Towards a Framework for Measurements of Power Systems Resiliency: Comprehensive Review and Development of Graph and Vector-based Resilience Metrics

Abstract

Integration of smart grids into conventional power systems has introduced new challenges and opportunities. Greater dependence on communication and measurement infrastructure, as seen in advanced metering infrastructures, has transformed power grids into cyber-physical systems, enhancing capabilities against high-impact-low-probability (HILP) events but also exposing vulnerabilities to cyberattacks. This challenges underscore the critical role of resilience in modern power systems.Contrary to reliability, resiliency is a relatively new but critical topic for power systems, and suffers from a lack of clear shared definitions. We propose a comprehensive literature review and a framework that synthesizes existing knowledge, including a categorization of recent quantitative resilience metrics. Secondly, we introduce a holistic and realistic resilience curve. The proposed curve is evaluated and compared with the state-of-the-art methodsand shows a clear improvement with the state of the art. Lastly, in response to the multifaceted nature of HILP events, the study introduces an innovative code-based vector of resilience metrics, providing a structured and practical reference to enhance clarity and reduce ambiguity. This study advances resilience understanding and enhancement in modern power systems by providing a comprehensive framework and key metrics, serving as a valuable resource for stakeholders.

Keywords: Quantitative Resilience Metrics, Power System Resiliency and Reliability, High Impact Low Probability Events, Smart Grids

1. Introduction

The power system is the beating heart of modern societies, its reliability and resilience in the face of disasters and failures crucially impact both the economy and daily lives. The issue of reliability in power systems is related to frequent and low-impact events, while resilience is concerned with HILP events, whether of human or natural origin. While modern power systems exhibit remarkable reliability, the surge in natural disasters attributed to climate change, as depicted in Figure 1, emphasizes the urgent need for enhanced consideration and improvement in resilience studies. The integration of smart grids in conventional power systems has led to increase the use of communication and measurement equipment such as Advanced Metering Infrastructure (AMI) [2], resulting in the creation of cyber-physical systems that have added many capabilities to the power grid. The digitization of systems has yielded enhanced resilience against natural disasters; however, it has increased vulnerability to cyberattacks [3](see Figure 2).

Nomenclature

List of abbreviations

ABCC	Average Betweenness Centrality of Critical Nodes
AC	Algebraic Connectivity
AFS	Average Falling Speed
AHP	Analytical Hierarchical Process
ALRIL	Average load Loss Ratio In case of Load curtailment
AMI	Advanced Metering Infrastructure
APDA	Active Power Deficiency of the Area
ARSS	Average Restoration Speed of System load
ATCS	Available Transmission Capacity of the Section
BESS	Battery Energy Storage System
CEENS	Conditional Expectation of Energy Not Supplied
CENS	Cost of Energy Not Supplied
CLLP	Current Load Loss Percent
CLOLE	Conditional Loss of Load Expectation
CLR	Critical Load Restored
CPARM	Cyber-Physical Resilience Metric
CPPS	Cyber-Physical Power System
CRC	Central Resilience Controller
CVaR	Conditional Value at Risk
DCAT	Dynamic Contingency Analysis Tool
DI	Degradation Index
EAGLE-I	Environment for Analysis of Geo-Located Energy Information
EDNS	Energy Demand Not Supplied
EENS	Expected Energy Not Supplied
EIU	Energy Index of Unreliability
ENE	Energy Not Exchanged
ENS	Energy Not Supplied
EPRI	Electric Power Research Institute
ESPC	Effective Shortest Paths between Critical nodes
FI	Fragility Index
FLISR	Fault Location, Isolation and Service Restoration
GMA	Generation Margins of Areas
GR	Graph Redundancy
HILP	High-Impact Low-Probability
LLD	Loss of Load Duration
LLI	Lost Load Index
LLO	Loss of Load Occurrence
LLP	Load Loss Proportion
LOLE	Loss of Load Expectation
LOLF	Loss of Load Frequency
LOLP	Loss of Load Probability
LSI	Line Strength Index
MER	Mobile Energy Resources
MG	Micro Grid
MRI	MG Resilience Index
MTTR	Mean Time to Repair
MVI	MG Voltage Index
NERC	North America Electric Reliability Corporation
NIAC	National Infrastructure Advisory Council
NLP	Node Loss Proportion
PCFD	Probability of Components Failed during Disaster
PES	IEEE power and energy society
PIN	Possibility of Isolated Node
PLLP	Post-disaster Load Loss Percent
PSI	Pole Strength Index
RAW	Resilience Achievement Worth
REAI	Resilience Assessment Index
REI	Restoration Efficiency of the Important load
RES	Restoration Efficiency of System load
RESC	Resilience Coordinate
RLRO	Ratio of Load Restored in One Hour
SAIFI	System Average Interruption Frequency Index
SG	Smart Grid
SRI	Severity Risk Index
TMTS	Transmission Margin of Transmission Section
TPL	Total Power Loss
TR	Topological Robustness
UKERC	United Kingdom Energy Research Center
VaR	Value at Risk
VI	Vulnerability Index
VoLL	Value of Lost Load

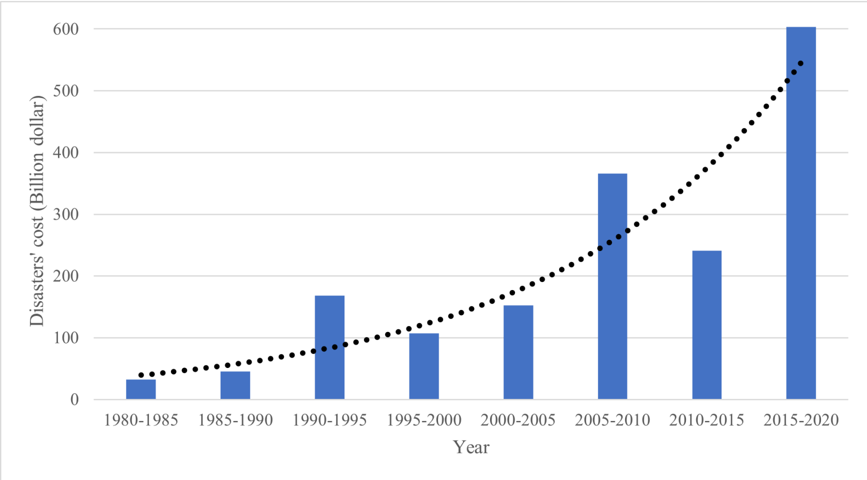


Figure 1: Billion-dollar disasters' cost in the U.S [1].

