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Review

Power Grid Infrastructural Resilience against Extreme Events

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Abstract: Extreme weather events are one of the main causes of large-scale power outages in distribution systems. The changing climate has led to an increase in the frequency and severity of these events, which, if not mitigated, are expected to lead to more instances of widespread outages and the severe societal and economic damages that ensue. Protecting the power grid against such events, which are high impact yet low frequency, requires a paradigm shift in grid design practices. In recent years, many researchers have focused on the resilience of the power grid against extreme weather events by proposing various grid hardening and/or redundancy solutions. The goal of this paper is to provide a survey of the literature related to the infrastructural resilience of the power grid against extreme events. Currently, no standard definitions or metrics exist for power grid resilience, and researchers adopt various models for quantifying and assessing it. Hence, a review of the most commonly used definitions and metrics for resilience is provided first, with a discussion of their advantages and disadvantages. Next, the paper presents an extensive and critical review of the solution methodologies proposed in the literature for improving the infrastructural resilience of the power grid. The shortcomings of the current solution methods and gaps in research are identified, followed by a discussion of the future directions in research.

Keywords: extreme weather; infrastructural resilience; natural disaster; power grid hardening; power grid resilience; grid reinforcement; resilience metrics

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1. Introduction

The increase in power outages associated with adverse weather events in the United States has had significant economic ramifications. Climate change has exacerbated the occurrence of extreme weather events such as hurricanes, heat waves, wildfires, and snowstorms. This, combined with increased power demands, is now regularly causing billions of dollars' worth of damage due to resultant power grid disruption. Between 2003 and 2012, 679 power outages were caused, which affected at least 50,000 customers, and up to 90% of these failures are attributed to disruptions in the distribution systems [1]. Some of the more prominent occurrences in recent memory include Hurricane Sandy in 2012, which left 8.5 million people without power [1]; the 2021 Texas winter storm, which affected a million residents [2,3]; and the 2017 Hurricane Irma in Puerto Rico, which affected power distribution to 6.7 million customers [4]. The economic costs associated with these disasters run into the hundreds of billions and, at the same time, lead to significant societal damage. For instance, the Texas winter storm resulted in multiple deaths because electric heaters and medical equipment could not run without power, leaving vulnerable people exposed to extreme cold and/or without critical life support [2,3]. One reason why power systems are particularly vulnerable to extreme weather events is that they are mainly designed and optimized for normal weather conditions and are not equipped to handle less common extreme weather events. While this is economically viable in the short term, it exposes the power grid to catastrophic failures that are costlier in the long run. Another essential dynamic to consider is that disasters that lead to shocks and stresses are often connected, making the risk two-fold. As such, the risk is multidimensional and self-perpetuating. For example, higher temperatures due to climate change result in higher power demands, therefore increasing the load on the power system. At the same time, there is a higher risk of adverse weather events, which means that when disaster strikes, it finds an already compromised power grid that is easier to knock down. It is, therefore, paramount that utility companies strengthen their systems' readiness for extreme events. During the past decade, there has been much focus in the literature on the resilience of the electric power grid against large-scale disturbances, mainly natural disasters. Figure 1 illustrates a keyword co-occurrence map of the recent publications on power grid resilience.

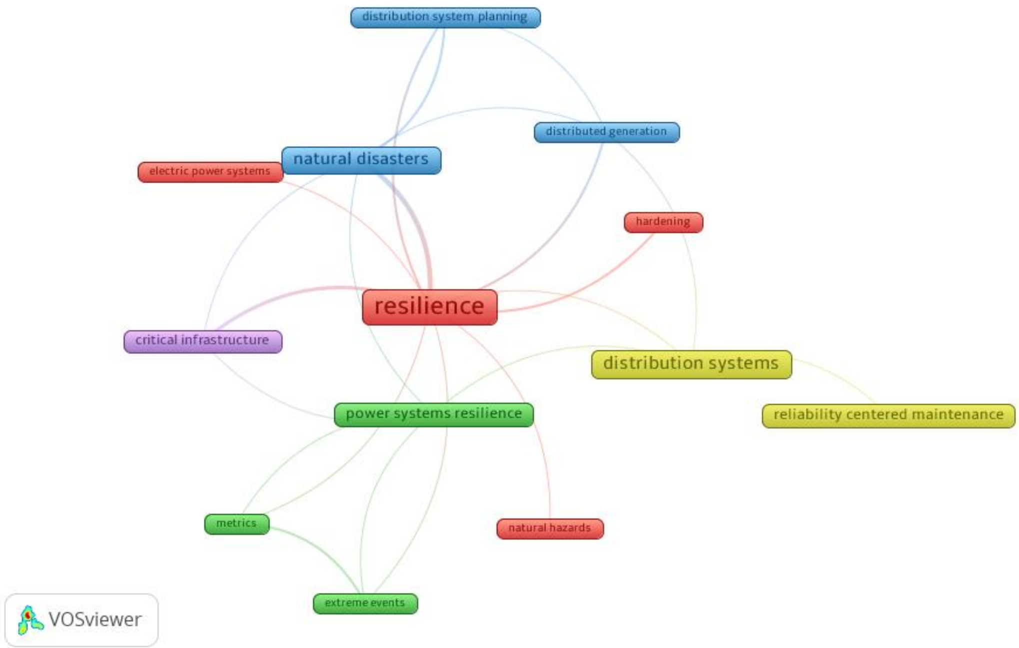

Figure 1. Keyword co-occurrence clustering view, made with VOS viewer, for references used in this paper related to power grid resilience.

