of degree, between, and net-ability were used to evaluate critical nodes and lines of power systems in [21]. The geodesic vulnerability index which measures how susceptible a complex network is to cascading failures based on geodesic distances between nodes is used in [22] and [23] to identify critical nodes and branches. The approaches presented in [16] - [23] are implemented on theoretical test feeders and therefore do not accurately capture the complexities of real-world power systems. Furthermore, although the proposed methods are effective in detecting critical components of power systems they do not offer targeted solutions for improving the resilience in the event of losing those critical components.

Other approaches to identify critical components of power systems include the use of Monte-Carlo techniques [24], [25], and [26]. Machine learning algorithms have also been explored in the identification of critical components. In [27], improved agglomerative hierarchical clustering is used to identify critical lines in smart grids by considering the topological and electrical properties of the lines. Another clustering algorithm, affinity propagation clustering, is applied in detecting critical lines that can cause cascading failures. [28] uses a combined random forest and classification and regression algorithms to perform vulnerability analysis in detecting critical components during a cascading failure simulation. The identification of critical components within a power system network can also be formulated as an optimization problem. In [29] the Non-dominated Sorting Genetic Algorithm II is used to solve a multi-objective problem to identify critical components that could enhance resilience. The objective functions are maximizing a resilience metric and minimizing the number of components that affect resilience. [30] also proposes an optimization-based model that identifies the most critical components of power grids based on the economic loss incurred as a result of a disruption caused by a critical component. The methods of critical component identification discussed so far do not factor in the impacts caused by the loss or failure of those components on consumers and power grid operators.

Identification of the critical components is only the first step toward improving resilience. It serves as a guide for the appropriate planning and strategies for a more targeted cost-aware investment. Many resilience enhancement strategies and measures have been explored in the literature centred around physical hardening and robustness. The main objective of grid hardening is to reduce the physical impact caused by catastrophic events by improving the robustness and resistance of the grid to those external shocks [31]. Some of the grid hardening measures proposed in [31] [32] to boost resilience include the use of underground feeder lines, elevating substations, and the use of more robust materials for poles and structures. [33] proposes a hardening framework for resilience enhancement by retrofitting substations based on the identification of critical substation components. With the evolution of traditional grid systems to cyber-physical systems, [34] proposes a strategy to harden both power and communication lines by building an alternative routing model between the power system and communication nodes. A combination of hardening measures and demand-side solutions like underground cables, energy storage units, and home battery inverters are proposed in [35] to improve distribution system resilience against a natural disaster. [32] - [35] do not consider the impact on consumers and/or service companies before and after the hardening measures. Furthermore, grid hardening measures, at the larger scale, are generally not cost-effective [32]. Another strategy for improving the resilience of power systems is the implementation of demand-side programs like demand response management. [36], [37] and [38] discuss different forms of demand response programs where coordination between the demand side and grids with DERs are used to enhance the resilience. However, the proposed frameworks are only designed for emergency situations with no considerations for normal grid operations. The case studies for the proposed methodologies are all theoretical test cases and make their results less applicable to real-world situations.

The integration of distributed energy resources (DERs) and microgrids also offer significant resilience benefits. The rapid increase in the penetration of DERs globally makes them a good alternative energy source in the absence of traditional bulk-power systems [39]. The possibility of forming microgrids with DERs that could be operated in grid-tied or off-grid modes as a response to disturbances in the main grid presents microgrids as a viable resilience enhancement strategy. Microgrids improve resilience by either serving a portion of a distribution system or splitting the whole distribution system into multiple microgrids [40]. In [41] the capabilities of microgrids to improve resilience are categorized into; converting existing power systems into microgrids, deployment of dynamic microgrids, networked microgrids and multiple-microgrids. A key aspect of power system resilience is a rapid restoration of service and microgrids are capable of that while maintaining the system's stability [42]. [43] proposes a quick service restoration scheme with microgrids and transportable energy storage. [44] proposes a rapid restoration framework in the form of switch control of microgrids and loads. [45] and [46] discuss using microgrids for post-disaster restoration by serving critical loads. Converting existing power systems into a microgrid is another effective way of resilience improvement [41]. Different methodologies have been used to split or convert power systems into microgrids to help with serving loads in the aftermath of catastrophic events. [47] and [48] propose frameworks that solve optimization problems to divide power networks into separate microgrids. In [47] the objective of the proposed framework is to maximize islanding success probability and minimize the interaction between the individual microgrids. [48] shows an accurate methodology to formulate mixed-integer programs for splitting existing networks into islands. Graph theory methods are also used in the partitioning of distribution systems into microgrids, for instance, [49] incorporates the graph theory into microgrids with protective zones and [50] uses structural and hierarchical model to partition distribution networks. However, the microgrid partitioning frameworks proposed in [47] - [50] do not factor in the cost analysis of DERs in the formation of the microgrids. Furthermore, the composition and nature of loads are not taken into account and only theoretical test cases were used.

Although extensive work has been done in the literature on criticality identification and resilience improvement, there is still a missing link between them. [51] [52] and [29] discuss power system resilience and critical components; however, they are limited to identifying the elements that affect resilience without proposing resilience-enhancing solutions and cost analysis. To establish a link between critical components and resilience, it is important to point out the impact of a failure of these components and assess their impact on the system and consumers to serve as a guide for investments. So far, the techniques for criticality assessment do not use the impact of critical components as a metric to identify them. In this paper, the authors introduce a methodology for assessing the impacts of losing power lines within a real-world distribution system and use it as a metric for identifying lines critical to resilience enhancement for targeted investments. The methodology uses the N-1 contingency criteria to perform an impact analysis of losing feeder lines in power distribution systems to determine critical lines for investments towards a more resilient network. Generally, in N-K contingency criteria, the impact of the simultaneous failure of K components out of N total components in a power grid is examined to help identify critical components for the systems reliability, security, and robustness [53], [54], [55] and [56]. Most of the power outages caused by natural disasters come from damages to power lines [27], [57], therefore the critical component of concern in this paper are lines within distribution networks. To understand the true impact of losing each line, N-1 criteria were used for the impact assessment of a power distribution network.