Table 1: An overview of the period of natural disasters in the U.S.[1]

Period	Number of Disasters	Events per Year	Cost (B$)	Fraction of Total Cost	Cost per Year	Deaths per Year
1980s (1980-1989)	33	3.3	209.2	8.30%	20.9	299
1990s (1990-1999)	57	5.7	319.5	12.70%	32.0	308
2000s (2000-2009)	67	6.7	592.0	23.60%	59.2	310
2010s (2010-2019)	131	13.1	948.5	37.70%	94.9	523
Last 5 Years (2018-2022)	90	18	607.2	24.20%	121.4	350
Last 3 Years (2020-2022)	60	20	443.4	17.60%	147.8	487
Last Year (2022)	18	18	171.5	6.80%	171.5	474
All Years (1980-2023)	348	7.9	2512.6	100.00%	57.1	360

In recent years, the frequency of natural events, including floods, earthquakes, storms, wildfires, droughts, ice storms, and other phenomena, has shown a significant increase, as indicated by statistics presented in Table 1. Table 1 shows that billion-dollar natural disasters have been increasing in frequency and cost in recent years due to climate change and global warming.

Several devastating events have negatively impacted power systems and communities in recent years. Hurricane Laura struck Louisiana in August 2020, causing widespread damage, power outages, and an estimated cost of $26.9 billion [4]. In June 2022, a powerful derecho inflicted extensive wind damage across several states, particularly impacting Michigan, Illinois, Indiana, and Ohio, with widespread destruction to homes, businesses, and infrastructure [1]. Figure 2 depicts the fundamental sources of HILP events, which may stem from cyber or physical attacks, as well as natural disasters. Additionally, the figure demonstrates the impact of system digitization on the operational aspects during HILP events.

Cyberattacks, although currently accounting for a limited portion of energy supply disruptions, pose a substantial and rapidly escalating threat. These attacks target critical aspects of cyber infrastructures, with a specific focus on integrity, availability, and confidentiality as shown in Figure 2 [5]. Availability-focused attacks seek to delay, obstruct, or compromise communication,

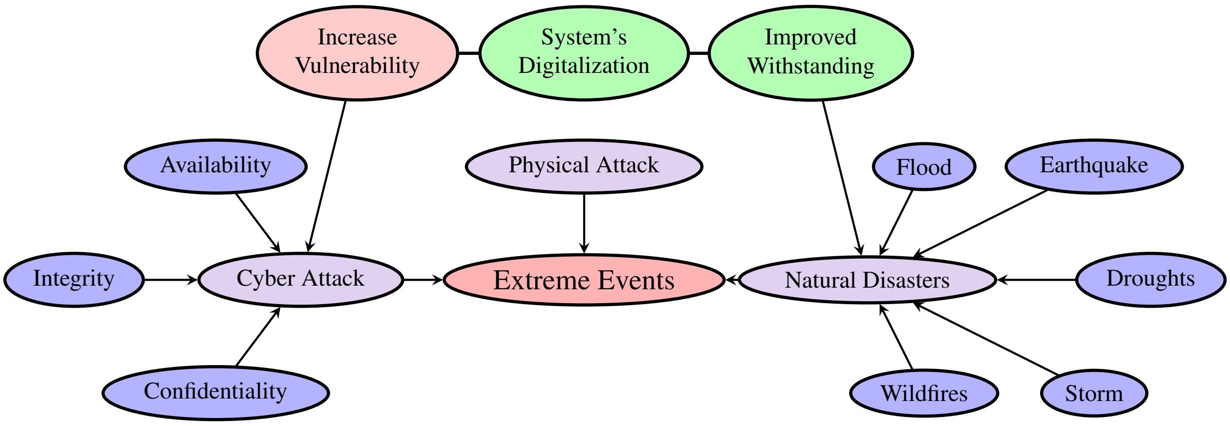


Figure 2: The underlying origins and types of HILP events.

while those targeting integrity aim to disrupt or modify data exchange, and those focusing on confidentiality strive to gain unauthorized access to information [5]. Notable instances of these attacks include KillDisk, BlackEnergy, Stuxnet, Industroyer 1 & 2, among others. Stuxnet, a malware with consequential impact on Iran's nuclear program, remained undetected for five years following its 2005 inception [6]. BlackEnergy caused a power outage affecting 225,000 customers in 2015, while the original Industroyer led electricity disruption in Kiev during 2016 [7]. The most recent occurrence took place in 2022, involving the Industroyer 2 event targeting the Ukrainian power grid, attributed to the Sandworm group [7].

The increasing trend of HILP phenomena has made the study of its consequences on the power grid under the title of resilience in the power grid a hot topic in recent years. Due to its novelty within the power grid domain, exact definitions and precise metrics for resilience are lacking in the literature, unlike the well-established concepts observed in reliability analysis. Various institutions such as EPRI, U.S. NIAC, NERC, UKERC, and IEEE PES have all provided definitions of resilience in the power system. Academic analyses have been conducted by scholars to compare these definitions [8]. Rather than proposing a new definition, in this manuscript, we adopt the IEEE PES definition as a reference. Resilience is: “The capacity to resist and reduce the impact and/or duration of disruptive events, which includes the ability to foresee, absorb, adapt to, and/or quickly recover from such an event [9].” This concise definition of resilience considers the period before, during, and after the HILP event, as well as essential features of resilience: absorbability, adaptability, and recovery capability.

The literature exhibits a zoology of definitions and measures of resilience. As defined in [10], resilience metrics, also called resilience index or resilience indicator, serve as tools for quantifying the resilience level of a power system. These metrics are typically utilized in the assessment of resilience cost-benefit considerations during both planning and operational phases. The discussion of quantification in articles can be classified into two categories: qualitative and quantitative.

In the qualitative category of articles, various solutions are presented such as the formation of micro-grids, the use of renewable energy resources [11], battery energy storage systems [12], mobile energy storage [13], energy management [14], demand response [15], network and pole hardening, vegetation management, and so on without using specific metrics. The categorization of qualitative assessments consists of checklists and questionnaires, matrix scoring across various system aspects, as well as the application of AHP methods [16]. They aim to show the qualitative improvement of their proposed method in network resilience. However, these models assess the resilience of systems without the use of numerical descriptors and are defined by their probabilistic nature, which makes them liable to errors. The accuracy of the model and the validity of the analysis depend on the underlying assumptions [8].

On the other hand, the present work focuses on quantitative analysis of resilience in the power network. The evaluation of resilience initially relied on metrics associated with reliability, given the inherent interdependence of these two concepts. Reliability metrics are specifically designed to address outages that occur due to one or two component failures (N-1 or N-2). However, they do not adequately account for large failures that result from unexpected extreme events. The prioritization of service provision for critical loads during outages caused by HILP events undermines the effectiveness of reliability metrics for evaluating resilience [17]. In [5], it is highlighted that the extensive quantity and intricate nature of resilience definitions in the context of energy systems present difficulties when it comes to determining suitable indicators and models for qualitative or quantitative evaluations. Study [18] pointed out an important deficiency in the development of metrics: the necessity of formulating metrics and indices that facilitate a comprehensive evaluation of power system resilience. This requires incorporating the various dimensions of resilience in order to conduct a comprehensive and exhaustive evaluation. As in reference [19], a comprehensive resilience metric should possess attributes such as usability, comparability, inclusiveness, scalability, quantifiability, and the consideration of uncertainties. Validating proposed measures and developing specific metrics for resilience in power systems are imperative. This includes designing specific metrics that encompass the spatial and temporal characteristics of disturbances, essential for accurate assessment and evaluation [17]. The identified gap lies in the lack of consensus regarding essential capabilities, measurement methodologies, and the relationship between resilience metrics and desired outcomes in the literature on power systems [10]. While various studies emphasize the need for standardized quantitative metrics [5] to assess power network resilience, a consensus is lacking, and the community consistently introduces new metrics. We further reinforce the existence of this research gap and the uniqueness of our study through a bibliometric analysis presented in Section 2.

