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Resiliency of electric power distribution networks: a review

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Abstract
Although relatively new in the context of power systems, the concept of resiliency is gaining increasing importance due to the growing vulnerability of electric infrastructure and the widespread outages triggered by extreme weather events. Unlike reliability studies, there still exists no well-agreed-upon method or criterion for quantifying the resiliency of power systems. This paper will lay out an overview of the concept of resiliency versus reliability and then review the foundational literature on power system resiliency with a focus on the distribution sector. The cwill be discussed as well..

Keywords DERs, Distribution networks, Extreme hazards, HILP events, Microgrid, Resiliency

Introduction

Severe natural disasters, including earthquakes, wildfires, floods, extreme temperature events, hurricanes, and harsh storms, account for a significant share of power grid failures, leading to substantial socio-economic losses globally each year [1]. For instance, in 2008, an unprecedented freezing event in China disrupted 39,033 transmission and distribution lines and led to the collapse of 2,037 substations, resulting in an estimated economic loss of nearly 100 billion yuan [2]. Similarly, the 8.8-magnitude earthquake in Chile in 2010 triggered widespread outages, affecting approximately 90% of customers [3]. The devastating 9.0-magnitude earthquake and subsequent tsunami in 2011 caused power disruptions for around 8.7 million customers [3]. More recently, in 2021 and 2022, the US experienced 20 and 18 extreme weather events, respectively, each inflicting over $1 billion in damages [4, 5].

Historical records indicate that between 1965 and 2012, natural disasters were responsible for over 30% of all power outages worldwide [6]. A study analyzing 933 major blackouts in the US from 1984 to 2006 found that extreme weather conditions accounted for 43.6% of these disruptions [7]. Additionally, a report by the President's Council of Economic Advisers and the US Department of Energy estimated that between 2003 and 2012, severe weather caused 58% of power grid failures in the US, leading to an inflation-adjusted economic impact ranging from $18 billion to $33 billion annually and affecting more than 147 million customers [8]-[9]. Reports from the National Centers for Environmental Information (NCEI) and the North American Electric Reliability Corporation (NERC) further underscore the significant role of extreme weather in initiating and exacerbating the most severe power outages in the US [8].

To name a few, in 2005, Hurricane Wilma damaged over 10,000 distribution poles across Florida [10]. The 2011 Superstorm Irene, which struck the Northeastern US, disrupted power for 6.7 million customers and caused approximately $10 billion in damage to power

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infrastructure [1]. Hurricane Sandy in 2012, recorded as the second most costly storm in US history [8], resulted in $71 billion in total damage [11], leaving around 8.7 million customers without electricity across 15 states and Washington, D.C. [1, 12]. During this event, about 65% of New Jersey's customers were disconnected from the power grid [13].

In 2017, multiple disasters severely affected the US power grid. A windstorm in Michigan in March left nearly 0.8 million customers without electricity [14]. The same year, Hurricane Maria caused $90 billion in damages, while Hurricane Harvey inflicted $125 billion in losses and power outages for approximately 0.22 million customers [11, 15]. Additionally, Hurricane Irma caused widespread destruction across several Caribbean islands and Florida, resulting in the near-total loss of electricity in Puerto Rico [15]. More recently, in February 2021, Winter Storm Uri triggered a large-scale blackout in Texas, leaving 4.5 million customers without power for four days [5, 16].

The frequency of extreme weather events and their associated financial losses have been increasing in the US over the past four decades [17]. According to [18], hurricanes are not only becoming more intense and frequent but are also moving approximately 20% slower in the North Atlantic compared to 70 years ago. As previously discussed, extreme weather is the leading factor contributing to the rising frequency and duration of power outages in the US [19]. The 2014 report by the Intergovernmental Panel on Climate Change also acknowledged the increasing likelihood and severity of such events in the future [20].

Various studies [1, 12, 16, 21]-[22] suggest that, unfortunately, the frequency and intensity of these disasters could continue to escalate due to climate change. This underscores the urgent need to strengthen the resiliency of US power grids to mitigate potential catastrophic consequences. Without proactive measures to enhance grid resiliency, the total annual economic loss incurred by utility customers could exceed $480 billion between 2080 and 2099 [19].

The rest of this paper is organized as follows. What is resiliency? section provides a comparative discussion over the concepts of resiliency and reliability, and then reviews how power system resiliency is defined in the literature. Distribution Systems Resiliency section first identifies the vulnerable sector of a power system and then reviews the studies on the resiliency of distribution systems. The section also goes over the learning-based methods currently being used for distribution system resiliency, and then points out a few important research gaps. Additionally, Distribution Systems Resiliency section responds to the question about whether renewables and EVs make power grids less susceptible. Finally, Conclusions section concludes the paper.

What is resiliency?

In this section, first, we point out the differences between resiliency and reliability and then go over the definition of resiliency.