Although more attention has been given recently to making the grid more resilient, a standard definition for power system resilience does not exist in the literature, and while different researchers are generally converging to the same sets of criteria, various definitions are being presented and adopted. A common theme for a resilient power system is one that has the capacity to withstand disturbances and continue to deliver energy to customers [5]. Some have further specified that resilience is defined against extraordinary events, referred to as high impact low frequency (HILP) events [6,7]. Many studies in literature specifically focus on the resilience of the power distribution grid [8–17] as it is more closely related to customers. For this, most use the definition from the US Federal Energy Regulatory Commission (FERC) [18], in which resilience is defined 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". Here, being able to withstand an event is further broken down into the ability to absorb its impacts and adapt to the changes caused by it. Moreover, the ability to anticipate the event is considered as yet another dimension of resilience. The definition by CIGRE working group C4.47 introduces additional dimensions listed as anticipation, preparation, absorption, sustainment of critically operated systems, swift recovery, adaptation, and implementation of the learned lessons from previous events [19]. In a more general context, the National Infrastructure Advisory Council (NIAC) [13] has listed four attributes of a resilient system, which are robustness, resourcefulness, rapidity, and adaptability: Robustness is the capacity of the system to withstand the impacts of an event without suffering severe performance deterioration or loss. Resourcefulness is the ability to initiate a solution by mobilizing resources such as information, capital, technology, and manpower. Rapidity is the ability to restore functionality and mitigate losses quickly. Finally, adaptability is the capability to learn new information from a HILP event and dispatch new solutions to increase the dimensions of robustness, resourcefulness, and recovery before the next event.

Strategies to improve resilience can be divided based on the timeline of the HILP event as *preventive measures*, which are adopted before the onset of the event; *corrective measures*, implemented during the course of the event; and *restorative measures*, which are employed after the event has run its course. Although these are decoupled from one another based on the timeline of their deployment, they can still impact the success rate of their counterparts. For instance, grid-hardening techniques that are normally implemented long before the onset of an event can lead to higher chances of success for a risk-based grid dispatch as the event is unfolding. Depending on the type and characteristics of the HILP event, some of these mitigation measures may be prioritized over others. For instance, solutions against short-duration events such as earthquakes are mainly focused on prevention and restoration, whereas for events that run a longer course, e.g., most weather-induced natural disasters, all mitigation aspects are considered. Figure 2 illustrates some of the general resilience solutions that can be applied in power systems.

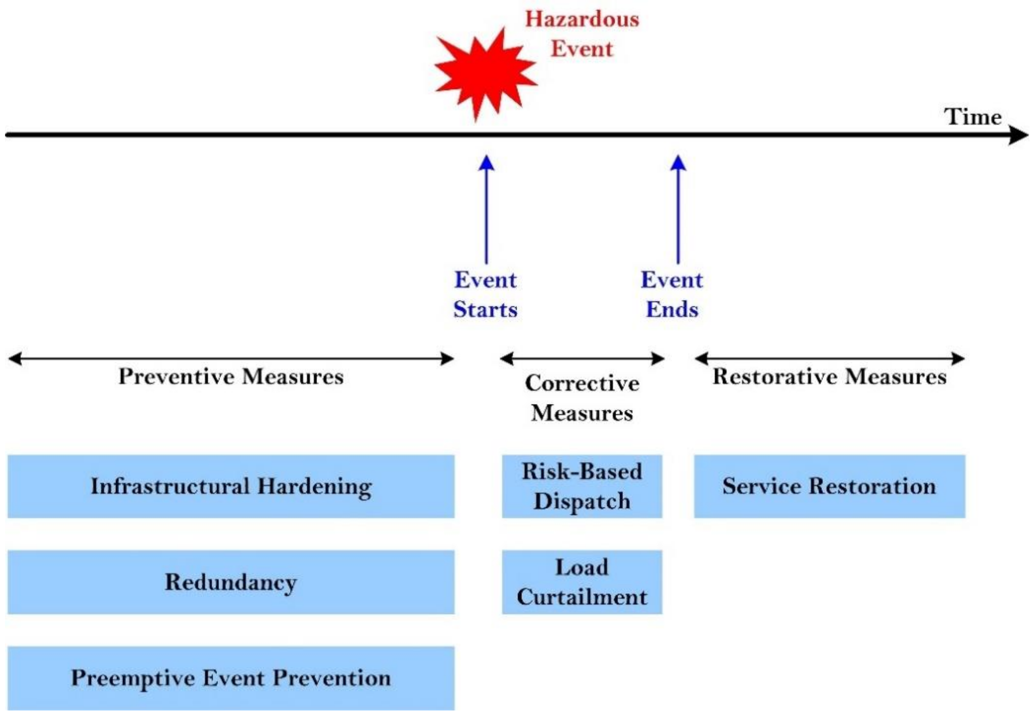

Figure 2. Overview of strategies for power grid resilience.

Before the onset of an upcoming HILP event, resilience can be achieved by hardening the infrastructure, e.g., using stronger overhead line poles/towers or reinforcing them by installing guy wires, elevating substations in flood zones, waterproofing control rooms, or replacing overhead conductors with underground cables. Pre-emptive strategies can also be adopted by reducing the chances of disturbances and/or outages, for instance by increasing the distances between phase conductors to reduce the chances of flashover due to conductor slapping or vegetation management to prevent line contract with tree branches. Lastly, redundant designs can be employed to increase the resilience of the power grid. Some examples could be installing multiple circuits in parallel, using main and backup transformer units, or expanding the generation reserve capacity of the system by deploying additional centralized or distributed energy resources. These solutions are naturally costly and take place over a longer horizon.

During the course of the event, however, the focus must be shifted to adaptive operation. The availability of lines, transformers, and/or generation resources may be impacted by the event, in which case, energy dispatch needs to adjust by supplying power via more reliable resources and/or routing power through more secure lines and substations. Load curtailment, either voluntary in the form of demand response or involuntary in the form of load shedding, may also be adopted to ensure the stability of the power system. Due to the possible uncertainties associated with the nature of most HILP events, i.e., their intensity, scope, or trajectory, the corrective energy dispatch must be risk-based in order to protect the grid against all likely scenarios. Finally, during the restoration phase, it is assumed that the event has ended and, as such, the focus is on using alternate energy sources and alternate routes to provide power to the outage area, i.e., healthy parts of the grid that are left de-energized due to the event. Various network reconfiguration strategies may be used here to allow for higher connectivity.

The focus of the present survey is on infrastructural resilience strategies, which are associated with the physical toughness of a network and its capacity to sustain a HILP event. Such strategies are cost-intensive and as such, must be implemented in an optimal fashion, i.e., minimum cost and maximum return on investment. Although many utilities may follow rules of thumb for grid reinforcement strategies, a more systematic way would be to develop mathematical optimization models to maximize grid resilience subject to various technical and budgetary constraints. Naturally, to assess the resilience of the power grid against HILP events, proper metrics need to be developed and adopted that can truly represent the various dimensions of resilience as discussed above. The rest of this paper is organized as follows. Section 2 provides a review of the various metrics that are used in the literature to quantify power grid resilience. Section 3 presents a survey of various solution techniques adopted to improve the infrastructural resilience of the power grid. A discussion of the shortcomings of the current approaches and future research directions is provided in Section 4. Finally, concluding remarks appear in Section 5 of the paper.