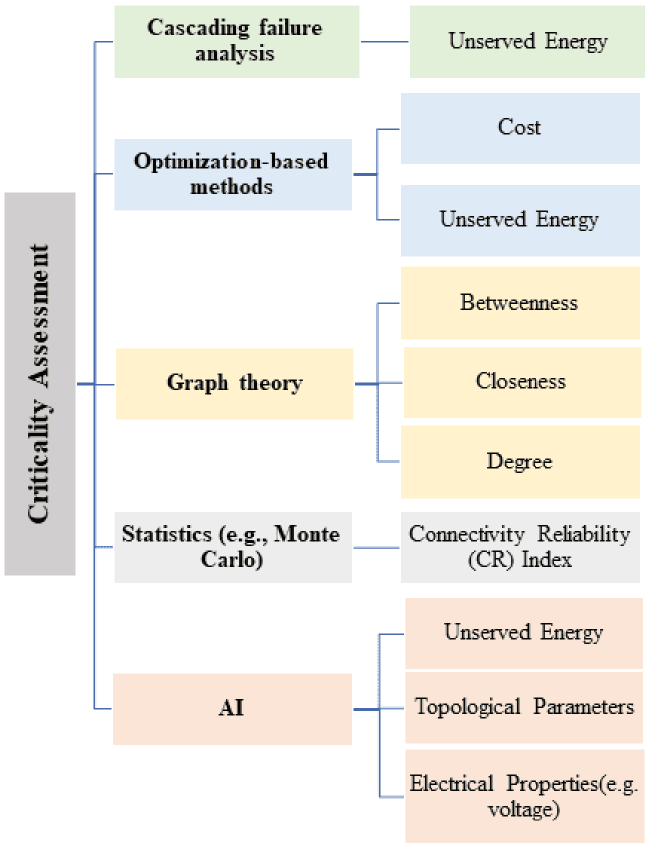

Fig. 1. Criticality assessment approaches

To bridge the research gap between resilience and critical components identification, this paper is introducing a framework that performs impact assessment to identify critical lines of an existing distribution system with N-1 contingency analysis on a real-world feeder to determine areas of the system that can improve resilience if investments are channelled there. To the best of the authors' knowledge, most of the existing studies on resilience enhancement and critical components identification lack cost and impact analysis. The current studies do not offer effective responses after identifying critical components. In fact, existing methods are mainly focused on DERs and microgrids operation in emergencies, and are mostly tested on theoretical or simplified systems. This paper presents a framework that takes into consideration the negative impacts of weather-related power outages to make smart investment decisions toward a resilience strategy that is compatible with the normal operation of the distribution system as well as emergencies. The main technical contributions of this study include:

1. Conducting criticality assessment through the N-1 contingency tests to quantify the impacts on the grid's resilience to provide targeted cost-aware investment options.
2. The use of resilience hubs as a tool to minimize the impacts of natural disasters and enhance the resilience of distribution systems and a bi-level optimization used to determine the optimal sizing and placement of DERs with the hubs.
3. Validating an impact-driven resilience enhancement framework in both normal and emergency operation modes.

The tools introduced can serve as a guide to operators and decision-makers on where and how to invest in their existing distribution systems to enhance energy resilience in the face of increasing weather-related threats.

The rest of the paper is organized as follows. Section 2 further discusses energy system resilience and introduces resilient metrics applied in our case, Section 3 discusses vulnerability assessment for power systems broadly and the vulnerability metric we are introducing. In section 4 the methodology used in identifying the most vulnerable areas in a distribution network is presented and applied to our case study. Simulations and results are presented in section 5. Finally, section 6 concludes the paper.

2. Energy System Resilience Metric

Energy system resilience is a multifaceted concept consisting of anticipation, avoidance, adaptation, and recovery [58]. Anticipation of a disruptive event helps avoid the disruption in the operation of an energy system and this is known as the 'safe-to-fail' strategy. Adaptation involves adjusting to abnormal conditions caused by these disruptive events by putting in place protection and energy management systems. A resilient energy system should also demonstrate the ability to quickly recover and restore its operation to normal pre-disaster status. An energy system goes through four states during HILP events, the original stable state, the disrupted state, the recovery state, and the stable recovered state. Anticipation and avoidance are considered in the original stable state, Adaptation is evaluated in the disrupted state and the recovery of the system is determined in the recovery state. Fig. 2 depicts the generic resilience curve showing the various states.

The level of a power system's resilience should be quantifiable and measurable, the tool or criteria to measure the resilience level is known as the resilience metric (RM) [59]. Resilience metrics provide a numerical basis to monitor changes

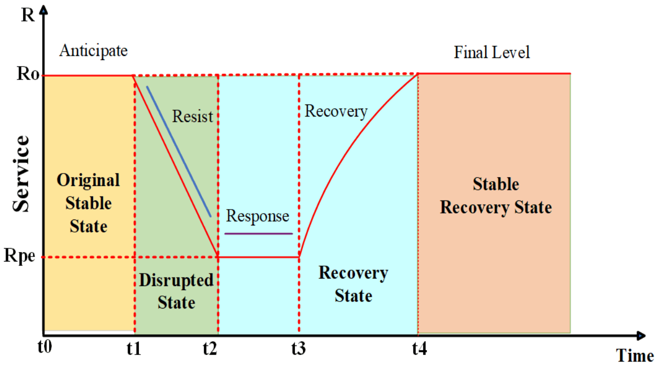

Fig. 2. Resilience curve showing the different states of a system after a disruption. Adopted from [58][41]

or show that a system's resilience has improved [60]. Just as the definition for resilience, there is no consistent basis for resilience measurement. However, in recent years researchers have come up with metrics and introduced different criteria to assess resilience by focusing on the development of formal methods and metrics to evaluate proposed grid resilience frameworks and investments. Resilience metrics are generally grouped into two main categories: attribute-based and performance-based metrics. Attribute-based resilience metrics are more qualitative and serve as a baseline for understanding the system's current resilience in comparison to other systems. Robustness, adaptability, and recoverability are some examples of attribute-based metrics. Performance-based metrics on the other hand are quantitative and determine how resilient a system is, they describe the system output in the event of disruptions. [60].

A conceptual framework for the classification of resilience metrics is proposed in [61]. At the top level, the metrics are divided into performance-based and non-performance-based metrics. The performance-based metrics are determined by the system performance like supplied load and the non-performance-based metrics are metrics of criteria of the status of an effective system and are determined by factors that affect a system before, during, and after a disaster. At the lowest level metrics like power, duration and frequency are used evaluate the performance of the resilience of a system.

Due to the novelty of these resilience metrics in power systems most of them are not widely applied and traditional reliability evaluation metrics like loss of load expectation (LOLE), loss of load frequency (LOLF) and expected energy not served (EENS) are still used to evaluate resilience enhancing methods [61]

The goal of this paper is to ensure consumers are still supplied with energy and reduce the amount of unserved energy in the immediate aftermath of natural disasters. An appropriate resilience metric in this case should measure how loss of loads or unserved energy is minimized. Therefore a combination of a specific performance metric of power and a reliability metric of expected unserved energy (EUE) is used to measure the unserved energy to evaluate the proposed resilience-enhancing technique.

3. Methodology and Case Study

The research methodology employed to perform vulnerability assessment on power systems and strategies to enhance power system resilience in the aftermath of natural disasters is discussed in this section. An existing 13.8kV distribution feeder is used as the case study, the feeder consists of 843 buses, 840 lines, and a 115/13.8 kV transformer with a total peak load of 5.4MW. Fig. 3 shows the topology of the distribution feeder. OpenDSS-G, the graphic interface of OpenDSS which is a distribution system simulator developed by the Electric Power Research Institute (EPRI) was used to draw Fig. 3.