Resiliency versus reliability

System reliability is evaluated based on the frequency and duration of power outages experienced by customers. Utilities primarily rely on two key indices to assess outage impacts: the System Average Interruption Frequency Index (SAIFI) and the System Average Interruption Duration Index (SAIDI). In contrast, resiliency is a relatively newer concept that gauges a power system's ability to sustain critical demand during extreme events—often classified as High-Impact, Low-Probability (HILP) events—when large-scale generation sources are disrupted for extended periods and numerous transmission and distribution components fail. Consequently, traditional reliability indices alone are inadequate for effectively measuring a power system's resiliency [23].

As highlighted in [24], reliability ensures a continuous power supply under normal operating conditions, whereas resiliency extends beyond this by addressing the ability to endure and recover from HILP events. According to [15], resiliency focuses on reducing unserved electrical load during large-scale, unforeseen outages, while reliability pertains to a system's capacity to handle frequent but less severe disruptions. Reference [25] describes resiliency as a system's capacity to anticipate, prepare for, endure, and effectively recover from disruptions. Moreover, as noted in [21], resiliency differs from reliability by emphasizing the strategic allocation of resources, such as DERs, microgrids, and line switches, to prioritize critical facilities like hospitals, data centers, and emergency services during restoration efforts.

Reference [21] claims that increasing a system's resiliency does not necessarily guarantee the improvement of reliability and vice versa. Furthermore, most power grids are designed based on anticipated faults and historical weather patterns, typically spanning a 50-year period. However, this design framework cannot fully capture the increasing frequency and severity of extreme weather events in recent years [1, 16]. In other words, while a system may be resilient to current climate conditions, it could still be vulnerable to future climatic shifts [26]. Additionally, as noted in [27, 28], the impact of HILP events cannot be accurately assessed using reliability indices alone. Due to these key differences, the literature advocates for conducting reliability and resiliency assessments as separate studies [29].

The authors argue that reliability is associated with the impact of endogenous factors (those originating within the system), such as component failures, on the performance of power grids. In contrast, resiliency pertains to the impact of exogenous contributors, such as natural disasters or extreme weather events, on the ability of power grids to recover and maintain functionality.

Definitions and metrics for resiliency

As previously mentioned, traditional reliability assessment focuses on a system's ability to supply power to all connected loads but does not account for external disruptions such as climatic hazards or HILP events. Consequently, there is a growing need to develop a new framework aimed at preventing or mitigating the consequences of natural disasters, including extreme weather conditions. The concept of resiliency originally emerged in psychology [30] and was later adopted in power engineering to describe a grid's capability to recover to its pre-disaster state following a major disruption. Resiliency is further categorized into two types: static and dynamic. Static resiliency evaluates system performance post-disruption without considering the time factor, whereas dynamic resiliency focuses on the speed at which the system restores normal operation [30].

Various organizations, researchers, and studies have sought to clearly define system resiliency. The US National Academy of Science describes resiliency as "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" [20]. Similarly, the Presidential Policy Directive 21 characterizes it as a system's capacity to adjust to changing conditions, endure disruptions, and restore functionality [15]. In [31], resiliency is defined as a system's robustness against HILP events, while [32] refers to it as a community's ability to recover from disruptions. Hollnagel [33] explains resiliency as "the ability to maintain effective barriers that can withstand the impact of adverse agents and the erosion that is a result of latent conditions." Meanwhile, [19, 23] describe resiliency as a holistic measure of system performance under disruptive conditions.

A more recent definition from the Federal Energy Regulatory Commission (FERC) describes resiliency as "the ability to withstand and reduce the magnitude and/or duration of disruptive events, which includes the capability to anticipate, absorb, adapt to, and/or rapidly recover from such an event". This perspective breaks power system resiliency into four key phases: (1) proactively strengthening the grid before an HILP event occurs, (2) responding efficiently to maintain system functionality during disruptions, (3) swiftly restoring operations to pre-event conditions, and (4) adapting the system's design and operations to minimize the impact of similar events in the future [1].

According to the IEEE Power & Energy Society (PES) Distribution Resilience Working Group, grid resiliency refers to the system's capability to recover within the first 12 hours following a severe weather event, as well as its overall ability to endure such disruptions [23]. Meanwhile, the US Department of Energy's Grid Modernization Laboratory Consortium advocates for a performance-based approach to measuring resiliency. It recommends indices such as "cumulative customer energy demand not served" and "critical customer energy demand not served" to quantitatively assess the system's resiliency [23].

For additional definitions of power grid resiliency, readers are referred to those given by the US Department of Energy (DOE) and North American Transmission Forum [23], the Industrial Control Systems-Computer Emergency Readiness Team (ICS-CERT), national labs such as the National Renewable Energy Laboratory (NREL), the Pacific Northwest National Laboratory (PNNL) [31], the CIGRE [1], and the UK Energy Research Centre [1, 15].