2. Resilience Metrics

Resilience metrics, also known as resilience indices or indicators, are a means for evaluating the level with which a power system can withstand a HILP event. The concept of resilience is complex and dynamic. Traditional reliability metrics such as the System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), Customer Average Interruption Duration Index (CAIDI), and other related indicators cannot be used here due to their inability to model catastrophic HILP events. In general, resilience metrics can be categorized into three groups: attribute-based, performance-based, and general. A breakdown of these groups can be seen in Figure 3.

Selecting the appropriate metric entails balancing trade-offs some of which are outlined in [20]. For instance, more complex metrics may need a larger quantity of data and higher technical expertise to be integrated into the model. On the other hand, less complex metrics need less data and are easier to develop and integrate; however, may be less effective in providing a true representation of the system's resilience. In addition, metrics can be *retrospective*, assessing the system's performance during past events, or *prospective*, predicting the system's resilience against impending or anticipated shocks. It is the responsibility of the analyst to prioritize trade-offs based on the objectives of the study and the availability of resources (data and expertise).

2.1. Attribute-Based Metrics

Attribute-based resilience metrics focus on characteristics of a system that contribute to its resilience. These are specific to system resources and reflect the state of the network. Some examples are the availability of transmission and distribution lines, availability of generators, network redundancy level, and/or availability of replacement components. Deriving such metrics requires a review of the system's behavior to identify the degree of the attributes present within it [20]. This is typically done through site visits, surveys, and follow-up qualitative assessments.

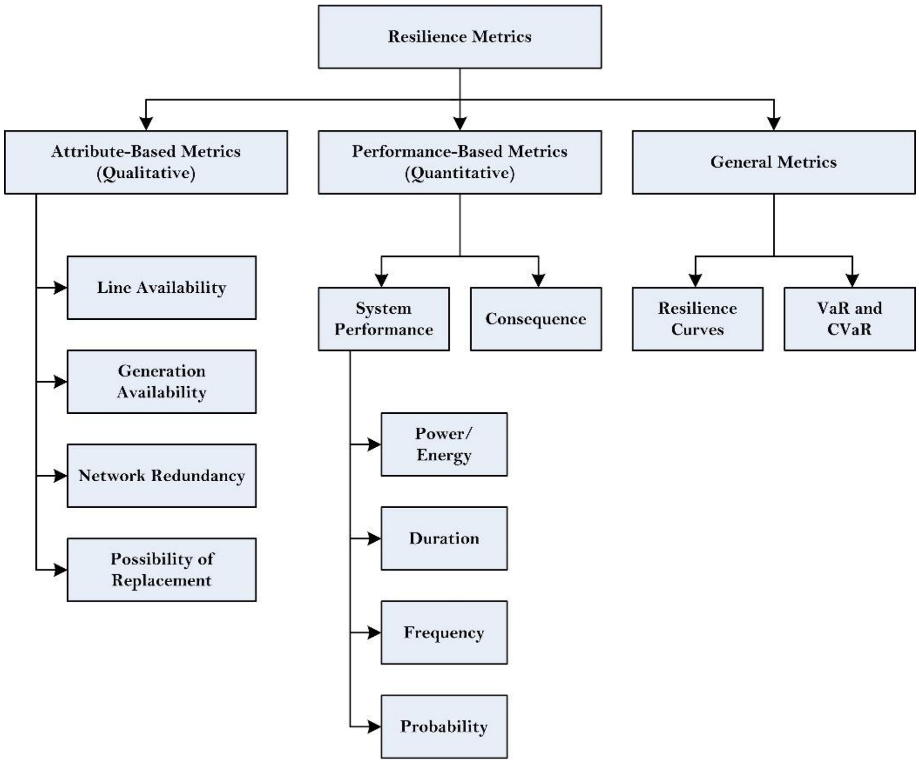

Figure 3. Classification of resilience metrics.

2.2. Performance-Based Metrics

Performance-based measurements, on the other hand, are obtained from quantitative information specifying the system's response to an event. These metrics can be used to assess the effectiveness of various reinforcement strategies implemented in the system [20]. System performance can be obtained from historical data during a specific period of study or by using a forecasting method such as Monte Carlo simulation. There are two subcategories of performance-based metrics: system performance and consequence [20,21].

System performance metrics, as the name suggests, model the performance of the power system in response to the HILP event and consider factors such as duration, frequency, or probability of interruption, the characteristics of load and generation, as well as how those characteristics develop over time. These metrics can be further divided as follows [21]:

- **Power/Energy**: indicates whether the load is supplied through the available generation capability.
- **Duration:** specifies time periods associated with loss of load, load reduction, load recovery, etc.
- **Frequency:** indicates the frequency or number of various catastrophic events impacting the system.
- **Probability:** determines the probabilities associated with various aspects of a HILP event's impact on a power system.

Consequence metrics, on the other hand, focus on the impacts of power outages on the end users and can be quantified in terms of financial impacts, social impacts, and security issues. They may also be associated with organizational or community resilience [21]. The cost measures related to load and generation loss belong to this metric.

Both attribute-based and performance-based metrics can be retrospective or prospective, depending on the approach. In general, the main difference between these metrics lies in their complexity and consistency. Attribute-based metrics are easier to model as they rely on qualitative or semi-quantitative expert knowledge and analysis. However, their heuristic nature can negatively affect their consistency or objectivity. Another disadvantage of attribute-based metrics is that they cannot assess the benefits gained from potential resilience improvements and the effectiveness of investments. Therefore, they are not as informative as performance-based metrics for grid resilience planning and investment strategies [20].

On the other hand, performance-based metrics can be very complex and normally have significant data requirements. This is because they must model the various stages of operation, disruption, and recovery, making them resource intensive. However, they can be more informative than attribute-based metrics: not only can they be used to assess the resilience of the system to past events, but they can also simulate how the system may be affected by potential future events. Moreover, these metrics tend to rely less on subjective or qualitative assessments, thus offering higher consistency and objectivity. As a result, performance-based metrics are receiving increasing attention in resilience planning and investment studies.