This paper aims to explore the multifaceted domain of quantitative resilience metrics in power systems. The study is driven by the increasing global challenges posed by natural disasters and cyber threats. With these events becoming more frequent and impactful, the resilience of power systems is crucial. Our motivation is further supported by recent bibliometric trends showing a growing interest in resilience metrics. The first objective of this work is to clarify the distinction between reliability and resiliency, highlighting their connection to power systems. This manuscript also seeks to address the ambiguity in defining and measuring resilience by emphasizing its importance in modern power systems and providing a thorough analysis of quantitative metrics. Finally, we propose a solution to the lack of standardized quantitative metrics for HILP events in existing research.

The main contributions of this review paper are as follows:

1. **Comprehensive collection of recent quantitative resilience metrics:** The paper metic-

ulously collects and categorizes quantitative resilience metrics, with a particular focus on articles published from 2019 to 2023. Utilizing bibliometric methodologies, trends in resilience metrics research are identified, highlighting the importance of such investigations for nations are more severely impacted by HILP events. Additionally, detailed tables are provided for each metric category, providing a thorough examination of this developing field of study.

2. **Integration of resilience curves:** This study extends beyond simple aggregation by integrating resilience curves from various sources, resulting in the development of a holistic and realistic resilience curve. The synthesized curve is then compared to actual extreme event data sourced from the EAGLE_I database [20]. Numerical analysis indicates that the proposed holistic resilience curve is more effective than standard resilient curves such as the resilience triangle in depicting real-world curves.
3. **Comparative analysis with ideal metric features:** This paper conducts a comparison of various metrics, evaluating their alignment with the desired characteristics of an ideal resilience metric. The analysis encompasses key attributes such as interpretability, scalability, comparability, quantifiability, and the ability to address HILP events and uncertainties. The evaluation employs a spider diagram, visually representing the comparative strengths and weaknesses of each metric in relation to these key characteristics. This allows for an in-depth investigation of the metrics' effectiveness, contributing to a detailed understanding of their suitability in real-world applications.
4. **Innovative code-based vector of resilience metrics:** As a forward-looking contribution, this review introduces a novel code-based vector of resilience metrics. It explicitly considers factors such as the degree of uncertainty, intended use for operational or planning contexts, temporal scope of events, physical interpretation of the metric, presence of a curve representation, and foundational principles based on either graph or power flow methodologies. Moreover, the vector underscores the importance of explicitly identifying the specific HILP event under consideration. This vector serves as a practical and structured reference for researchers and stakeholders, aiming to reduce ambiguity and facilitate clarity in the field of resilience metrics.

This review paper is organized in the subsequent way : Section 2 describes our methodology for collecting papers. Section 3 provides a comprehensive review of the literature that proposes resilience metrics according to the classification scheme adopted in this article. Section 4 presents a comparative figure for these metrics and evaluates their strengths and weaknesses. It also proposes a comprehensive code-based vector of resilience metrics that encompasses all the classification categories. The conclusion section 5 offers suggestions for future research and summarizes the main findings of this review.

2. Methodology

To conduct a systematic analysis of the literature that introduced metrics for resilience, we employed the bibliometric technique. This method allowed us to examine the patterns and trends of the publications in this field and to identify the most influential authors, journals, and topics.

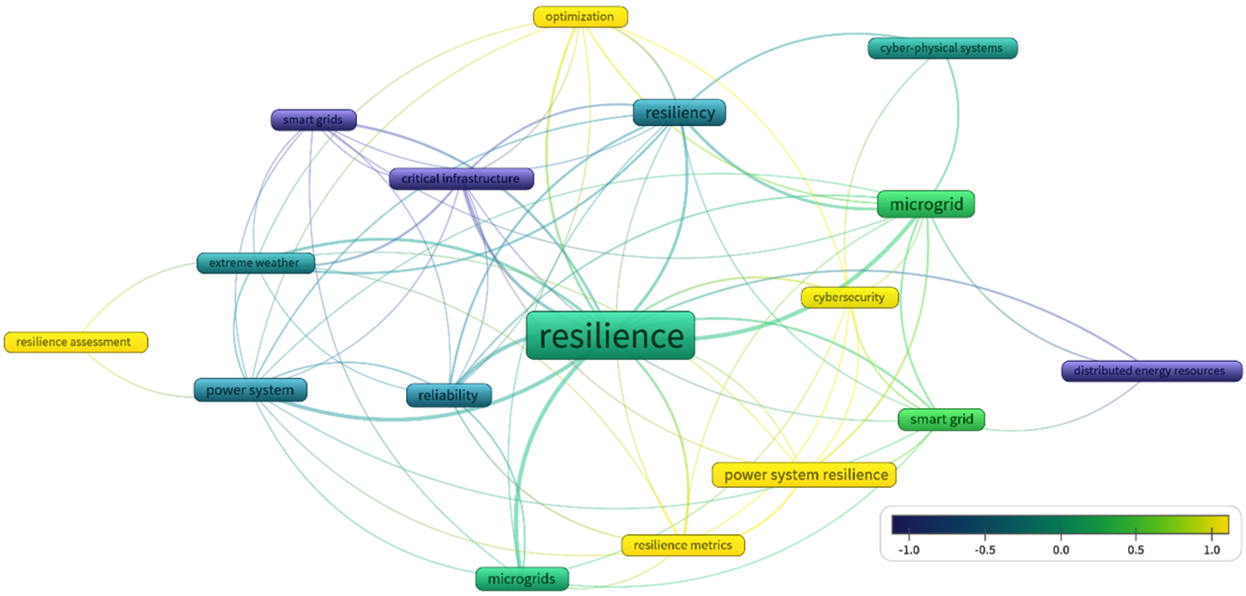


Figure 3: Most common keywords in the studied literature.