The above-reviewed studies provided literal expressions for power grid resiliency, which have had relatively little usage, and at present, there are no established frameworks, metrics, and regulatory standards that are well agreed upon by power engineering communities and utilities for its analysis [1, 21, 30, 34, 35]. Nevertheless, several recent research efforts have tried to describe resiliency in quantitative terms [13, 21, 36–44]. In the majority of them, the resiliency criterion is the unserved load. According to [20, 30], prior studies primarily employed indices such as loss of load frequency, loss of load expectation, expected energy not supplied, and availability as a resiliency index. For example, [21] proposed the "expected probability of interruption (EPI)" for long-term, and the "expected energy not served per interruption (EENS)" as well as "expected outage duration per interruption (EOD)" for short-term resiliency assessments.

A general approach to quantifying a power system's resiliency is the multi-phase resiliency trapezoid shown in Fig. 1, where F(t) denotes a generic system performance function, often defined as the ratio of the supplied loads to total demand after being weighted by their priority.

A disruptive event strikes the system at t_0, initiating the degradation phase. During the "event progress" period, spanning from t_0 to t_1, power supply to certain loads is disrupted, leading to a decline in $F(t)$. Once the extreme event subsides, the system reaches a resistance state at t_1. Between t_1 and t_2, the utility undertakes damage assessment, gathers information regarding fault locations, and isolates them from the functional sections of

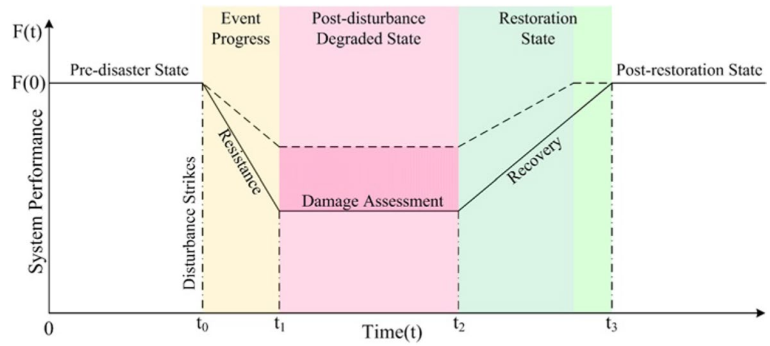

Fig. 1 Multi-phase resiliency trapezoid, adopted from [38]

the network. During this stage, the system continues to operate but at a reduced capacity.

The third phase begins at t_2, during which corrective actions, such as network reconfiguration, utilization of DERs, and integration of energy storage systems, are planned and executed to restore the system to its original operational state. At this point, utility crews may be dispatched to repair the damaged infrastructure. As the interrupted loads are progressively restored, $F(t)$ starts increasing over the period from t_2 to t_3. When utility power is fully reinstated at t_3, the system transitions into the final recovery phase.

It is important to note that the transitions between system states in Fig. 1 are represented as linear solely for ease of understanding. In reality, they may exhibit nonlinear behavior, depending on system attributes, prevailing conditions, and the nature of the disruptive event [38].

The resiliency trapezoid encapsulates three key attributes of a disruptive event: (a) the rate and extent of performance decline, (b) the duration for which the system remains in a degraded state, and (c) the speed at which the system recovers to pre-event conditions. A resiliency metric, denoted as R, quantifies system resiliency as the area under this trapezoid. Any strategy aimed at improving resiliency should focus on maximizing this area. The area under the curve can also be normalized with respect to the rectangle $(t_3 - t_0) \times F(0)$, as formulated in (1).

$$R = \frac{\int_{t_0}^{t_3} F(t).dt}{(t_3 - t_0)F(0)}, \quad R \in [0, 1] \tag{1}$$

The dashed-line trapezoid in Fig. 1 would represent the system behavior when there were additional resources (e.g., microgrids) responding to the event. The dashed-line trapezoid possesses a larger area under the curve.

Distribution systems resiliency

Power distribution networks have been found to be more sensitive to extreme weather events, wind in particular. Hence, this section will focus on the resiliency of distribution systems.

Most vulnerable section of a power system

Among the various sectors of power systems, enhancing the resiliency of distribution networks demands substantial focus, as they are particularly susceptible to extreme weather events and climate-related hazards. It is reported that distribution networks are responsible for 92% of all electric service disruptions in the US [19]. For instance, Hurricanes Wilma and Katrina led to the destruction of 12,400 and 72,500 utility poles, respectively [19]. Between 2003 and 2012, approximately 680 outages in the US were attributed to weather-related incidents, with 80%–90% stemming from failures in distribution systems [4, 13, 45].

As reported in [37], nearly 70% of all electric service interruptions originate from contingencies within distribution networks. Additionally, [11] highlights that close to 90% of hurricane-induced power outages occur within distribution grids. The vulnerability of distribution networks to natural disasters is exacerbated by a combination of factors, including cascading line outages, their radial configuration, and the scarcity of backup resources [21].

Several studies have emphasized that wind-driven climatic hazards, such as hurricanes, tornadoes, and extreme wind events, are among the most frequent threats [7, 21] and represent the greatest resiliency-related risk to distribution systems [21, 45]. A risk assessment leveraging data-mining techniques on historical outage records suggests that the US power grid is especially vulnerable to severe wind events [15]. Given their susceptibility to weather-induced disruptions, distribution systems are often considered the weakest link in power grids from resiliency perspective [23, 46].