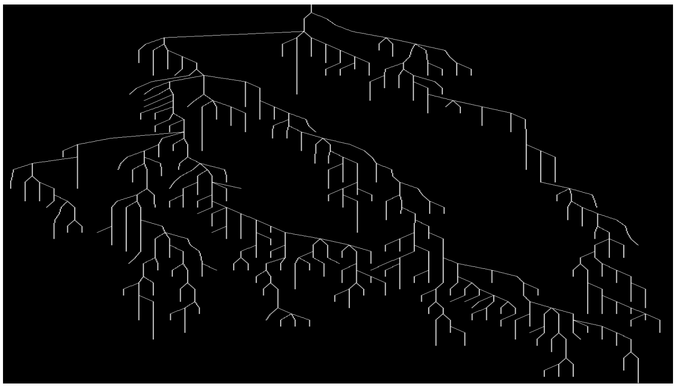

Fig. 3. Topology of distribution feeder as case study

To perform the impact assessment on the distribution feeder, the N-k contingency analysis is conducted to identify the most critical lines in terms of negative impacts on the system. In the N-k contingency, k components out of a total of N are taken out of the system and their impacts are observed. In this case, it is N-1 contingency criteria because to find the true impact of the individual lines each must be taken to know the impact of their loss. The impact of losing lines is measured by how much load is curtailed as a result of losing the line and that is the unserved loads. The entire process is presented in Fig. 4.

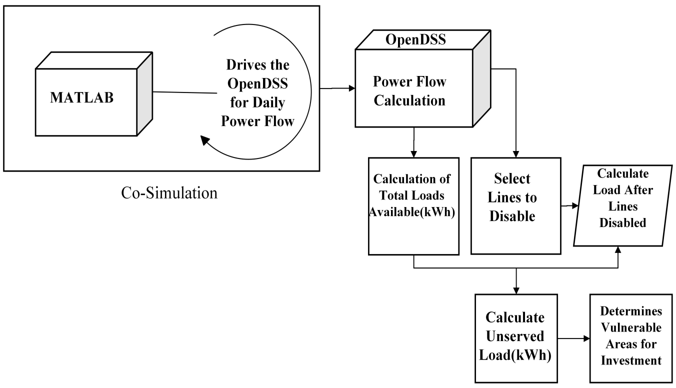

Fig. 4. Research methodology flow chart

Matlab is paired with OpenDSS to perform the simulation over a specific time horizon. Daily power flow is performed by OpenDSS to calculate the total load available in the normal operation of the distribution system, it then proceeds to disable the lines and calculate the total loads available as a result of disabling the lines. OpenDSS can perform one power flow scenario at a time and cannot iterate through all 840 lines of the distribution network. Therefore, a co-simulation platform is created with Matlab to form the COM interface to perform multiple power flow iterations and calculate the unserved kilowatt-hours after each iteration.

During the iteration for each line, the total available load is calculated, then the line is disabled and another power flow is run to calculate the available load after losing the line, the unserved load is calculated by subtracting the total served load after disabling the line from the total load under normal conditions. The line is then enabled for the next iteration for subsequent lines. Fig. 5 shows the results for a single iteration. The unserved kilowatt-hours for each line are obtained by calculating the area under the unserved load curve.

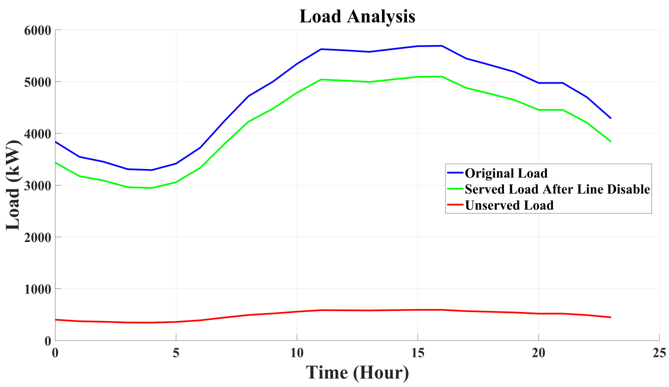

Fig. 5. Load analysis before and after disabling a single line, L61

The lines with the largest unserved kilowatt-hours are identified as the most critical lines. This indicates which areas are to be prioritized for investment for resilience enhancement. Investment options include the hardening of the vulnerable lines and the integration of DERs to reduce unserved loads. Generally, hardening in power systems refers to physically strengthening or improving power system infrastructure to make it less susceptible to disruptions caused by extreme events [34] and line hardening in particular is defined as strengthening certain lines that will not be tripped during certain conditions in [62]. Some hardening measures include undergrounding of lines, upgrading poles and structures with more stronger and robust materials, relocating facilities and network elements to areas less prone to casualties, and redundant routes for lines [32]. Hardening measures though effective can still be overcome by some natural disasters of higher strength. Also, these measures are not cost-effective especially when implementing them for an entire network, the impact assessment performed in this paper would help operators and policymakers to make smart investment choices to direct investment to the most critical lines to enhance system resilience by prioritizing lines for hardening. Another investment option is the integration of DERs, this option can be used to supplement or as a more economical alternative to hardening. Also, the integration of DERs offers long-term resilience solutions in place of line hardening in the event critical lines are lost since some natural disasters like high-category hurricanes or wildfires can overcome hardening. The DERs considered for this case study are solar PVs and battery energy storage systems (BESS). Due to the intermittency of PV, which is paired with BESS to supply loads at times PVs do not have enough capacity to serve loads.

One of the effective ways to enhance power system resilience with the integration of DERs is the formation of microgrids due to the ability of microgrids to form islands and their potential of sustaining the penetration of renewables [63]. Transforming the existing grid is one of the effective ways to use microgrids for resilience enhancement and that is the approach explored in this research methodology.

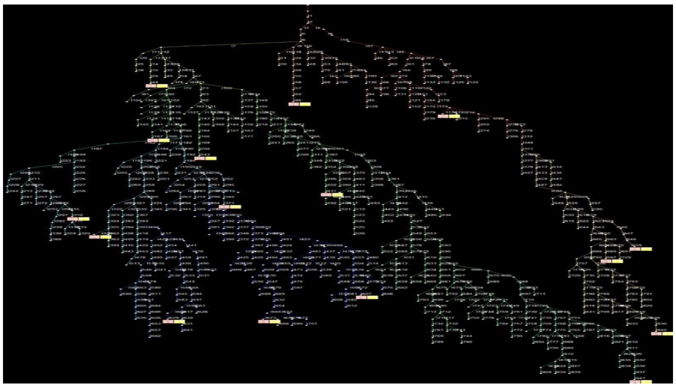

Fig. 6. Distribution network partitioned into 16 hubs with DERs

3.1. Partitioning of Network Into Zones

To ensure better management of resources and loads in the aftermath of a natural disaster, the existing distribution network will be partitioned into smaller hubs or zones operating as microgrids. Integration of DERs with existing grids comes with many operational challenges like over/under-voltages at DER buses, increased overloads, and protection coordination [64]. The DERs are optimally allocated at buses to eliminate any operational challenges and ensure the distribution system operates normally with their integration. To split the network into independent islands in OpenDSS, energy meters were placed at the DER buses. The energy meter determines the parts of the network each DER set is responsible for and this forms the basis of the zones. the zones formed by matching the total peak load within a particular region with the initial DER capacity and considering the control and protection of other circuit elements.