Utilizing the Scopus platform, our investigation centred on sourcing scholarly articles pertinent to the field of resilience metrics. To this end, a search strategy was devised, employing the query ”TITLE-ABS-KEY ((”power system” OR ”electrical grid” OR ”microgrid”) AND (”resilience” OR ”resilient” OR ”resiliency”) AND (”quantitative” OR ”quantification” OR ”metric” OR ”quantity”)).”. The outputs of our query were constrained by two criterion: a contemporary timeframe from 2019 to 2023 and an adherence to the English language. As a result, an initial pool of 325 articles was identified from the Scopus collection. Following this, a comprehensive assessment was conducted, whereby each article underwent careful examination to ascertain its relevance to the scope and goals of our review study. Through a meticulous process of examination and refinement, we identified 54 articles that served as the foundation for our thorough review study. We specifically chose articles from the initial pool that utilized or introduced quantitative metrics. If an article used metrics identical to those in previously selected articles or measured the same quantity, it was omitted from consideration. To examine the conceptual framework of these articles, we conducted a lexical analysis based on the frequency of words that appeared more than 9 times in the articles. We justified our data collection method by the word trends, which clearly indicated that our research covered the main aspects of power system resiliency and resiliency metric in a comprehensive manner (see Figure 3). According to Figure 3, words such as resilience metrics, resilience assessment, cybersecurity, and extreme events are seen as trends in more recent studies (the scale in Figure 3 represents subtract mean divided by the standard deviation of the year of publications of each word). This attests to the novelty, emergence, and necessity of the metric concept in resilience studies applied to the power system domain. Although the initial search began with the assistance of bibliometric analysis, our resource pool expanded through an in-depth review of these articles. In the end, a total of 87 articles have been considered for this manuscript. To achieve this, we examined the relevant references in the primary pool articles. The

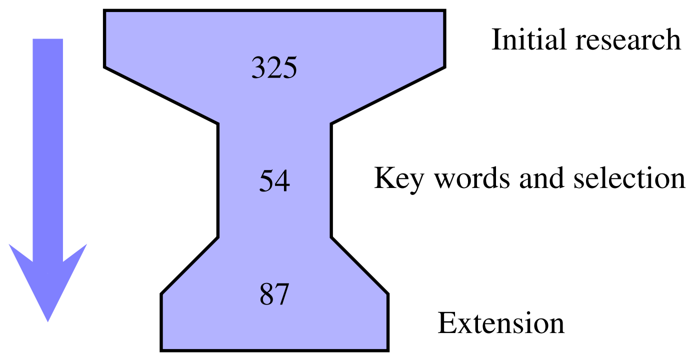


Figure 4: Methodology for selecting and including relevant articles.

methodology for selecting and including relevant articles is depicted in Figure 4.

The interrelation between Figure 5a and Figure 5b highlights the motivation for scholarly work on resilience. Figure 5a reveals that countries with high economic risk, such as the United States, China, Iran, United Kingdom, Italy, and India also have the highest number of publications on resilience-related topics. Figure 5b depicts the economic vulnerability to natural hazards, which implies a pressing need for enhancing resilience in the face of potential disasters.

Having established the research gap and the significance of the topic in the preceding sections, the next section will critically examine the various resilience metrics proposed in the literature. This will enable us to identify the strengths and limitations of the existing approaches, as well as to highlight the opportunities for further development and innovation.

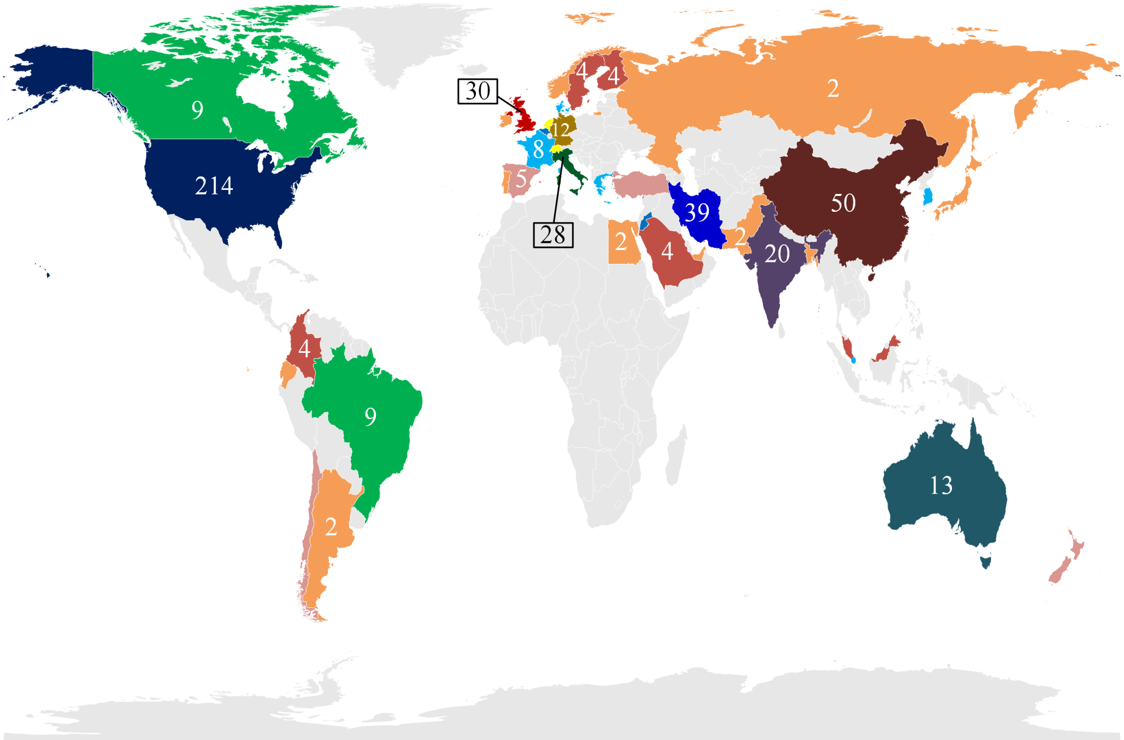
3. Metrics classification

Incorporating a specific focus on resilience metrics, a comprehensive framework for evaluating resilience is depicted in Figure 6, primarily based on the IEEE PES definition.