In regard to the vulnerability of the distribution sector against HILP events, the rest of this paper will be focused on some of the research efforts that aimed to evaluate and/or improve the resiliency of power distribution systems.

Literature review on distribution systems resiliency

Power distribution systems have traditionally been designed to adhere to reliability standards that account for anticipated, or credible outages, while excluding HILP events that exceed typical N-1 or N-2 contingency scenarios. Given that the US power grid infrastructure has aged significantly over time [10], there is a pressing need to reassess current planning methodologies to incorporate resiliency considerations in the design of distribution networks [10, 47].

Following the occurrence of an extreme event, different sections of the affected power system will transition into one of the following states: a) Grid-connected, the segment remains operational and continues to receive power from the main utility grid. b) Islanded microgrid, the segment becomes part of a temporarily isolated section due to line disconnections and/or physical damage. In such cases, network reconfiguration may be employed to reroute power from either the primary substation or available DERs. This altered network topology may persist for several hours or even days until damaged infrastructure is repaired. c) Failed, the segment itself is rendered inoperative due to direct component failure [21].

Network-side perspectives

Two overarching strategies have been explored to enhance grid resiliency: one focuses on minimizing outage duration through corrective actions, while the other seeks to mitigate the severity of disturbances via preventive actions [8, 46]. As noted in [48], conventional resiliency enhancement techniques are largely response-driven (corrective measures) and aim to curtail downtime. These include ensuring an adequately staffed and well-trained workforce, maintaining backup supplies, implementing proactive planning, improving communication frameworks, optimizing scheduling, and deploying mobile command centers.

On the other hand, network hardening (preventive measures) aims to diminish the potential impact of disruptions [48]. Suggested approaches in this category include undergrounding distribution lines, reinforcing and upgrading utility poles, structural strengthening, installing guy wires, conducting vegetation management, elevating substations, and relocating power infrastructure to areas less exposed to extreme weather conditions. Additionally, incorporating redundant power routing can enhance overall system resiliency. However, hardening efforts can sometimes shift vulnerabilities rather than eliminate them entirely. For instance, burying power lines reduces exposure to wind and storms but increases susceptibility to flooding and complicates repair work. Furthermore, such modifications can be significantly more expensive—underground installations are estimated to cost two to ten times more than their overhead counterparts, and they can pose challenges for system restoration [8].

Consequently, designing a resilient yet cost-effective distribution network remains a substantial challenge [13]. In addition to hardening strategies, utilities have also tried solutions such as deploying distributed generators (DGs) and strategically placing line switches to re-energize affected feeders [10, 49]. When automated, these line switches facilitate remote network reconfiguration, allowing for dynamic power rerouting during outages, thereby reducing restoration times and improving system flexibility [10]. According to [25], grid hardening strategies are strongly influenced by topology reconfiguration and distributed generation (DG) installation. Reconfiguring distribution networks serves multiple purposes, including enhancing resiliency and alleviating congestion. When combined with DG integration, line switch placement, and microgrid formation, it enables greater operational flexibility and adaptive network control. However, formulating this as an optimization problem presents significant challenges, particularly in handling network topology constraints [42].

Typically, distribution networks are operated in a radial configuration for several technical reasons, such as simplifying protection coordination and minimizing short-circuit currents. However, certain urban areas may feature meshed or partially networked systems [50]-[51]. Consequently, any optimization model for reconfiguration must rigorously enforce the radiality constraint, which dictates the selective operation of line switches (or sectionalizers) to divide the network into a set of distinct islands. Within each island, DG dispatch and load shedding strategies must be optimized to maximize served demand.

Extensive research has focused on formulating the radiality constraint in distribution network reconfiguration problems [43]. However, most studies assume a single connected network rather than multiple self-sufficient islands. Only a limited number of works have proposed radiality constraints that account for dynamically formed islands, typically employing one of three main approaches: a) Utilizing graph-theoretic methods, where the network is modeled as a spanning tree under the assumption that each node, except the root, has a single parent [43]. b) Introducing explicit constraints to eliminate any detected cycles (loops) within the network [43]. c) Starting with an initial radial network and iteratively removing an alternative edge whenever a loop is identified during the reconfiguration process.

Despite their potential, these approaches have limitations. The first method requires predefined root nodes for each island, which are unknown at the start of the optimization. The second method suffers from exponential computational complexity, making it infeasible for large-scale systems. Meanwhile, the third method lacks an analytically expressible formulation, complicating its direct integration into optimization frameworks [43].

Reference [10] explores resiliency enhancement through various distribution grid hardening strategies, including undergrounding power lines, reinforcing substations, and deploying backup distributed generators (DGs). Similarly, the study in [52] presents an optimal line-hardening approach, incorporating provisional microgrids to strengthen distribution system resiliency against specific extreme weather events. Both works rely on resiliency indices analogous to those commonly used in power system reliability analysis.