Table 1 lists some of the most notable attribute-based and performance-based metrics used in the literature.

Table 1. Most common attribute-based and performance-based metrics used in the literature. The following abbreviations are used in the table: Customer Average Interruption Duration Index (CAIDI), System Interruption per customer (DIC), Energy Not Served (ENS), Expected Energy Not Supplied (EENS), Load shedding (LS), Risk Achievement Worth (RAW), System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Total Weighted Load Shedding (TWLS), Value of Lost Load (VOLL).

Attribute-based	Resources	Infrastructure	Transmission Lines Available and Online [22]
Performance-based	Performance	Power	ENS [23–25], VOLL [23], LS [26–32], TWLS [32], RAW [13], Power delivered [13,15]
		Duration	Restoration Time [33], SAIDI [24,25], CAIDI [34]
		Frequency	Frequency of service disconnection [35], SAIFI [24,25], DIC [35]
		Probability	Probability of supply interruptions, probability of power not delivered [13], EENS [14,25]
	Consequence	Economic	ENS cost [27], load shedding cost [9], customer outage cost [23,33], VOLL cost [34]

2.3. General Metrics

In addition to the attribute-based and performance-based metrics discussed above, general metrics may also be adopted to reflect various aspects of performance, functionality, and/or impacts. For example, a resilience curve (see Figure 4) or a more advanced trapezoidal resilience curve (see Figure 5) can be used as a general metric because they both explain various aspects of performance or consequence. Of course, these metrics can be converted into more specific performance or consequence indicators, for instance by calculating various areas or distances indicated on the curve. Alternatively, they can be used to relate various probability measures to different system attributes. The second group of methods are referred to as the Value at Risk (VaR) and Conditional Value at Risk (CVaR).

2.3.1. Resilience Curve

Resilience curves demonstrate the multidimensionality and temporal evolution of resilience. As shown in Figure 4, the resilience triangle is one of the most commonly used resilience curves in the literature [22]. First conceived as a measure for assessing resilience against earthquakes, it depicts the evolution of system quality over time. The quality indicator can be based on any of the attributed-based or performance-based metrics previously discussed, e.g., energy or power supplied, number of customers supplied, number of available transmission or distribution lines, etc. Despite being easy to interpret, such graphs cannot capture all the various resilience dimensions that might be experienced by typical power systems, such as how quickly the system degrades once the event starts, or the various degraded states that the system may experience [22].

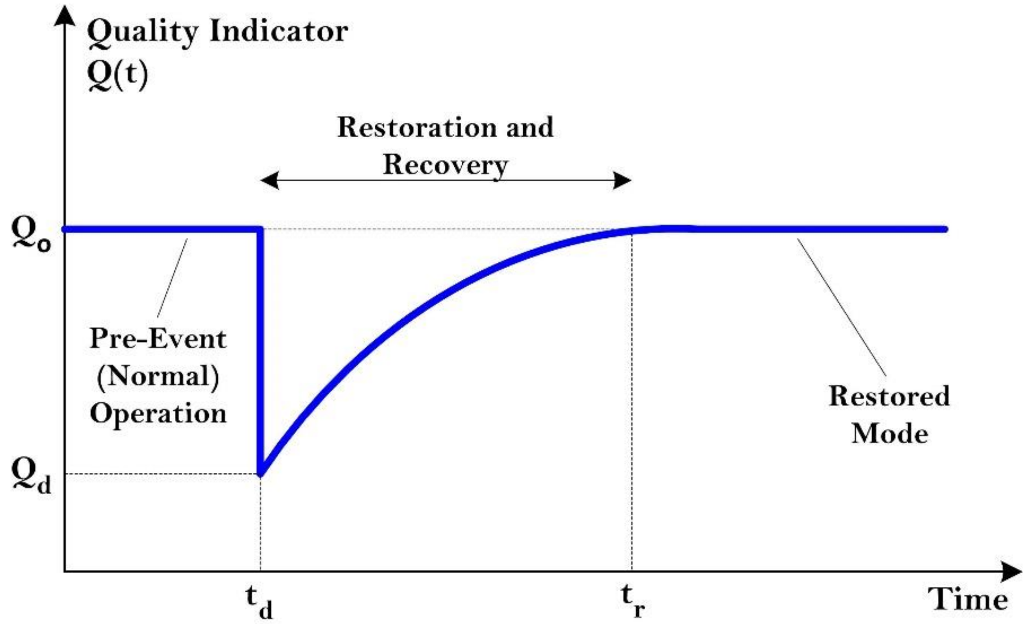

Figure 4. Resilience Tringle Curve, adapted from [22]. System degradation occurs at time t_d and service is restored at t_r. Area under the curve indicates the loss in the quality indicator Q.

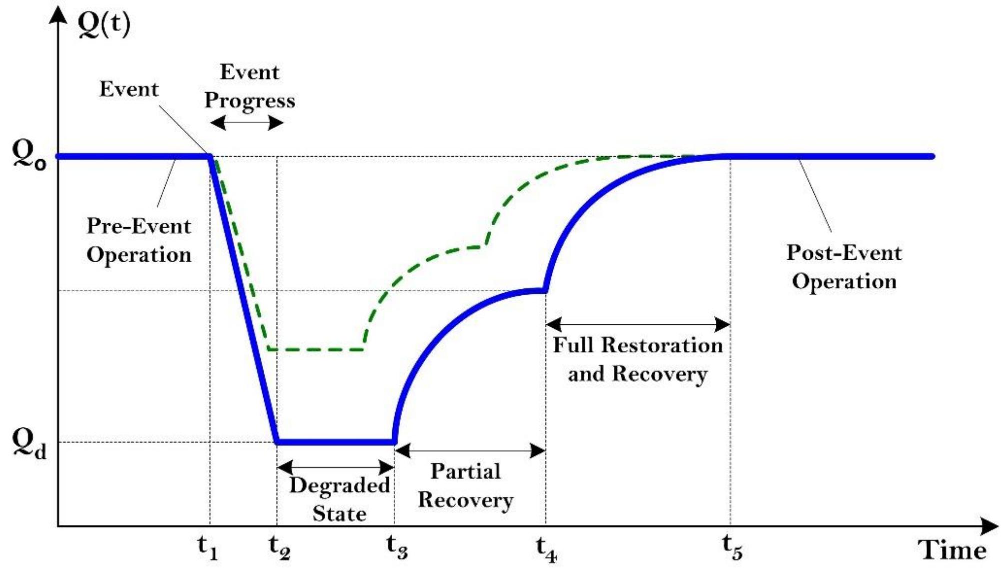

Figure 5. Trapezoid Resilience Curve, base case (blue solid line), and improved case (green dashed line), adapted from [22,36].