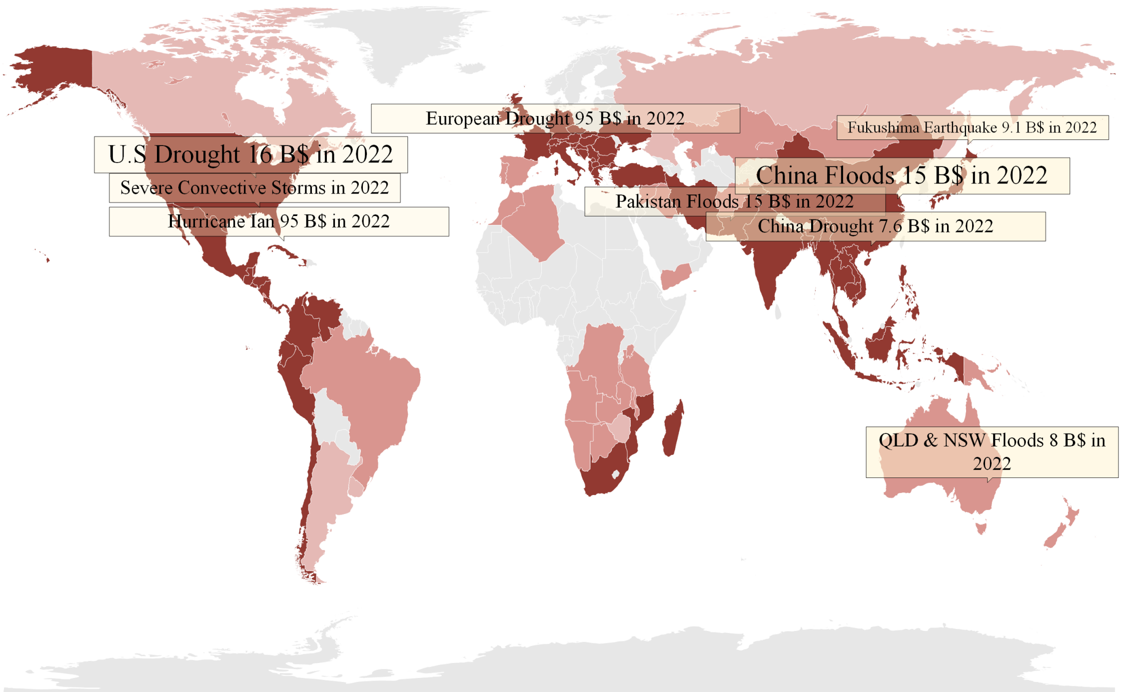
Resilience metrics are meaningful across the three stages of pre-event, during-event, and post-event, as depicted in Figure 7 [19]. During the pre-event stage, they serve to inform enhancements of system components, conductor burial, and the strengthening of transmission lines. During HILP events, these metrics guide corrective actions and emergency response, including load shedding and islanding protocols. In the post-event phase, they contribute to damage assessment and play a role in system recovery endeavours. This includes various initiatives such as the formation of microgrids and the deployment of mobile energy resources.

The research conducted in [23] highlights the vital features that resilience metrics must have in the context of resilience investment, operation, and emergency planning. As per the framework proposed in [24], resilience metrics should incorporate several essential elements. These include their usefulness in decision-making, ability to facilitate comparisons across different systems, applicability in both operational and planning contexts, scalability in terms of time and geography, quantifiability, reflection of uncertainties, support for a risk-based approach, and consideration of recovery time.

We have identified 7 key categories to classify and analysis power systems' metrics, shown in Figure 8. It is important to note that the percentages represented in this pie chart do not sum



(a)



(b)

Figure 5: a): Number of articles obtained via bibliometric analysis, published by countries. b): Global hazard total economic loss risk distributions (adapted from [21, 22]). Color encodes the magnitude of losses.

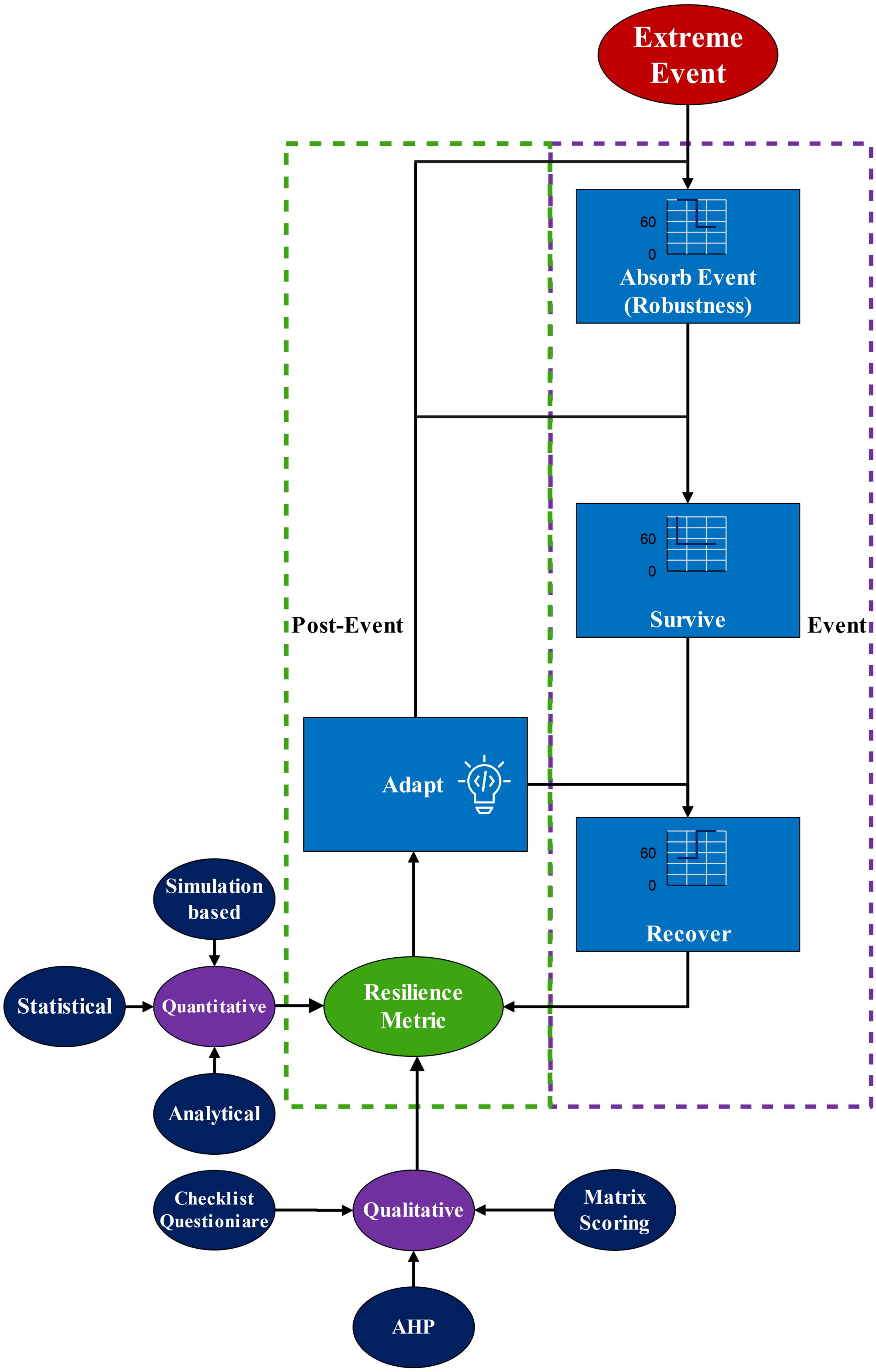


Figure 6: Resiliency Framework illustrating the key stages of Absorb, Survive, Recover and Adapt, with a specific emphasis on Resilience Metrics.