Several other studies have also investigated precautionary resiliency measures. For instance, line hardening [10], vegetation management [13], DG deployment [53], and pole reinforcement [13] have been attempted as viable strategies for enhancing system robustness. The impact of optimally allocating DERs to partition the distribution network into self-sufficient microgrids and its effect on system resiliency is explored in [54].

Reference [1] focuses on transmission system resiliency planning, utilizing DERs in a mixed-integer linear programming (MILP) framework and employing Benders decomposition for solution efficiency. A similar MILP-based approach is adopted in [55], leveraging graph-theoretic techniques introduced in [56] to enforce radiality and microgrid connectivity constraints within distribution system resiliency optimization. The enforcement of graph-theoretic radiality and connectivity constraints is also evident in [57]. The study in [58] applies an MILP formulation for bi-objective network reconfiguration, optimizing both reliability and resiliency.

At the transmission level, [59] investigates microgrid sizing to improve grid resiliency against hurricanes. Other studies focus on post-event restoration by utilizing microgrids for enhancing distribution system resiliency [8, 53, 60]-[61]. The bi-level optimization model in [62] determines investment strategies, incorporating substation hardening, new line construction, and DER integration. The first level of the model addresses network reinforcement, while the second level simulates post-event response and system restoration using a sequential Monte Carlo algorithm, an approach also seen in [21].

Reference [59] proposes a framework for evaluating the impact of DER penetration on system resiliency, quantifying its effectiveness at varying deployment levels. Additionally, heuristic search algorithms are employed in [63] to determine the optimal restoration sequence and resource allocation in pre-event planning for distribution system recovery.

Modeling approaches

In the literature, two primary MILP modeling techniques, robust optimization and stochastic optimization, are commonly used for formulating resiliency-related optimization problems in power networks. For instance, the study in [13] introduces a tri-level robust optimization framework that incorporates distribution pole reinforcement, vegetation management, and a combined approach. To address the coupling challenges between the first and second levels, the authors develop a greedy heuristic algorithm. Similarly, [53] employs robust optimization-based strategies for grid hardening. Four-level resiliency enhancing optimization models are also seen in the literature (e.g., [64]).

On the other hand, stochastic optimization techniques have been widely applied to model resiliency enhancement in distribution grids. References [10, 65] formulate the resiliency improvement problem as a two-stage stochastic mixed-integer programming (MIP) model to address extreme weather events. The same stochastic MILP approach is also utilized in [10, 45] to minimize investment costs related to grid hardening, DG placement, and the installation of remote-controlled line switches. Reference [66] extends this methodology by developing a fuel-based long-term DG allocation strategy using two-stage stochastic MILP to improve distribution system resiliency against extreme hurricanes. A similar stochastic programming framework for resiliency-oriented distribution system design is investigated in [45]. Meanwhile, [4] incorporates conditional value-at-risk (CVaR) to propose a two-stage risk-averse stochastic optimization model for long-term resiliency planning of active distribution networks facing wind-induced extreme events.

Further advancements in stochastic and robust resiliency modeling are seen in [19], where the authors propose a multi-stage stochastic robust optimization framework. To solve their maximization model, they integrate a mixed-integer solver with a heuristic differential evolution algorithm. Reference [38] explores chance-constrained stochastic distribution network partitioning as a means to enhance power grid resiliency.

Source-side perspectives

Many modern DERs are non-dispatchable and lack grid-forming capabilities, meaning they cannot independently restart in the absence of an energized grid—a feature known as black start. The restoration time and resiliency of a power distribution network are significantly influenced by both the location and technical characteristics of its black start units.

However, incorporating new generators with black start capability is highly cost-intensive, with initial investments reaching millions of dollars and ongoing maintenance and testing expenses amounting to hundreds of thousands of dollars [14]. Due to these substantial costs, determining the optimal procurement of black start resources has been explored in multiple studies, such as [67].

Meanwhile, the rapid expansion of non-dispatchable DERs, particularly photovoltaics (PVs), has introduced a trade-off between cost-effectiveness and system resiliency. To address this challenge, several studies have examined the integration of PVs with energy storage systems, leveraging them as dispatchable energy sources for resiliency enhancement [48]. For instance, the work in [68] focuses on optimally sizing battery energy storage systems (BESSs) within a distribution network to enhance resiliency against earthquakes. Similarly, [69] proposes a multi-objective model for the sizing and placement of BESSs and PVs to strengthen power system resiliency. Reference [70] demonstrates that if the resiliency benefits of PV-battery systems are properly valued, the investment in storage solutions can be financially justified.

Recent advances in learning-based methods for distribution-system resiliency

Recent years have witnessed a surge of data-driven techniques applied to power distribution systems, particularly in the context of outage prediction, restoration, and resiliency planning. Building on advances in computational intelligence, researchers are leveraging modern learning frameworks and large-scale models to tackle challenges ranging from localized risk assessment to system-wide restoration and decision support. The following subsections highlight three key directions shaping this landscape.