A modified version of this curve, known as the trapezoidal resilience curve, offers a more comprehensive model. This curve can be broken down into five stages of normal operation, event progress, degraded state, partial response and recovery, and full infrastructure recovery (see Figure 5). A framework was proposed in [22] to provide a more quantitative characterization of resilience (see Table 2). These measures allow for quantitative comparison of various resilience strategies or systems, for instance, system preparation by adjusting the quality level before the onset of an event, the rate of quality degradation, the lowest quality level obtained during or following an event, or the amount of time spent at the lowest quality level before restoration process starts, to name a few.

Table 2. Quantifying resilience based on the trapezoidal resilience curve [22].

Resilience Measurement	Mathematical Calculation
How fast does the resilience drop?	$\frac{Q_0 - Q_d}{t_2 - t_1}$
How low does the resilience drop?	$Q_0 - Q_d$
How profound is the post-disturbance degraded state?	$t_3 - t_2$
How swiftly does the system recover?	$\frac{Q_0 - Q_d}{t_4 - t_3}$

2.3.2. Risk-Based Metrics

As mentioned before, performance-based metrics can be defined using probability distributions, for instance, the expected value of lost energy during an event. This method can be used when the system's resilience is evaluated over a long period of time or for many potential scenarios. However, the probability distribution functions characterizing power outages during HILP events are heavy-tailed [37]. This may negatively impact the effectiveness of metrics based on expected values, medians, or standard deviations, in that such values might underestimate the risk of the extreme event. To address this, other risk-based metrics are defined in the literature [37], namely Value at Risk (VaR), which indicates the upper quantile of potential losses and informs about the percentage of losses that are greater than this threshold, and Conditional Value at Risk (CVaR), which measures the expected value of losses that fall above the VaR (see Figure 6).

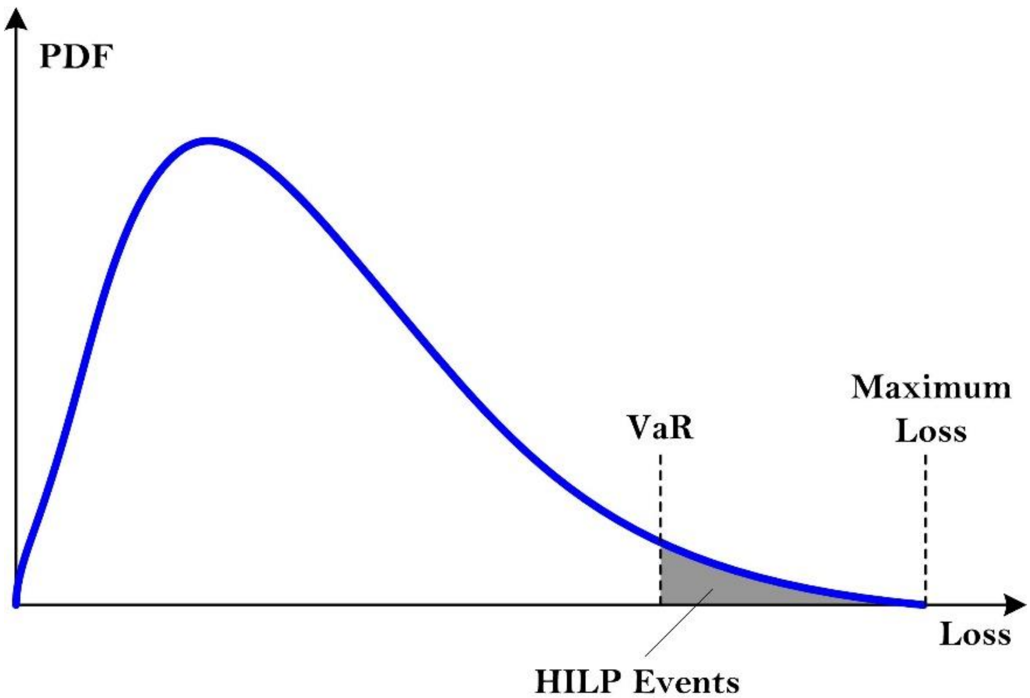

Figure 6. VaR and CVaR evaluation for a heavy-tailed probability density function.

3. Infrastructural Resilience

Various strategies exist that can improve the infrastructural resilience of the power system against HILP events. Most of these techniques focus on either reinforcement of grid components or creating redundancy in design. In this section, a general discussion of resilience strategies is first presented, followed by an in-depth analysis of mathematical approaches and methodologies reported in the literature.

3.1. General Solutions

3.1.1. Reinforcing Overhead Line Structures

The majority of power transmission and distribution networks are supported by overhead lines, mainly due to their lower costs compared to underground cables. In order to ensure safe and secure operation and avoid potential flashovers, sufficient safety clearances must be maintained between a conductor and other structures such as other conductors, the tower, nearby equipment, or trees and vegetation nearby. Safety clearances are standardized based on system voltage levels but must also take into account environmental factors such as average wind speeds in the region or extreme ambient temperatures. Extreme weather events can increase the chances of flashovers, e.g., contact between phase conductors (slapping) due to high winds, or excessive conductor sag due to extreme ambient temperatures (or conversely, due to excessive icing load). In addition, overhead towers and poles are vulnerable to extreme weather events such as high winds of tornadoes and hurricanes or excessive icing load during winter storms.

Overhead line structures can be reinforced in a variety of ways, for instance, by upgrading wooden poles to metal lattices, using stronger materials for the towers, increasing the safety clearances between conductors and grounded objects or other conductors, or using guy wires to provide extra support against high winds. Of course, the typical lengths of overhead lines will significantly add to the costs. Hence, such approaches can be implemented for sections of the circuit that are more at risk.