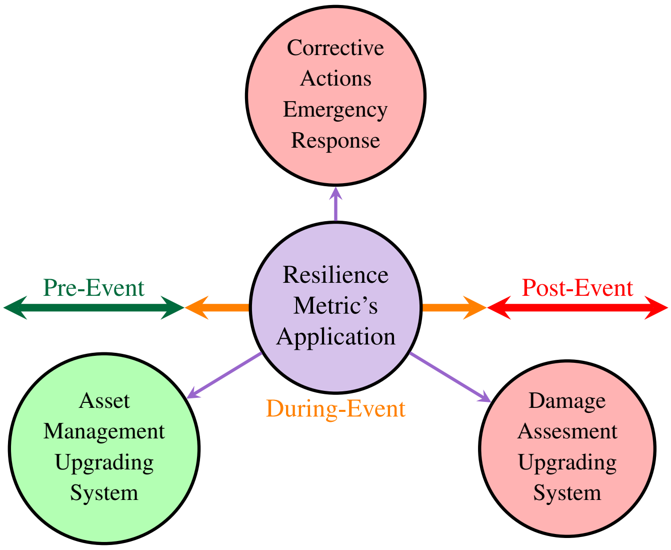


Figure 7: Applications of resilience metrics.

up to 100% due to overlaps in some categories. It allows the construction of a comprehensive analysis of the resiliency metrics. In the following, we justify and review these classes and the associated metrics. A comprehensive table is provided that summarizes the metrics at the end of each section. Each table includes references, brief metric descriptions, whether they relate to planning or operations, visualization aspects, whether they are flow-based or graph-based, the resilience periods they cover, consideration of uncertainties, reliance on reliability metrics, and incorporation of distributed energy resources.

3.1. Operational and planning metrics

Metrics can be classified according to their relation to operational or planning requirements. Operational requirements concern actions that are taken in response to the occurrence of a HILP event, while planning requirements concern actions that are taken to prevent and mitigate a future HILP incident.

3.1.1. Operational metrics

The metrics featured in the articles serve mostly operational purposes, with a substantial portion of them assessing energy provision relative to total energy demand, which can generally be expressed as in Eq. (1):

$$\mathcal{R} = \frac{\int \text{Weighted Served or Unserved Loads}}{\int \text{Weighted Total Loads}}. \tag{1}$$

By selecting and weighting loads, researchers using these metrics aim to prioritize critical loads, [25]. Equation 2 calculates the resiliency by incorporating weights for both critical and

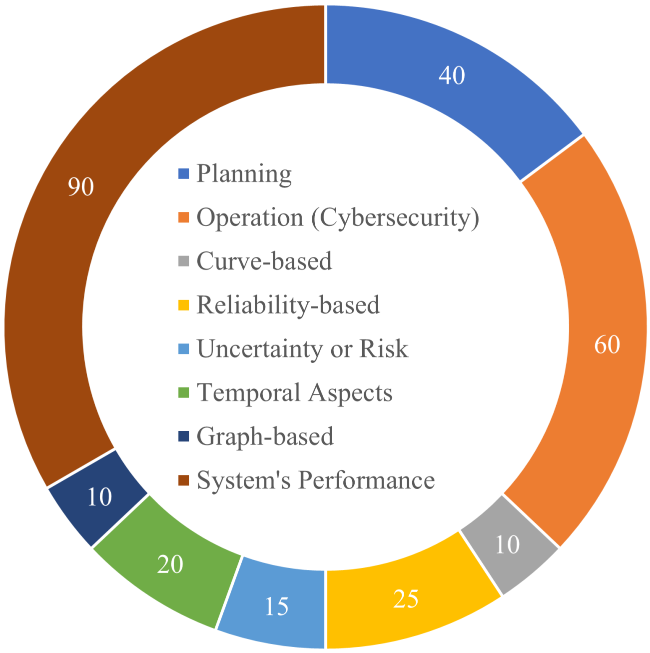


Figure 8: Categories of resilience metrics and associated percentage of reviewed works.

regular loads:

$$\mathrm{RI} = \frac{\sum_{t=t_1}^{t_2} \omega_{CL}\left(P_{i,t,s}^{Demand,CL} - P_{i,t,s}^{ENS,CL}\right) + \omega_{RL}\left(P_{i,t,s}^{Demand,RL} - P_{i,t,s}^{ENS,RL}\right)}{\sum_{t=t_1}^{t_2} P_{i,t,s}^{Demand}}, \tag{2}$$

where ω_{CL} represents the weighting factor for critical loads, while ω_{RL} denotes the weighting factor for regular loads. The start and end of the programming time are respectively t_1 and t_2. Operational metrics extend beyond the assessment of system lost load. Other metrics evaluate various facets of the system's performance, encompassing time-based metrics for appraising repair and transportation duration. Additionally, there exist metrics to assess vulnerability, restoration rate, fragility index, voltage stability index, as well as indices related to nodes and branches [19, 26, 27]. A detailed analysis of these metrics will be provided in the subsequent sections. System lost loads is a commonly used metric in operational articles; it is also a key concept for resiliency. For these reasons, we emphasis on it in this section.

Some of operational metrics are described below with more details. In [28], using adaptive Severity Risk Index (SRI), the most effective operational solution to prevent the destructive effects of the HILP event is determined to be defensive islanding. Islanding aims at dividing the power system into smaller sections that can supply the required energy. Taking into account the cascading

Table 2: Summary of operational metrics. Metrics are related to planning (P) and/or operational (O). Column V stances for Visual or Curve-based metrics. Metrics can be flow-based (F) or graph-based (G). Time aspect can be Pre-disturbance (Pre), during disturbance (Dur) - which can be Disturbance progress (DP), Degraded state (Deg), or Restorative state (Res) - and after disturbance (After). The type of uncertainties can be deterministic (D), stochastic (S) or risk-based (R). Column Re stances Reliability-Based metrics when column DER indicates Distributed Energy Resources.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[30]	Determining VoLL to prioritize critical loads	O	-	F	Dur/After	D/S (ENS)	✓	-
[31]	Critical load and infrastructure restoration considering the service time	O	-	G	Dur	S	-	✓
[33]	Calculating resiliency with considering loads' importance	O	-	F	Dur	S	-	✓
[32]	The ratio of both recovered AC and DC loads to the total demand	O	-	-	Dur	S/D	-	✓
[35]	Assessing resiliency of transient and steady states of the power system.	O	-	F	Dur	D	-	✓

and stochastic effects of these events, defensive islanding may lead to a deterioration of network conditions. SRI supports the operator in reaching a decision regarding defensive islanding through consideration of network structure, load conditions, and the severity and probability of incidents [28]. The effectiveness of deploying defensive islanding can be evaluated by establishing SRI threshold value (i.e., $SRI > SRI_{\text{thres}}$) [29].