What's new in ML-based outage prediction

When it comes to machine learning (ML) and artificial intelligence (AI), it is seen that the literature has shifted from static classifiers toward spatiotemporal [71], graph-aware, and uncertainty-aware learning for both occurrence and duration of outages [72]. For instance, hurricane and storm-driven risk modeling now uses multi-modal data, including weather reanalysis, vegetation, soil moisture, asset topology, advanced metering infrastructure (AMI), and outage management system (OMS) records. This modeling is accomplished using gradient boosting, CNN/LSTM/Transformer hybrids, and graph neural networks (GNNs). The aforesaid models improve localized risk mapping, daily incident forecasts, and restoration time estimates, enabling proactive staging of mobile crews, Power Repair Materials (PRMs), and switching plans. Representative examples include spatiotemporal ML reviews and utilities' large real-world datasets for outage occurrence and duration prediction [73]. Moreover, this trend includes GNNs for operational risk forecasting, and conformal prediction to quantify uncertainty for decision-makers [74]. On the events-of-interest side, newer studies tackle extremes (long-tail outages) with tailored loss functions and data-rebalancing strategies, while others fuse hydrometeorological precursors like flood risk with power interruptions via multi-task Transformers that jointly predict substation flooding and outage hazards. These directions are especially relevant to resilience planning under compound hazards [75]. On the other hand, public benchmarks, such as PowerGraph, are emerging to study cascading failures and graph learning at scale, supporting reproducibility and transfer learning across networks. As utilities open de-identified outage/AMI feeds, sharper generalization and more robust uncertainty quantification are expected [76].

RL for service restoration in distribution systems

RL has progressed from single-agent heuristics to graph-based and multi-agent controllers that co-optimize switching, DER dispatch, and load reconnection under topology changes and rather long-term horizons [77]. Indeed, graph-based RL explicitly models the power grid as nodes/edges, capturing network-wide interdependencies during fault isolation and service restoration. Concurrently, multi-agent RL learns policies that outperform handcrafted rules by effectively coordinating the actions of sectionalizers, tie-switches, and DERs within large search spaces. Recent studies emphasize safe RL, constraint handling, and operator-aligned reward shaping along with open benchmarks to accelerate sim-to-real maturation [78].

Large-scale AI models (Foundation models & LLMs)

The emergence of foundation models, including Large Language Models (LLMs) and large graph/vision-time models, is creating new opportunities in specialized fields like power systems. These models are notable for their advanced capabilities in generalization, transfer learning, and few-shot adaptation, which allows them to solve novel problems with minimal training data. In power systems, early examples show LLMs acting as planning or dispatch copilots; graph-pretrained backbones improve grid-state inference and fault prediction. For distribution resiliency, these models can be utilized to: (1) unify multi-modal data such as text work orders, sensor streams, and geospatial layers for richer situational awareness; (2) provide code and plan-generation for switching sequences with human-in-the-loop validation; and (3) support rapid scenario synthesis such as storm "what-ifs" and PRM placement sensitivity. The initial results from a domain-tuned LLM for dispatch and generalizable GNNs suggest tangible promise, paired with utility reports discussing opportunities/risks like latency and data governance [79].

Research gaps and opportunities

As it is seen, extensive research has been carried out on power system resiliency, leading to a rich and diverse body of literature. These contributions have greatly advanced our understanding of how to model, assess, and enhance the resilience of modern power networks. Nevertheless, despite these valuable efforts, certain research gaps remain unaddressed. In the following two subsections, some of these open areas that require further investigation are outlined.