For this case study, The distribution feeder was partitioned into sixteen hubs for uniform distribution of loads to the DERs based on assigned priority points of the loads. Each load is assigned a priority point based on the impact suffered as a result of losing power, loads like hospitals and fire departments have the highest points followed by commercial loads like restaurants and hotels with residential loads having the least points. These points are aggregated and the loads are evenly distributed for each of the 16 hubs. Some of the zones or hubs have more lines and buses than others, this is because the zones with fewer buses and lines have a larger concentration of highly prioritized loads. The main objective is to minimize unserved loads as a result of losing the grid due to natural disasters and that should still be the case even when lines are damaged with the zones or hubs. Fig. 6 shows the 16 zones indicated by different color codes with DERs.

3.2. Optimal Placement and Sizing

The DERs should be sized and placed at locations where the impacts would be minimized should lines be damaged. To do that, an optimization problem is set up for each hub to identify the optimal buses to situate the DERs. The objective function is to minimize the unserved kilowatt-hours with respect to the costs of PVs and BESS after losing lines to natural disasters. This is important because even though the whole feeder has been partitioned into islands to enhance its resilience, some lines within the hubs could still be damaged. The optimal sizing and allocation of DERs based on this objective function will ensure resilience is still improved by serving most of the loads within each hub. The improved grey wolf optimizer (IGWO) was chosen to solve this optimization problem because it is one performer for optimal sizing and allocation of renewable energy resources within power systems [65]. article algorithm algpseudocode

The logic and algorithm behind the optimization problem are shown in Algorithm 1, it explains how the DERs are moved from one bus to the other and the N-1 contingency criteria for feeder lines is performed at each bus to determine unserved loads. With the use of the meta-heuristic improved grey wolf optimizer borrowed from [66], optimal bus position, PV and battery sizes are determined for minimizing the unserved loads and DER cost for each zone.

3.2.1. Objective Function

The objective function as stated earlier is to minimize unserved loads (UL)as a result of losing lines within the feeder and reduce the cost of the DERs required to serve the loads. The unserved loads are calculated by moving the DERs from one bus to the other and performing N-1 contingency analysis of feeder lines at the bus DERs are connected. At each bus, the N-1 analysis is conducted for all the sizes of PVs and BESS in a specified range. The bus position, PV and BESS sizes that result in the least unserved loads are the ideal optimal position and sizes. However, since the goal is to invest smartly the cost of the DERs should also be considered to ensure effective economic investments while alleviating the effects of natural effects on power systems to optimal levels.

The mathematical representation of the objective function is shown below. The decision variables are PV size, BESS size & capacity, and placement. The overall objective function is obtained by combining the unserved load and cost objective functions into one formulated in (1).

- Decision Variables
  - PV_i = PV size at bus i in kW
  - Bs_i = BESS size at Bus i in kWh
  - Bc_i = BESS capacity at Bus i in kW

Algorithm 1 Optimal DER Sizing and Allocation with IGWO

```
Define:
    DER elements: PV and BESS
    List all lines
    List all buses
    Optimization Parameters:
        IGWO parameters (e.g., population size, max iterations, convergence criteria)
        Maximum number of buses
        Maximum PV size
        Maximum BESS size
Initialize PV and BESS sizes randomly within defined limits
Initialize IGWO population with random positions for PV and BESS
Initialize the best solution and its fitness value
N = 10                              ▷ Number of search agents
Max_iteration = 20                  ▷ Maximum number of iterations
for iteration in 1 to Max_iteration or until convergence do
    for each wolf in IGWO population do
        for each bus do
            for each PV and BESS size do
                for each line in the circuit do
                    Solve Power Flow
                    Calculate Unserved Load
                    for each line in the circuit do
                        Disable the line
                        Solve the power flow
                        Calculate the unserved load
                        Unserved load = Total Load - Total Load Without line
                        Enable the line to normal state
                    end for
                end for
                Calculate fitness based on unserved load
                Update the position of the wolf using IGWO algorithm
            end for
        end for
        Implement Optimization with IGWO
        Update the best solution if the current solution has a better fitness value
        Update IGWO parameters based on the current fitness and positions
        Apply IGWO algorithm to optimize PV and BESS sizes
    end for
end for
Return the best solution found
```

- B_p = Bus position

- Objective Function
  - Z = Total Unserved Load
  - N = Total number of Buses
  - T = Total number of Lines

$$Z = \sum_{i=1}^{N}\sum_{j=1}^{T} UL_{ij} + PV_{size} + BESS_{size} + BESS_{cap} \quad (1)$$

3.2.2. Constraints

The minimization of our objective function of unserved loads and cost of DERs will be subjected to constraints shown in (2) to (5). The calculation of unserved loads during N-1 contingency analysis should always follow (2) where P_{Gi} and P_{Di} are the power injected and demanded at bus i respectively, $G_{ij)}$ and $B_{ij)}$ are the conductance and susceptance between buses i and j respectively, $\theta_{ij)}$ is the voltage angle between buses i and j and V_i and V_j are the bus volatges at buses i and j respectively.

The second and third constraints shown in (3) and (4) are on the sizes of PVs and BESSs, this is very necessary because without this constraint the sizes of the DERs would be extremely large to ensure all loads are served. The DERs are capped by the peak demand of the respective zones. Equation (5) formulates the bus position constraint referring to the list of bus numbers within a particular zone. The fifth constraint is the SOC constraint shown in (6), this is to avoid total depletion and overcharging of the BESS in order to prolong the lifespan of BESSs.

$$P_{Gi} - P_{Di} = V_i \sum_{j=1}^{T} V_j (G_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij}) \quad (2)$$

$$PVsize_{min} \leqslant PV_i \leqslant PVsize_{max} \quad (3)$$

$$BESSsize_{min} \leqslant B_i \leqslant BESSsize_{max} \quad (4)$$

$$B_{pmin} \leqslant B_p \leqslant B_{pmax} \quad (5)$$

$$10 \leqslant SOC \leqslant 90 \quad (6)$$

3.2.3. Improved Grey Wolf Optimizer - IGWO

The Grey Wolf Optimizer (GWO) is a meta-heuristic algorithm that copies the leadership hierarchy and hunting strategies of grey wolves proposed in [67]. The pack of grey wolves is divided into four groups alpha, beta, delta, and omega and are referred to as the search agents in optimization applications. Alphas are considered the leaders of the pack and are responsible for decision-making, the beta and delta groups of search agents are the next in command and help the alpha in decision-making and the omega search agents and are the followers. The hunting behavior of the search agents involves three main steps; they first track, chase and approach the prey, the second step is pursuing, encircling and harassing the prey until it stops moving and the final step is to attack the prey. This hunting behavior aligns with the interest of solving an optimization problem and therefore the GWO is modelled on this.