The Value of Lost Load (VoLL) is employed in optimal mobile energy resources (MER) dispatching to prioritize critical loads [30]. The ability of a system to restore critical loads using microgrids is assessed via a resilience metric developed in reference [31]. This stochastic metric is developed with a focus on two restoration levels: (1) the restoration of critical loads and (2) the restoration of power system infrastructure, such as damaged poles and lines. A similar metric takes the prioritization of critical loads for AC and DC hybrid microgrids into account [32]. In a comparable study, a resilience metric for assessing the impact of typhoon weather conditions on critical loads has been introduced [33]. The study measured load loss rates before and after the deployment of distributed generation. [34] proposes a network reconfiguration approach as a temporary corrective tool by employing various resiliency metrics, including grid flexibility to evaluate system resourcefulness, outage recovery value to minimize outage costs and outage capacity recovery to assess the speed of recovery actions. In [34], a novel set of operational metrics is introduced to distinguish between the steady and transient states of the power system. The transient state's resilience is determined via machine acceleration and deceleration, whereas steady-state resilience is evaluated based on parameters such as the number of congested power lines, voltage deviations, and reactive and active power generation. Operational metrics are summarized in Table 2.[1]

3.1.2. Planning Metrics

Resilient planning in power systems has received comparatively less attention in research than operational aspects. The employment of Loss of Load Expectation (LOLE) and Loss of Load

[1]Details on each reviewed metrics can be found in the supplementary data associated with this article.

Table 3: Summary of planning metrics.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[40]	Operational cost of disrupted and non-disrupted microgrids.	P	-	F	Pre	D	-	-
[41]	The ratio of BESSs discharge energy to the demand energy by critical loads during an emergency.	P	-	F	Pre	S	-	-

Frequency (LOLF) metrics served as valuable tools in the strategic planning aimed at reinforcing the transmission network through redundancy mechanisms and enhancing its overall robustness [36]. Likewise, Expected Energy Not Supplied (EENS) and Energy Index of Unreliability (EIU) are used for long-term planning of the network under network reinforcement in three forms: robust (increasing system resistance), redundant (additional equipment and backup), and responsive (increasing the speed of response) in three distinct modes of flood, wind storm, or both. It has been demonstrated that the combined effect of flood and wind storms is higher than that of the other scenarios and that the robust state has a greater impact on reducing the EENS value [37]. From a resilience perspective, the examination of various development scenarios for the National Electricity Transmission System (NETS) of Great Britain (GB) was conducted in [38]. Notably, occurrences in which electricity production fell short of demand, known as Loss of Load Occurrence (LLO), were recorded, along with the duration of each occurrence, known as Loss of Load Duration (LLD).

A cost-based resilience metric was introduced in a separate study focusing on traffic and post-conflict bridge reconstruction. This metric is based on the resiliency integral equation, which can be obtained from network performance considerations. By incorporating cost considerations into the metric, a comprehensive evaluation of resilience is achieved, allowing for a more thorough analysis of the network's ability to recover and withstand disruptions in the aftermath of conflicts [39]. Another cost-based resilience metric is proposed to evaluate the resilience of microgrids by considering the operational costs of both non-disrupted and disrupted multi-energy carrier microgrids [40]. The system resilience $\mathcal{R}$ is modeled as the exponential of negative ratio of the increase in multiple energy carrier microgrid operation costs γ due to disruptive events, as seen Eq. (3)):

$$\mathcal{R} = e^{-\frac{(\gamma-\gamma_0)}{M}}, \tag{3}$$

where γ_0 is the operation cost during the normal operation, and M is the total energy resource. Considering the inherent uncertainty of earthquakes, a novel metric has been developed for Battery Energy Storage Systems (BESSs) planning in earthquake scenarios [40]. This metric serves as the problem's objective function by quantifying the proportion of BESSs discharge to the total power required by critical loads. Planning metrics are summarized in Table 3.

3.1.3. Mixed Metrics

Some metrics address both operational and planning considerations. For instance, the FLEP metric proposed in [42] incorporates both aspects with the performance change in resilience trapezoid (see Figure 9b). In the operational part, this metric involves notions such as lost power and energy and the recovery time. In the planning part, this metric depends on the choice of performance and considers notions such as the number of lost lines, their recovery time, and their service time. The EENS and LOLF indices, which represent anticipated amounts of unsupplied energy and the frequency of load loss per year, were presented in [42] to evaluate the effects of adverse weather events on the operation. Furthermore, the Resilience Achievement Worth (RAW) index was proposed to determine the critical elements within the transmission network. This index serves the purpose of ranking transmission lines and facilitating a comprehensive examination of the network's vulnerable points within the discourse of infrastructure analysis.

In the study conducted in [43], a bi-level optimization framework was employed to address network infrastructure selection and subsequent operational assessment during earthquake events. The first level focused on identifying suitable network infrastructure proposals, while the second level evaluated the network's operation under earthquake conditions. ENS and VoLL were integrated into the objective function of the post-contingency dispatch (PCD) model, aiming to minimize operating costs in the second level. The concept of Cost of Energy Not Supplied (CEENS) is introduced to facilitate resilience analysis and effectively minimize EENS. By incorporating CEENS into the first level of network planning, they successfully obtained an optimal infrastructure configuration that enhances network resilience.

3.2. Reliability-based metrics

Resilience and reliability are interdependent characteristics of the power system. Consequently, the metrics employed to evaluate these two dimensions frequently overlap, necessitating a coordinated strategy [23]. In the early literature on resiliency, researchers frequently employed reliability criteria as a direct means of evaluating resilience. Specifically, the LOLE and the LOLF in [36] were utilized to demonstrate the impact of wind on the transmission network's probability of failure. The findings indicated that enhancing the network's infrastructure and implementing redundancy mechanisms resulted in a decrease in the values of these two criteria within the system. This decrease, in turn, signifies an increase in the system's resistance and resourcefulness. LOLP represents LOLE without considering the duration of the interval [44]. CLOLE is defined in [45] to incorporate the LOLE metric in the context of a generic disturbance, specifically a winter cold snap. Building upon prior research, a related study delves into the influence of wind conditions on the EENS and LOLF indices [46]. ENS is defined as the product of LLO and LLD in [38]. In another study, EIU which is EENS normalized by total energy demand, is also utilized [37]. Similar to EENS, EDNS is derived from the probability and impact of each scenario [47], [44]. To consider the anticipated energy curtailment across multi-microgrids, [48] introduced a simple measure that aggregates curtail loads and their probabilities during the time slot. By incorporating the risk probability associated with HILP events, CEENS proposed to improve EENS [43]. Multiplying the ENS metric by the energy cost at the time of the disaster and the outage penalty cost per scenario, respectively, yields the total loss of utility revenue and the total outage penalty cost [49]. Similar to the metric mentioned earlier, [50] introduces the outage recovery cost index along with system flexibility and outage recovery capacity indices. The concept of ENE is introduced in [51] to consider bidirectional power flow in smart grids, when coupled with the emergence of prosumer models and building upon the precedent of ENS within conventional power systems.