Research gaps in traditional approaches to distribution-system resiliency

Reference [8] formulates the problem as MILP without considering the radiality constraints. Likewise, the methods suggested in [80–82] are demonstrated on an already radial feeder and radiality constraints are not explicitly enforced. The authors in [53] do not consider the option of topological reconfiguration in their proposed robust optimization. The contingency set in [51] contains only single branch outages. Reference [83] does not address the connectivity constraint of the microgrids. The significant number of dummy binary variables used in [84] to address the issue of subgraph connectivity will considerably increase the computational complexity. The formulations proposed in [6, 31, 69] are non-linear and cannot be easily embedded in other operational and planning optimization models. As a result of ignoring voltage and reactive power in DC power flow, the final solutions in [14, 85–87] have to be re-checked for AC feasibility. The techniques proposed in [39] are limited to the transmission level. Neither [43] nor [66] account for renewable energy sources (e.g., PVs). They consider only fuel-based (dispatchable) DGs, which are easier to subjugate due to their lack of intermittency. Likewise, the two-stage stochastic MILP models developed in [10, 45] do not consider renewable energy sources or batteries scheduling. Authors in [15] are considering lead acid batteries, which might be phased out by Li-ion and/or other advanced batteries for PV applications. Another shortage in the literature is disregarding the requirement of grid-forming generators in viable microgrids. According to IEEE Std. 1547.4–2011.4, an island must have at least one unit responsible for generating reference voltage and frequency during a system disturbance or have black-start capabilities [38, 88]. The approach presented in [35] quantifies a distribution system's resiliency without detailed modeling of the striking event and the DERs/microgrids and lacks the consideration of reactive power and voltage constraints. Authors in [19, 89] adopt heuristic methods, which involve searching algorithms that are analytically inexpressible, require the fine-tuning of several parameters, and do not guarantee to find a globally optimal solution [58]. Although desirable, optimization-based formulations such as those given in [13, 90], and [91] are not sufficiently simple and computationally scalable. Similarly, the scale of the formulation models proposed in [8, 57, 67] grows quadratically as the system size increases. Monte-Carlo methods, such as [21, 62], are computationally burdensome as they need to deal with large simulation samples. The metrics used in [90, 92, 93] are difficult to interpret. Some important resiliency improving measures, such as the installation of line switches and DGs, are missing in [13]. Reference [94] studies the impact of DERs on power system resiliency without determining the proper size and site of the DERs. Some previous studies even assumed the same size for all DGs [10, 53], which is not necessarily optimal. Robust and worst-case optimization approaches, such as those in [13, 19], and [53], often result in overly conservative solutions. Moreover, as noted in [29], it can be argued whether robustness is able to adequately capture resiliency. Reference [41] suffers from the restrictive condition that each microgrid is assigned exactly one DER. This imposed condition is also present in [12, 41, 55]. In such a case, the number of islands is predetermined, resulting in suboptimal solutions. In [38], the grid-forming generators are pre-positioned. In [12, 41], the DERs are pre-assigned to the microgrids. In [8, 12, 57, 95], the number of islands is predetermined. It is also assumed in [8] that the post-disaster topology is known, while it is not in reality. Reference [96] does not address how the post-disaster microgrids are formed. Furthermore, it is missing in [10, 13, 21, 42, 66] how the slack bus of each island is determined. Reference [1] considers DERs as generic and did not clarify how the type of each DG is determined in the power flow calculations.

Another shortcoming seen in prior studies is the quantitative resiliency metrics they adopted. These metrics are heterogeneous and are assumed to be interchangeable with conventional reliability indices. For example, [97] adopt SAIDI and SAIFI for assessing resiliency. Firstly, the computation of reliability indices requires a considerable amount of insight into the system under study. Secondly, the interchangeability and potential correlation between resiliency and reliability (as well as security and robustness) has not been fully investigated and validated yet. So, the literature is still suffering from the lack of a well-established and unanimously agreed-upon resiliency metric [21]. Table 1 lists some of the indices utilized in the literature to represent system resiliency. Further details can be found in [27].

Table 1 Some of commonly used resiliency indices

Reference	Objective (resiliency index)
[97]	SAIDI & SAIFI
[98]	Fiedler value
[45, 53, 99–102]	Load shedding cost
[59, 103]	Expected energy not supplied
[104–107]	Uninterrupted load

Additional critical gaps seen in the existing literature on power system resiliency can be outlined as follows. Many prior studies, such as [30, 108–113], have primarily concentrated on investigating and modeling the type and nature of extreme events affecting power grids. These works aim to model HILP events and assess the extent and likelihood of the associated damage. However, their approach has limitations. First, extreme events, particularly those influenced by climate change, are often recent and unprecedented, leaving us with a limited historical dataset for accurate prediction and management. Second, resiliency frameworks that focus on specific types of extreme events (e.g., [114]) are not universally applicable to all potential threats [115], as they view the problem from the perspective of the event (the attacker). It is notable that a system that is resilient against certain types of events may be vulnerable to other types of events [35].

An alternative and complementary approach involves prioritizing the perspective of the power network (the defender). Unlike information about extreme events, which is frequently scarce or uncertain, data about the power network itself is abundant and can serve as a foundation for developing a more versatile and resilient strategy.

Identifying the duration of outage events in distribution networks can be further investigated. Reference [116] attempts to address this need for transmission networks by modeling outage and restore processes from utility data. Also, the cost/penalty associated with unserved energy (value of lost load) is not well defined and the numbers adopted in the literature vary widely (e.g., from $14 per kWh in [45] to $370.2 per customer per hour in [117]).

Another interesting area of opportunity would be the proposal of indices that not only measure the resiliency and topological flexibility of the current power network but also direct the growth of the system during its construction so that the resiliency constraints are maintained [98, 118].