In the mathematical modelling of the hunting behavior, the fittest solution is considered as the alpha, the second and third best solutions are referred to as the beta and delta respectively, and the rest of the solutions are considered to be omega. Therefore, the GWO algorithm is guided by alpha, beta, and delta with the omega wolves following. The grey wolf strategy can be modelled mathematically by formulating equations to represent encircling the prey and hunting stages.

$$D = |CX_p - AX(t)| \tag{7}$$

$$X(t+1) = X_p(t) - AD \tag{8}$$

Equations (7) and (8) model the encircling behaviour, where t is the current iteration, X and X_p are the position vectors of the prey and a search agent respectively. A and C are coefficient vectors given by:

$$A = 2ar_1a \tag{9}$$

$$C = 2r2 \tag{10}$$

where r_1 and r_2 are random vectors in [0,1] and a linearly varies from 2 to 0 through the iterations. The hunting stage is modelled by defining the movements of alpha, beta and delta search agents by (11), (12) and (13) respectively.

$$D_\alpha = |C_\alpha \cdot X_\alpha(t) - X(t)| \tag{11}$$

$$D_\beta = |C_\beta \cdot X_\beta(t) - X(t)| \tag{12}$$

$$D_\delta = |C_\delta \cdot X_\delta(t) - X(t)| \tag{13}$$

The α, β, δ generally have a better knowledge of the prey's position and the remaining pack of the wolves follow. The positions of α, β, δ grey wolves at the t^{th} iteration are updated as follows:

$$X_1 = X_\alpha(t) - A_1 \cdot (D_\alpha) \tag{14}$$

$$X_2 = X_\beta(t) - A_1 \cdot (D_\beta) \tag{15}$$

$$X_3 = X_\delta(t) - A_1 \cdot (D_\delta) \tag{16}$$

$$X_{(t+1)} = \frac{X_1 + X_2 + X_3}{3} \tag{17}$$

The GWO algorithm, however, has some limitations according to [66]. The α, β, δ leading ω agents in search of the optimal solution can lead to entrapment in a locally optimal solution. The entrapment in a local optimum can also be a result of a reduction in the diversity of the grey wolf population and not taking into consideration the individual hunting behavior of the wolves. [66] makes modifications to the original algorithm and proposes the Improved Grey Wolf Optimizer to overcome these issues. The proposed solution involves three steps initializing, movement, and selecting and updating. The main modification is made in the movement phase where the dimension learning-based hunting (DLH) search strategy is introduced to factor in the individual hunting of the wolves. The combination of the two search strategies improves both the local and global search ability of IGWO. In [66], IGWO was compared with other optimization algorithms and it proved very competitive and in most cases was the superior algorithm. The enhanced balance in finding the local and global search in IGWO makes it a suitable candidate for our application where the search agents have to roam through several buses and at each bus hunt through different sizes and capacities of DERs to find the appropriate solution, the minimum value of the objective function and also obeying the boundaries of the constraints.

As mentioned earlier, the entire simulations were performed with OpenDSS version 9.6.1.3 paired with MATLAB R2023a on a Windows 10 computer with processor configuration of Intel(R) Core(TM) i7-9700 CPU @ 3.20GHz 3.00 GHz and 32.0 GB RAM.

4. Results and Analysis

In this section, the results of the criticality assessment and resilience enhancement methods introduced in the previous section are discussed. The immediate aftermath of hurricane Delta was considered for this analysis by using a real solar profile on October 4, 2020 from the Louisiana Solar Energy Laboratory (LaSEL) shown in Fig. 7. The BESS' were modelled to compliment the solar PVs by discharging at night when the solar PVs are not generating any power and charge during the day by the extra power from the solar PVs.

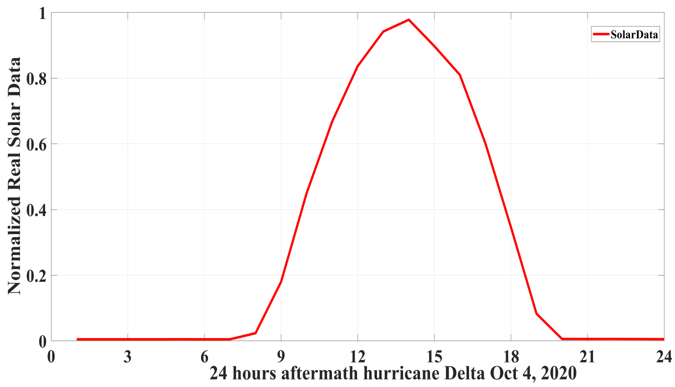

Fig. 7. Normalized solar power generation October 4, 2020

The impacts of loss of lines are analyzed by measuring the amount of unserved loads. The unserved load associated with the disabling of each line is calculated based on Fig. 5. The result of the criticality assessment performed on the case study is shown in Fig. 8.

The results show that lines at the top of the feeder are the most critical to the system's operation and resilience since losing those lines has more negative impact than the lines further away from the feeder. This is due to the radial topology of the network as seen in Fig. 3, The line (L1) that connects the main feeder to the rest of the network results in total curtailment of all loads when it is disabled. The loss or disabling of lines that are connected to L1 also results in high unserved loads. These lines are considered most critical and that is where any effort to

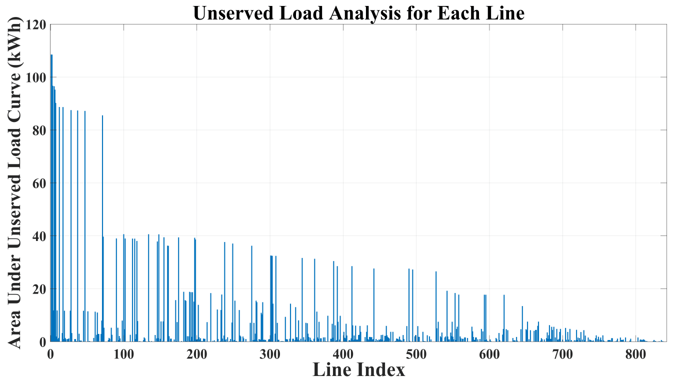

Fig. 8. Impact of losing each line in an 840-Bus utility feeder

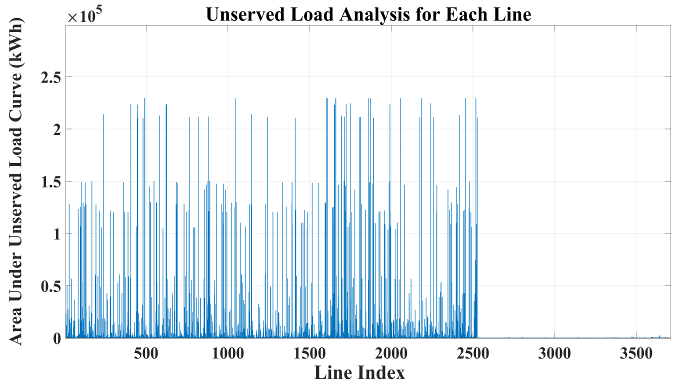

Fig. 11. Impact of losing each line in an IEEE-8500 node test feeder

improve the system's resilience should be directed. The criticality assessment method was tested on other distribution networks with different topologies to confirm the versatility of the proposed method. Figs. 9, 10, 11 are the criticality assessment results for IEEE-34 Bus, IEEE-123 Bus and IEEE-8500 node distribution test systems respectively in OpenDSS.