3.1.2. Vegetation Management

Vegetation growth near overhead structures can cause several issues. Tree branches can grow close to the line, causing a flashover, or strong winds can result in branches swaying close to the conductor or snapping and falling on it. In fact, broken tree branches falling on overhead lines are believed to be the primary reason for distribution network power outages during storms in the United States [38]. To avoid these problems, many utilities perform regular vegetation management to maintain a restricted vegetation area near those structures. These practices are governed by certain standards and legislation [38,39].

3.1.3. Underground Cabling

An alternative to the reinforcement of overhead structures is to replace them with underground cables. These cables are protected against most weather events, and hence, are less likely to be affected by environmental factors. Constructing an underground cable, however, can be significantly more expensive than installing an overhead line, depending in part, on the voltage level and environmental factors [40]. In addition, locating a fault in an underground cable is more challenging and time-consuming, which can increase the cost of maintenance. Hence, any cabling project must carefully weigh the costs and benefits. In fact, it is believed that selective undergrounding, as opposed to a complete replacement, may provide the optimum return on investment. It should also be pointed out that underground cables are more susceptible to surge flooding, which frequently occurs following hurricanes [40].

3.1.4. Hardening Substations

Substations house transformers, breakers, disconnect switches, busbars, and sometimes control and protection assets. Failure of a substation due to an extreme event may, under certain circumstances, force all connecting lines to go out of service, leading to a major outage. Substations, such as overhead lines, are exposed to all environmental events, and air-insulated substations are particularly susceptible to storms and debris. Substations also face a significant threat from flooding, especially in coastal areas where storm surges, tropical precipitation, or tsunamis are more likely to occur. Improved flood monitoring is one way to protect substations, since it allows the system operator to de-energize the system before it gets damaged or loses control. Elevating substations and utilizing modular, enclosed components is another option that may be economically feasible, particularly at distribution voltage levels [41]. The cost–benefit may not justify the transformation at the transmission level due to having significantly higher safety clearances, which may require raising the substation to a much higher level. Of course, no matter the costs, substation relocation or elevation may still be less expensive than the construction and upkeep of adequate flood protection in the form of berms and dams [41].

3.1.5. Network Redundancy

Adding redundancy to the power network can also increase its resilience. This includes building additional (perhaps parallel) transmission and distribution lines and increasing their capacity to be able to handle higher loads if other parts of the network fail. In addition, providing alternate routes with network reconfiguration means can allow for the bypassing of damaged lines, lowering the likelihood of cascading failures.

A summary of the advantages and disadvantages of the general solutions discussed above is presented in Table 3.

Table 3. Comparison of various infrastructure resilience strategies.

Technique	Advantages	Disadvantages
Reinforcing overhead line structures	Improves the line and tower's mechanical integrity during storms and icing loads.	Expensive unless performed targeted
Vegetation management	Reduces the likelihood of flashover or line damage due to contact with vegetation.	Many outages caused by vegetation occur outside the right of way zone, which is not maintained. May have negative environmental impacts.
Underground Cabling	Protects the conductor against many environmental factors	Expensive, both for installation and maintenance. Not suitable for all environments and locations.
Hardening substations	Protects them against environmental events, especially flooding.	Expensive at the transmission level
Network Redundancy	Introduces flexibility and robustness. Increases the success rate of corrective measures.	Expensive

3.2. Situational Awareness

The power grid is a complex collection of sensitive devices and systems such as insulators, towers, conductors, and fittings that are highly interdependent for an interruption-free operation. The failure of just one component might lead to the failure of the entire infrastructure, resulting in a large-scale power outage. Because the power lines run typically through harsh natural environments where they are exposed to the elements, including extreme weather, this is a fairly common occurrence. Further, regional blackouts often cause cascading grid failures in multiple regions, accompanied by secondary disasters such as forest fires that further exacerbate the economic and societal costs [42]. As such, regular power inspection to ensure that each of those units is working optimally is a crucial exercise in ensuring the continuity of the power supply. Ideally, an efficiently running inspection regime is needed in order to pre-emptively and accurately identify components that are in need of maintenance or replacement [43]. When that system works optimally, the likelihood of power line failure is greatly reduced. The problem is that line inspection is plagued with inherent problems, including harsh natural environments, extensive range, and a shortage of components. There are various types of power line inspection. These include traditional techniques such as manual ground surveys and helicopters, both of which are reliant on human visual observation [44]. The drawback of these traditional inspection methods is that they are cumbersome, costly, risky, and have a low-efficiency level [45]. As a result, utility companies have been adopting higher-tech inspection methods that are less prone to human error and physical limitations. One such method is infrared detection technology which enables instant and safe detection of faults without the need for physical human presence or contact [46]. Power distribution companies are leveraging inspection and fault diagnosis artificial intelligence and deep learning [47]. The proliferation of cost-effective Unmanned Aerial Vehicles (UAV) and digital imaging technology also provides an additional technique for them to efficiently diagnose power grid issues [48]. UAV inspection is done in two phases: data collection and data analysis. The UAV is maneuvered over crucial power grid infrastructure to capture images and videos of the different components, which are then sent to workers who are trained to spot various signs of failure or imminent failure. Because of its versatility, low cost, high efficiency, and high security, UAV inspection is increasingly replacing and complementing traditional human inspection methods. When combined with satellite imagery and artificial intelligence, the inspection is a very potent tool for minimizing errors and loopholes that are inherent to traditional power line inspection [49].

3.3. Solution Methodologies

Several optimization models are proposed in the literature for enhancing power grid infrastructural resilience. Resilience may be modeled as an objective function, a constraint, or both. Examples of objective functions can be minimizing load curtailment, minimizing the cost of load loss [50,51], maximizing social welfare [16], or minimizing the expected cost of restoration/operation [15,52]. Including load curtailment as an objective function to be minimized provides more operational flexibility, since it can be used under worst-case scenarios. On the other hand, having an upper bound constraint on the amount of load to be shed can, at times, become problematic, e.g., when physical damage to some lines prevents access to certain load areas. When it comes to resilience metrics (see Section 2), current research has mainly relied on performance-based (quantitative) metrics, although other metrics have also been used, e.g., the trapezoidal resilience curve [16] or the expected CVaR of damage loss, which is modeled in [53] based on the cost of load shedding, the cost of repairing broken lines, fuel costs, and the cost of turning on/off specific generators.