Research gaps in learning-based approaches to distribution-system resiliency

One significant research gap is the lack of verified safety and robust constraint handling in RL-based restoration. Current RL controllers often optimize for only performance metrics, such as outage duration, without formal guarantees on network limits or operator safety rules. Future work should include explicit safety constraints, runtime shields, and operator-approved switching protocols, together with standardized evaluations that reflect practical limits on crews, switching rates, and communication delays [119]. A second priority is simulation-to-field transfer and human-in-the-loop (HITL) operation. RL and graph-based policies trained in simulators must operate reliably under real conditions with uncertain asset data and variable DER behavior. Techniques such as domain randomization, offline RL on historical outage logs, and interfaces that allow operators to review or override AI-generated plans will be crucial to keep operators in control during abnormal conditions [78]. There is also a need for uncertainty-aware ML focused on extreme events. Outage predictors should expose calibrated uncertainty (prediction intervals, conformal sets) and focus on tail risks (compound heat-wind-flood). Multi-task spatiotemporal models that couple weather impacts, such as flooding of yards/cables, with outage dynamics are promising for staging PRMs and microgrid islands [71]. Another promising direction is foundation and large-scale AI models tailored to power systems. Graph-pretrained neural backbones and domain-specific LLMs could unify diverse data, such as geospatial layers, sensor streams, and work orders, into a common representation. These models could automatically draft switching plans, generate crew instructions, or rapidly synthesize disaster scenarios, provided they incorporate guardrails such as retrieval-augmented generation from approved manuals and transparent reasoning paths [79]. Advancing transparent and causal ML methods is equally critical. Interpretability techniques (i.e., feature attribution or counterfactual reasoning) and causal frameworks that distinguish between weather exposure and network vulnerability can help utility entities prioritize investments. This includes vegetation management, pole replacements, or sectionalizing equipment, and support for explainable siting of portable resources [120]. Robust progress will also depend on data readiness and shared benchmarks. Although initial datasets like PowerGraph have emerged, broader open corpora that combine OMS, AMI, SCADA, and geospatial data, while respecting privacy, are still limited. Standardized metrics and tasks will enable reproducible comparison and accelerate innovation [121]. Finally, multi-objective resilience planning can integrate ML/RL with investment planning (i.e., PRM prepositioning, hardening portfolios) using risk-averse formulations such as CVaR/DRO and closed-loop evaluation where outage forecasts feed restoration policies and feedback improve forecasts.

While LLM has the ability to produce results, even with RAG-based methods, it is imperative to devise fast-validation method. Even though it can produce results in a short period of time (a few seconds to a few minutes), sometimes it is not easy to validate the generated results in such a short period of time.

More agent-based LLM applications can be studied to let multiple LLMs cooperate together, each of which is tuned to focus on a part of the task and utilizes dedicated tools. For example, one agent can be the central routing agent, and one agent can be tuned to call the tool to solve power flow and feed the results back to the central routing agent. Letting LLM solve power flow itself is not reliable at all, but allowing LLM to use a tool that is fully designed, tested and validated by engineers to calculate the power flow can be a reliable way to fully utilize LLM's potential while reducing the risk of hallucination.

More resilient grids with renewables and EVs?

The integration of renewable energy sources, particularly wind and PVs, into power grids has grown significantly over the past few decades. However, their widespread adoption has introduced notable challenges, primarily due to the intermittent nature of these resources and their impact on power system operations. While the literature reflects both skepticism and optimism [122]-[123] regarding renewables, the latter perspective is more widespread. Despite their environmental advantages, renewable energy systems are often more susceptible to extreme weather conditions compared to traditional fossil-based power sources. For instance, offshore wind turbines are particularly prone to damage from hurricanes and high wind speeds [124].

According to [125], as the penetration of variable renewable energy sources exceeds 30%, grid integration challenges become more significant due to their intermittent nature. However, recent studies suggest that, when properly integrated, higher levels of weather-dependent distributed energy resources (DERs) can actually enhance grid resiliency by reducing the severity of blackouts and vulnerability to extreme weather events [126]. Diversifying DERs further helps mitigate these exposure-related challenges. Additional solutions proposed in the literature include: 1) significant expansion of fast-responsive energy storage capacity, a strategy also highlighted in [127]; 2) increased transmission infrastructure to import power from regions with renewable-dominated resource mixes; and 3) demand-response resources, such as EVs, which adjust electricity consumption patterns based on renewable energy availability [124].

The National Renewable Energy Laboratory (NREL) has successfully demonstrated that an entire campus can be powered exclusively by renewable energy sources, including wind, solar, and battery storage. As noted in [128], this concept has the potential to be scaled up for achieving 100% renewable energy operations at the level of statewide or regional power grids. Moreover, NREL has illustrated how these renewable systems can recover from blackout conditions through the use of grid-forming inverters.

A rather cautious attitude is seen in the literature when it comes to the impacts of EVs on a power grid's resiliency [129]. EVs, as mobile energy storage units, can help improve power system resiliency if integrated and managed properly. Otherwise, a large fleet of EVs would hit the grid for charging should the HILP event involve an evacuation.

Conclusions

This paper reviewed the resiliency of electric power distribution networks, identifying them as the most vulnerable sector of a power grid. Most large-scale outages are caused by weather-related extreme events, particularly wind-induced hazards, underscoring the need for enhanced resiliency measures. Currently, the major research gap is the lack of a well-agreed-upon metric for measuring a power grid's resiliency, and conventional reliability indices are inadequate for this purpose. At the same time, the extent of resiliency must be transparent and measurable, as achieving a fully resilient power grid is neither economically feasible nor technically practical.

Although various approaches, including grid hardening, network reconfiguration, microgrid formation, and DER integration, have been explored, their effectiveness remains case-dependent. Additionally, the high penetration of renewable energy sources and EVs presents both opportunities and challenges for power system resiliency.

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Authors' contributions

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

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