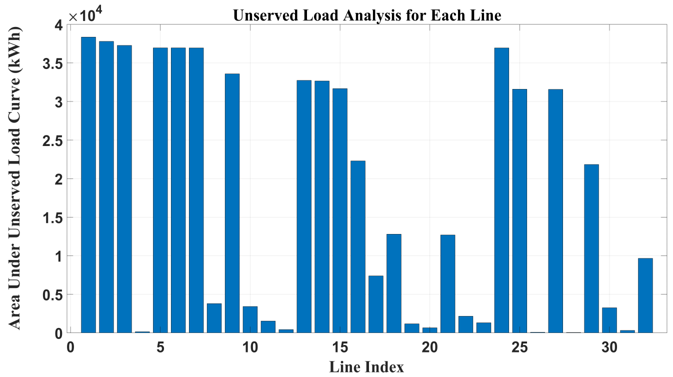

Fig. 9. Impact of losing each line in an IEEE 34-Bus System

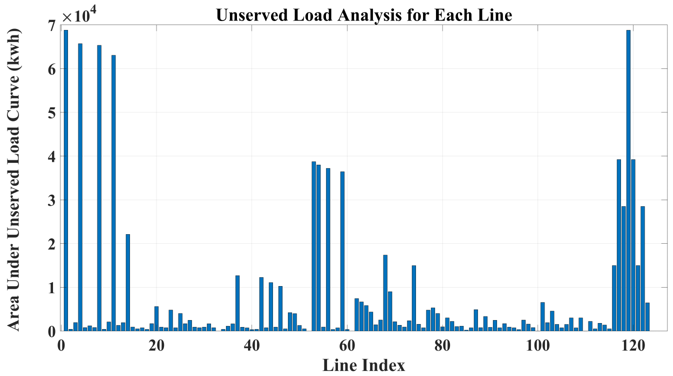

Fig. 10. Impact of losing each line in an IEEE 123-Bus System

The results indicate that the criticality of feeder lines is linked to the topology of the distribution network and every system has its peculiar criticality. It is therefore important to undertake a critical components impact assessment for each system to ascertain the critical components and areas to make the right investment for the system's resilience improvement.

Having identified the most vulnerable lines of the system, the next step is to implement the investment options of DER integration to enhance the system's resilience. As mentioned in the previous section, the distribution network has been partitioned into hubs or zones and operated as microgrids for resilience enhancement. The DERs for each zone were optimally sized and placed to minimize unserved loads with minimal investments in DERs in the event of losing the grid during a natural disaster.

For each hub, the N-1 contingency analysis is performed for three different scenarios to compare their impacts and show the efficacy of our resilient enhancement methodology. First, N-1 contingency analysis is performed in normal grid operation. In the second scenario, the same analysis is performed when the grid is lost due to a natural disaster and replaced with DERs to form a microgrid operating in a grid-forming mode. The loss of the grid is simulated by disconnecting the line that connects the grid to the rest of the zone. The DERs are placed at the top of the feeder, that is the bus that connected the grid before it was lost, thus replacing the grid. In this scenario, the DERs are sized by matching the peak load of the zones. In the third scenario, the optimization problem is solved to determine the optimal bus position for the placement of the DERS and the optimal sizes of the DERs. The DERs are then sized and placed accordingly with the zones operating as grid-forming microgrids for the N-1 contingency analysis. The results for all three scenarios for each zone are shown in Fig. 12 to Fig. 27.

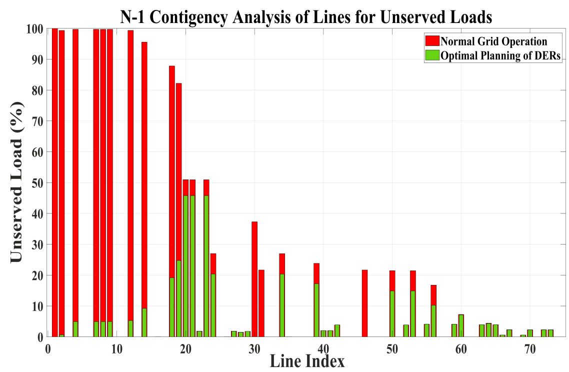

Fig. 12. Zone One Results from N-1 Contingency Analysis

In the performance of normal grid operation and the second scenario when the grid is replaced the DERs are very identical, the only difference is the line at the top of the feeder connecting the grid is not considered in the second scenario because it is assumed to be damaged from the natural disaster. Therefore the comparison of results is for normal grid operation and optimally planned DER operation. The results from Fig. 12 show a much-improved system resilience when the DERs are optimally placed and sized. For zone one the largest unserved load observed is as low as 45% when optimal planning is implemented compared to 100% when grid operated or DERs are not optimally planned. And most lines do not result in any unserved load in the optimal planning scenario.

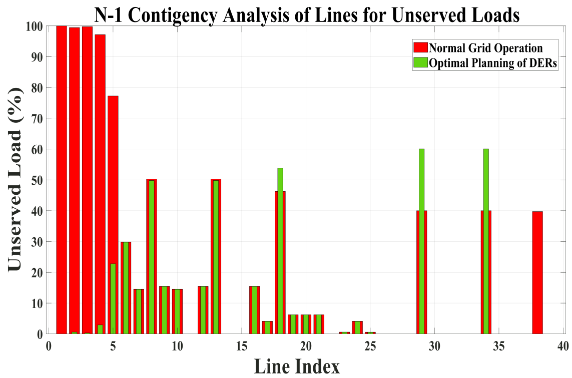

Fig. 13. Zone Two Results from N-1 Contingency Analysis

All the zones show similar results for normal grid operation and when DERs replace the grid, which is expected because the DERs are now playing the role of the grid in that case. Also, in each zone, the optimal planning implemented vastly improved resilience by unserved load measurements therefore meeting our main objective of resilience enhancement. Zones 10 and and 12 experienced the best performance with the highest unserved loads in these zones being less than 28%, Zone 5 follows with its highest unserved load at 32%. Other zones like 3 and 14 also recorded impressive results by having their highest unserved loads at less than 40%, with zones 1 and 6 at less than 50%. It is worth mentioning that these reported highest unserved loads are for few lines in N-1 analysis and most cases only single lines record that, which means most lines when lost during natural disasters do not even result in loss of loads when optimal planning is in place. This means that when these resilience enhancements are implemented during the aftermath of natural disasters the loss of many lines would not result in loss of any load.

Some of the zones like seven and eleven have their highest unserved loads at 70%, though this is pretty high, they represent a much-improved performance when compared to normal grid operation and DERs in place of grid performances. As mentioned earlier, these higher percentages of unserved loads are the results of losing a single line, the performances of the remaining lines show improvement in the resilience of the zones or hubs and can be seen from Fig. 22. The average percentage of unserved loads in both normal, non-optimal DER and optimal planning operations are summarized in Table 1.