Long-term planning for infrastructural resilience requires modeling uncertain parameters such as event type/location, load profile, weather profile, damage level, or repair duration. As such, the problem is often characterized as robust optimization or two-stage stochastic optimization. In tri-level robust optimization, power system resilience planning may be considered a "defender-attacker-defender (DAD)" strategy [54,55]. Here, the system planner is the defender who chooses the optimum locations for line hardening, tie-switches, distributed energy resources (DER), or mobile energy storage in the first stage. Natural disasters are viewed as attackers that try to maximize load shedding in the second stage. Due to the nature of the model, a worst-case scenario is often considered. After the event occurs, the system operator implements a post-disaster restoration strategy to minimize load shedding as the third stage. Two-stage stochastic optimization, on the other hand, may take into account the cumulative influence of stochastic fault occurrences on the planning choice. In the first stage, decisions regarding line hardening, tie-switch/recloser placement, and siting and sizing of DER units are made, with the goal of reducing planning and operational costs for a variety of (N—k) fault scenarios. In the second stage, available resources (determined in the first stage) are utilized and/or dispatched with the goal of minimizing the load shed or other economic losses. For instance, this approach was adopted in [52]. Different from DAD, this technique considers the impact of every potential scenario rather than just the worst-case.

Decision variables used in the optimization models differ depending on the timeline of analysis. Medium-term approaches may consider installation of DER units or tie-switches/reclosers. In this case, the location of DER/switches and the size of DER would be considered as the main decision variables. Longer-term approaches may consider more expensive options such as the reinforcement of lines, transformers, and the control room, which may include replacing overhead lines with underground cables. In this case, the decision variables could be the choice of elements and components that are candidates for reinforcement. This is best modeled as binary variables assigned to each potential candidate.

The optimization model is always solved subject to a variety of constraints. First and foremost, the budget limitation is a crucial constraint with a significant impact on the outcome of the model. In addition, various operational constraints may need to be taken into account, for instance, power flow constraints, power balance, node voltage and angle limits, and line flow limits. Other constraints may include conditions for binary variables, for instance when a certain number of candidate lines or nodes are identified for line hardening and tie-switch/DER installation, respectively [52,56]. In the most general case, the problem becomes mixed-integer and nonlinear, whose complexity rapidly increases with the size of the model. Hence, many researchers adopt linearization techniques for instance linearized DistFlow models to express active and reactive power balancing equations at each node [15,56]. Maintaining the radiality of the distribution network may be another constraint to be considered [52,57].

Table 4 provides a summary of how the problem is formulated in the literature.

Table 4. Survey of solutions in the literature for infrastructural resilience enhancement. Constraints are listed as (1) budget and investment cost constraint, (2) load shedding amount/cost, (3) repair time/cost, (4) damage status, (5) operation constraints, and (6) other constraints. The following abbreviations are used for the solution methodologies: DAD: defender–attacker–defender, GA: genetic algorithm, MILP: mixed-integer linear programming, OvS: optimization via simulation. SMIP: stochastic mixed-integer programming. Other acronyms used in the table are as follows: DR: damage repair, LOLE: loss of load expectation, LS: load shedding, TWLS: total weighted load shedding.

Study	Decision Variables	Objective Function	Constraints						Formulation	Resilience Criteria	Test System
			1	2	3	4	5	6			
[52]	Line hardening DER placement Adding line switches	Min (Planning cost + Expected operating cost)	✓	✓	✓	✓	✓	✓	SMIP	Cost (LS & DR)	IEEE 34, 123
[15]	Pole hardening DER placement Adding line switches	Min (Planning cost + Expected operating cost)	✓	✓	✓		✓	✓	SMIP	Cost (LS & DR)	IEEE 123 bus
[58]	Adding line switches	Min (LOLE for possible fault scenarios)	✓	✓		✓	✓	✓	SMIP	LOLE	IEEE 31, 94, 123 bus
[57]	DER placement	Min (Planning cost + Expected operation cost for selected scenarios)	✓			✓	✓	✓	SMIP	Cost of Unserved Load	IEEE 33, 123 bus
[16]	Pole hardening DER placement	Min (Social welfare)	✓				✓	✓	GA	Social Welfare	IEEE 33 bus
[9]	Pole replacement Tree trimming	Min (Planning cost + Load shedding under worst case scenarios)	✓	✓	✓	✓	✓		DAD	LS	EPRI 69 bus
[10]	Line hardening Bus hardening DER placement	Min (EENS)	✓			✓	✓	✓	Stochastic Optimization using OvS	CVaR	IEEE 14 bus
[54]	Line hardening	Min (Planning cost+ Load shedding under worst case scenarios)		✓			✓	✓	DAD	Cost of LS	IEEE 3000 bus
[55]	Line hardening DER placement	Min (Planning cost+ Load shedding under worst case scenarios)	✓			✓	✓	✓	DAD	Cost of LS	IEEE 33, 123 bus
[59]	Line hardening DER placement	Min (cost of planning, load shedding, vehicle travel time under worst case scenarios)		✓			✓	✓	DAD	LS	IEEE 33, 123 bus

Table 4. *Cont.*

Study	Decision Variables	Objective Function	Constraints						Formulation	Resilience Criteria	Test System
			1	2	3	4	5	6			
[60]	Line hardening DER placement	Min (cost of planning and annual net operation)	✓				✓	✓	DAD	LS	IEEE 33, 123 bus
[32]	DER placement Gas storage placement	Min (cost of planning + TWLS caused for worst-case scenario)	✓			✓	✓	✓	DAD	TWLS	IEEE 33 bus
[50]	DER placement	Min (Operation cost)		✓		✓	✓		DAD	LS	WSCC 9 bus, IEEE 118 bus
[27]	Vegetation management Pole hardening Pole repair	Min (ENS + planning cost)	✓	✓	✓		✓	✓	GA	ENS	Actual dist. grid
[11]	Substation hardening	Max. difference between cost of damage without and with hardening	✓	✓	✓	✓	✓	✓	Fault tree minimal cut set method	Cost of LS	Actual dist. grid
[56]		Min (ENS for selected scenarios)	✓	✓			✓	✓	SMIP	ENS	123 bus

4. Remaining Challenges and Future Directions

It is generally believed that the concept of power-grid resilience has the potential to fill in some of the gaps in power system planning that are not properly addressed by reliability metrics and analysis. However, there is currently no consensus on the definition of resilience, or how to quantify, model, and assess it. Hence, standard definitions and metrics are required, similar to what is currently utilized in the field of power system reliability, in order to be able to objectively compare models and solutions.