Table 1. Average unserved load percentage per zone

Average Total Unserved Load (% of Total Load)			
ZONES	Grid	Non-Optimal	Optimal DER Planning
1	18.8	17.3	5.01
2	22.4	19.8	11.1
3	20.2	18.3	6.2
4	28.4	24.7	14.1
5	20.8	18.4	4.3
6	27.5	23.7	9.3
7	16.1	14.9	8.9
8	14.2	13.1	9.0
9	19.7	17.4	6.1
10	18.3	16.3	3.5
11	18.9	17.4	14.1
12	18.1	16.7	2.1
13	26.9	24.7	17.9
14	22.6	20.9	4.3
15	21.8	19.6	9.3
16	17.3	15.8	13.7

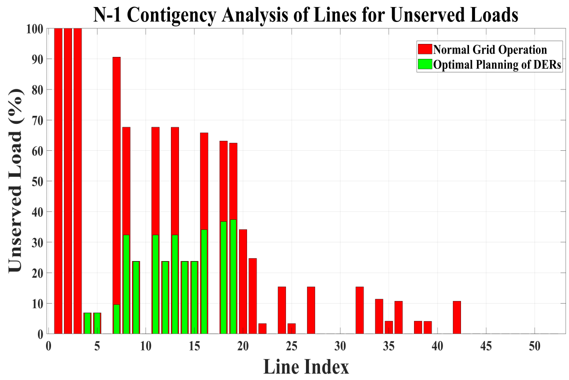

Fig. 14. Zone Three Results from N-1 Contingency Analysis

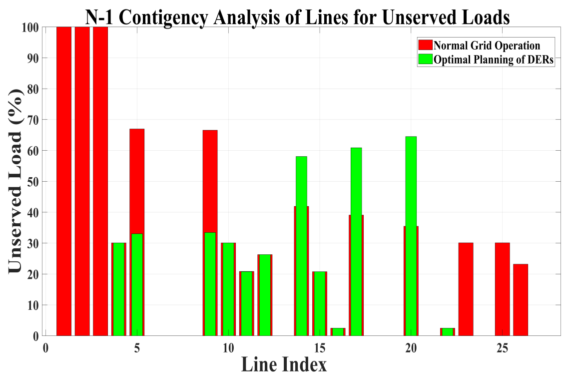

Fig. 15. Zone Four Results from N-1 Contingency Analysis

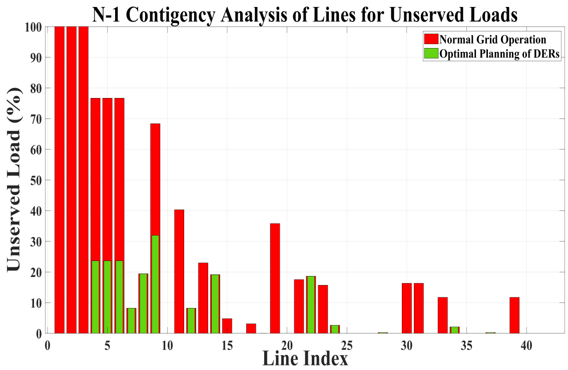

Fig. 16. Zone Five Results from N-1 Contingency Analysis

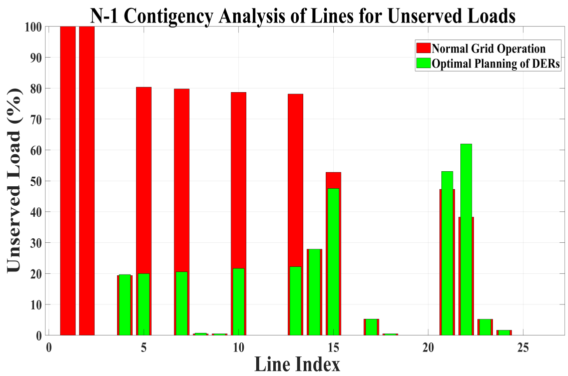

Fig. 17. Zone Six Results from N-1 Contingency Analysis

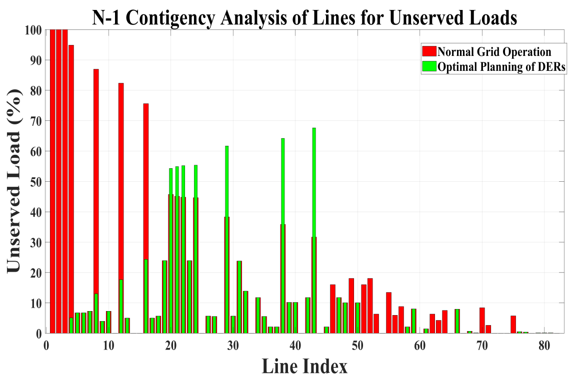

Fig. 18. Zone Seven Results from N-1 Contingency Analysis

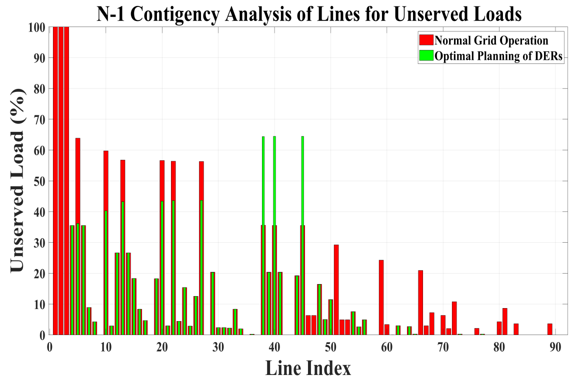

Fig. 19. Zone Eight Results from N-1 Contingency Analysis

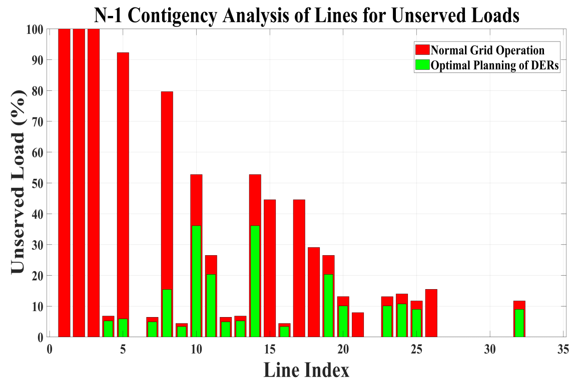

Fig. 20. Zone Nine Results from N-1 Contingency Analysis

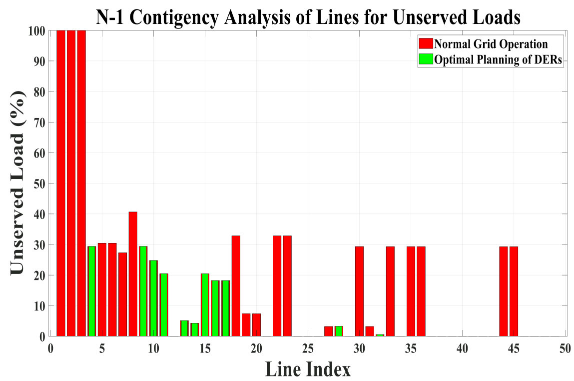

Fig. 21. Zone Ten Results from N-1 Contingency Analysis

5. Conclusion

This research explored alternative ways of bolstering the resilience of the existing power system instead of replacing it which is highly costly and inconvenient. We introduced a methodology to help revamp existing power systems to enhance their resilience in the face of natural disasters in a cost-efficient and convenient manner. N-1 contingency criteria which is traditionally employed in reliability analysis of power systems was used to perform an impact assessment of losing lines and resilience analysis to identify areas within a power network in need of urgent investment for resilience enhancement. A combination of existing reliability and resilience metrics was used to determine critical lines of the system and measure resilience.

To improve the resilience of power systems beyond the hardening of vulnerable lines, the use of DERs and partitioning the existing network in hubs or zones and operating them as grid-forming microgrids was proposed. These DERs were optimally sized and placed within each hub to ensure loss of loads is minimized during natural disasters when the main grid is lost. To implement this proposed methodology, a real-world distribution feeder was used as a case study. With the use of N-1 contingency analysis, impact assessments were performed on the feeder lines, and the critical lines were identified. The proposed resilience enhancement strategies were also applied to this ex-

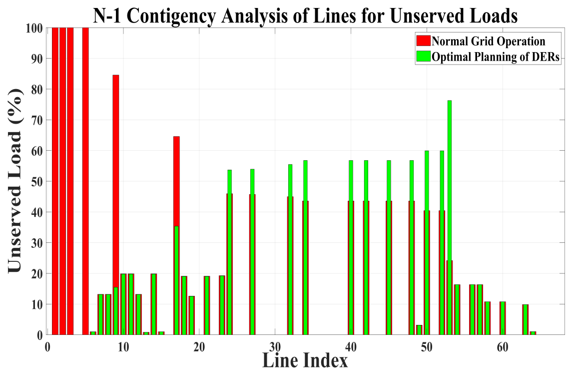

Fig. 22. Zone Elleven Results from N-1 Contingency Analysis

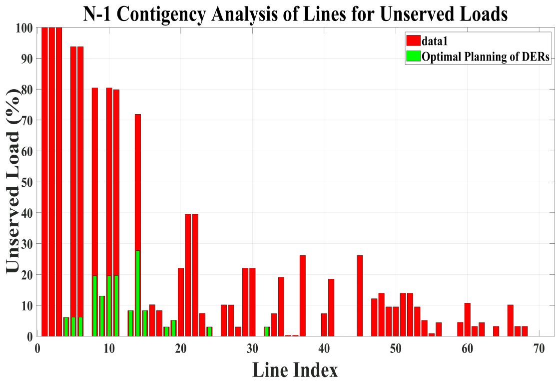

Fig. 23. Zone Twelve Results from N-1 Contingency Analysis

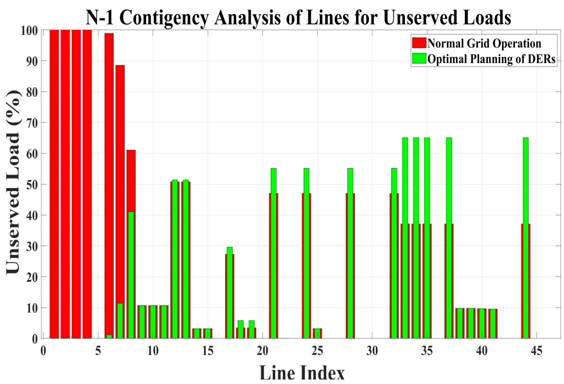

Fig. 24. Zone Thirteen Results from N-1 Contingency Analysis

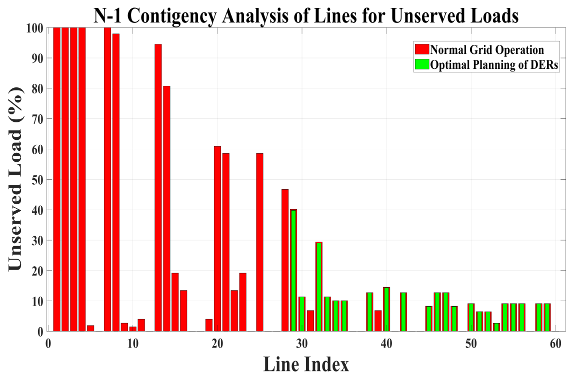

Fig. 25. Zone Fourteen Results from N-1 Contingency Analysis

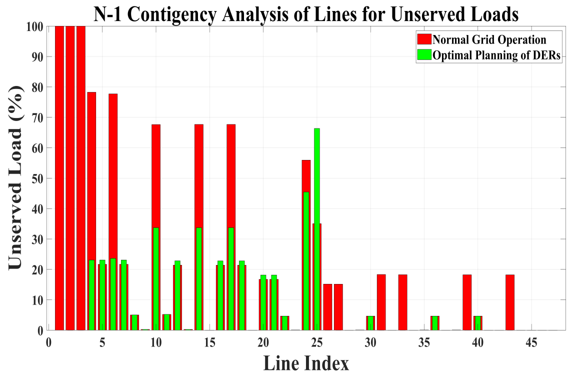

Fig. 26. Zone Fifteen Results from N-1 Contingency Analysis

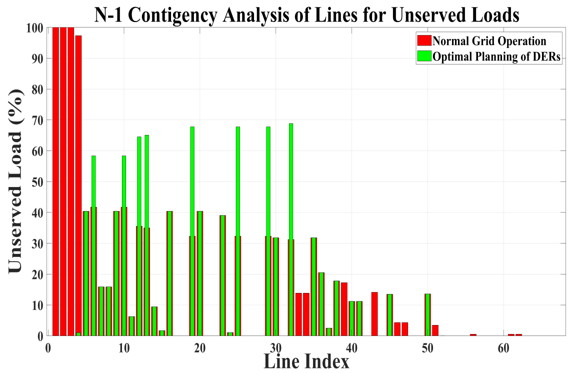

Fig. 27. Zone Sixteen Results from N-1 Contingency Analysis

isting feeder by dividing it into sixteen zones and optimally sizing and placing DERs in each zone. Each zone was then run as a grid-forming microgrid on their own.

The Resilience of each zone was evaluated by measuring the unserved loads when each line was lost with the goal of minimizing the amount of unserved loads. The results proved the effectiveness of our proposed resilience strategies as the amount of unserved loads due to losing each line was immensely reduced when compared to the amount of unserved encountered when no resilience enhancement is implemented or randomly placing DERs to improve resilience. In many instances, the loss of some lines would not result in any load curtailment due to the implementation of our proposed optimal planning.

Therefore the proposed resilience enhancement strategies could help in making smart investment decisions that would greatly improve the resilience and reduce the vulnerability of existing power distribution systems.

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