The lack of a universal set of metrics and definitions aside, models proposed in the literature suffer from some significant shortcomings as discussed below.

First, power-grid resilience is associated with HILP events, predominantly due to natural disasters. As such, it is necessary to link the topology of the power grid with the spatial and temporal attributes of the event under study. This allows for more accurate models and predictions for damage and outage scenarios. In addition, the effectiveness of different infrastructural reinforcement strategies can be more objectively assessed this way. However, such a link does not currently exist in the literature and needs to be addressed. Further, developing resilience metrics that take events, weather, infrastructure, and operations into account is still a work in progress. Ideally, such metrics must also be capable of modeling the dynamics of the event as it unfolds.

Another shortcoming of the current methodologies is related to the multi-objective nature of the optimization model. Power-grid resilience can be viewed from various technical, economic, and societal angles, encompassing objectives and constraints that may at times be contradictory to one another. Forming aggregate objective functions or prioritizing a group of objectives over others, as is currently done in the literature, can lead to solutions that are subjective and biased. Different solution methodologies are therefore needed that are able to find the Pareto optimal solution within this multi-objective framework. This way, individual objective functions can be simultaneously optimized while considering the impacts they have on other objectives. Goal programming approaches are one example of methodologies that allow for finding the Pareto front in the problem's solution space.

Similarly related to the previous shortcoming, the societal impacts of large-scale outages are often overlooked in the literature or modeled in a rather simplified and subjective manner. Traditionally, power system planners have been considering certain load points such as hospitals, emergency rooms, fire stations, and police stations to be the high-priority ones, while residential load centers are assigned a lower priority level. The fact that the former group has a critical role in facilitating relief and recovery in the aftermath of a natural disaster is not under debate. However, residential demand cannot and should not be viewed as homogenous across the power system. Numerous studies have shown that large-scale outages impact individuals in different ways, with socially vulnerable groups being disproportionately affected. Hence, a proper resilience planning study must be conducted as a sociotechnical analysis, rather than a purely technical one. The vulnerabilities of individuals against long-duration outages must be quantified, for instance, by considering their potential health vulnerabilities to lack of power, their ability to prepare for an event in advance, and/or their ability to evacuate to safety upon need. Those aspects of social vulnerability should then be incorporated into the design phase, e.g., where to reinforce, as well as the restoration phase, e.g., how to prioritize areas for energization. Of course, such an approach may require a trade-off between technical and societal constraints, which can be accommodated by the nature of Pareto front optimization models.

Most solutions proposed in the literature consider uncertainties in model inputs and parameters. However, the majority of statistically based approaches use empirical models that are case-dependent, making it difficult to generalize or apply the findings to other systems. More advanced fragility models are needed that are able to predict damages to various grid components under different disaster-induced scenarios. Similarly, models for component repair and replacement are often subjective, creating another area for improvement.

The review of the literature underlines the importance of balanced investment decisions since each mitigation strategy has certain limitations and advantages. Models that focus on one or only a few reinforcement strategies are, therefore, likely to provide sub-optimal solutions. In addition, a truly representative model must include all uncertainties, e.g., associated with demand, structural fragility, weather data, event progression attributes, road availability (for fuel and repairs), and fault initiation. Needless to say, the sheer number of uncertain parameters in conjunction with the normally nonlinear and mixed-integer nature of the problem will likely result in significant tractability issues. Many of the existing two-stage stochastic optimization or robust optimization models will likely be affected by the curse of dimensionality. Therefore, more efficient multi-level or decomposition-based algorithms are needed that are able to effectively tackle such mathematically challenging models.

Lastly, resilience studies and models depend on a large amount of outage management data, e.g., geographical size of the outage, number of customers affected, circuits and components impacted, crew dispatch strategies, etc. This data is understandably highly sensitive and as such, closely protected by electric utilities. Naturally, lack of access to realistic data can negatively affect the effectiveness and/or practicality of the solutions developed in the literature. One solution could be to develop standardized test cases using accurate operation, infrastructure, and event models that can provide a common baseline for the comparison of different methodologies and a trusted platform for implementation in real life.

Regardless of the mitigating measures adopted for power grid resilience against extreme events, disasters happen, and equipment failures are an inevitable part of power grid operation. Power-line failures can be very dangerous to humans who come into contact with them either accidentally or in the case of reconstruction, and workers have to face it as an occupational hazard [61]. Many safety procedures employed by institutions are naturally based on past experiences, and it is typical for them to document mistakes so as to codify lessons that can prevent future disasters. However, very few institutions apply these acquired lessons. It is important that institutions make a deliberate and concerted effort to enable the transference of these safety lessons to fieldworkers [62]. Authors in [63] advocate for the implementation of a safety training program that includes the identification of hazards, evaluation of risk situations, and general awareness of safety issues as a requisite step to reduce health and safety concerns during post-disaster response. It is important that areas with downed power lines are marked as danger zones and cordoned off so that only sufficiently qualified and equipped employees come into contact with them. Other personnel should ideally stay at least 10 feet away from those areas [64].

5. Conclusions

The necessity and urgency of strengthening the electric power grid against severe events have been highlighted by the recent large-scale and long-duration power outages brought on by extreme weather events. The changing climate and the increasing trend in the severity and frequency of those events further underline the importance of preparing power and energy systems for high-impact, low-frequency disasters. The purpose of this study is to provide a survey of how the infrastructure resilience of the power transmission and distribution networks can be quantified, assessed, and improved. An overview of definitions and metrics used for power grid resilience was provided, followed by a discussion of general mitigation strategies for infrastructural resilience. A survey of the solution methodologies proposed in the literature was then presented, focusing on the metrics adopted, objective functions and constraints considered, and algorithms used. Finally, the paper concluded with a discussion of the shortcomings of the existing methods and some suggested areas for future research.

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