This metric represents the accumulated difference between expected and actual power exchanges across all participating agents.

In [52], authors present metrics defined for individual and group components, to measure resilience based on reliability concepts such as availability. The metrics include power supply metrics using minimum downtime and minimum uptime, outage based on the System Average Interruption Frequency Index (SAIFI) metric in reliability, recovery speed or restoration speed, disruption speed similar to the failure rate in reliability, resistance, and brittleness related to the performance loss due to the damage to the network components in a specific location. Dependent resilience metric is also introduced, which is useful when using energy storage. The main difference between reliability metrics and resilience metrics is that the former are only evaluated when extreme events occur, while the reliability metrics are considered for infinite time. This difference allows the assessment of adaptation capability and planning ability in the metrics proposed here. It is also suggested that by specifying the period, they can use their metric at the time of disruption, the short time after the occurrence, and the time of the repair process. In [53], the authors improved the resiliency power supply metric presented in previous work. The authors emphasized that the original metric does not prioritize loads, so they weighted the loads to give them an advantage and improve the metric. By applying this weighting, the metric incorporates both the number of customers affected by the outage and the factors that indicate the magnitude of critical load loss during the outage.

Equations (4) to (8) present common reliability metrics, [37, 38].

Let N be the total time frame. LOLF, in Eq. (4) captures the frequency of load loss events, where LLO denotes the occurrence of load loss at each time step:

$$\mathrm{LOLF} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{LLO}_i. \tag{4}$$

Similarly, LLD represents the duration of each load loss occurrence. LOLE, in Eq. (5) is the expectation of load loss:

$$\mathrm{LOLE} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{LLD}_i. \tag{5}$$

The ENS, EENS, and EIU metrics are widely employed in resilience studies. They can be derived and interpreted from the reliability metrics LLO and LLD; it illustrates the intricate relationship between resilience and reliability. ENS is the instantaneous index capturing both the duration and the amplitude of a load loss. It is calculated by multiplying LLO and LLD:

$$\mathrm{ENS} = \mathrm{LLO} \times \mathrm{LLD}. \tag{6}$$

EENS is the average of all ENS values.

$$\mathrm{EENS} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{ENS}_i \tag{7}$$

Table 4: Summary of reliability-based metrics.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[36]	Frequency and duration of power outages.	P	-	F	Pre	S	✓	-
[37]	Energy was not provided during the HILP event and the normalized of this number.	P	-	F	Pre	S	✓	-
[52]	Up and down time, power outage, disruption speed, resistance, brittleness, energy reserve.	P/O	-	F	Pre/Dur/After	D	✓	-
[53]	Power supply to prioritize loads.	O	-	F	Dur (Restoration)	D	✓	-
[45]	Conditional Loss of Load Expectation	P/O	-	-	Pre	S	✓	-
[50]	Served loads, interruption cost, recovery capacity.	P/O	-	F	Pre	D	✓	-
[48]	Expected energy curtailment during a disturbance for multi-microgrid system.	O	-	F	Dur	D	✓	✓
[51]	Energy not exchanged (both generation and consumption).	O	-	F	Dur	S	✓	✓

EIU, defined in Eq. (8), denotes the normalized form of EENS, with E representing the total demand.

$$\text{EIU} = \frac{\text{EENS}}{E}. \tag{8}$$

In Table 4, we summarize reliability-based metrics.

3.3. Uncertainty aspects of metrics

In terms of resilience, metrics can be categorized according to whether they assess the system under deterministic, stochastic, or risk-based conditions. Given that the majority of metrics are applied to deterministic optimization problems, or they are inherently deterministic, we focus here on those metrics specifically designed for stochastic optimization problems or inherently stochastic.

SRI is derived from the probabilities and consequences of different scenarios, where the consequences are measured by the amount of load shedding required to reach a stable state in the system [28]. In [29] defensive islanding strategies rely on the SRI to identify weather-prone high-risk branches and evaluate the network topology. In another study, a risk-based approach was adopted to enhance resilience strategies [46]. This involved the introduction of the RAW index, which represents the percentage enhancement in the resilience indices under the assumption of perfect reliability across all transmission lines.

CEENS risk-based metric was developed to adapt EENS for resilience research. The researchers focused on analysing the extreme values of the EENS Probability Density Function (PDF), i.e. the right tail, as these values exhibit a significant surge during HILP events [43]. In a related study, the Conditional Value at Risk (CVaR) of EENS was utilized as a resilience metric. This metric captures the desired confidence level ranging from 90% to 95% [54]. Value at Risk (VaR_a) and CVaR_a represent the maximum power loss with $a\%$ confidence and the average loss in the most unfavourable $(1 - a)\%$ scenarios, respectively [47]. In addition, a discrete form of CVaR is proposed for direct use in optimization problems [55]. Likewise, both LOLE and CLOLE stochastic formulations are represented in [45]. Through a different approach that incorporates the rate of change in CVaR, the RESC metric is introduced [56]. This metric serves to assess the cumulative influence of climate variations over a defined time span, diverging from the conventional practice of analysing the system solely within a specific HILP event. To enhance RESC and Smoothness Index (SI) [57] metrics, the REAI is introduced to encompass varying event intensities on a damaged grid [58].

In reference [59], the proposal of the Risk-based Contingency Analysis Tool (RCAT) is presented. RCAT incorporates per-scenario and per-stage metrics (reliability metrics), load impact metrics, per-event metrics (accounting for metrics distributions rather than single numbers), and asset-level performance metrics (attributed to failures at the component level). Employing a risk-based methodology, a metric centred on the area beneath the resilience performance curve is optimized as the primary objective function [60].

The uncertainty of wind turbines has been modelled in [61] using a two-stage scenario-based framework. Subsequently, the metrics of resistance, recovery, and resilience were formulated based on the objective function. In another study, a resilience metric was introduced by calculating the ratio of recovered loads to the total loads, taking into account the prioritization of loads in different scenarios [62]. In Table 5, we summarize metrics that pertain to uncertainty.

3.4. Temporal aspects of metrics

Resilience studies encompass distinct temporal phases, notably before, during, and after the HILP event. Within this section, we conduct a detailed examination of the metrics, with a specific emphasis on their temporal utilization.

The FLEP metrics are intended to assess resilience across distinct phases, including pre-event, during-event, and post-event phases in relation to HILP events [42]. In the during-event stage, three substages are evaluated: progress of the disturbance, post-disturbance performance degradation, and recovery. The resilience index considering the duration of extreme events (RCID) is also proposed for during-event stage [63]. By introducing a code-based resiliency metric, the authors achieved the provision of resiliency across various operational time intervals, ranging from 10 to 10^6 in the concept of numerical codes [64].

LOLE and LOLF are utilized to plan the transmission network, which can be regarded prior to the occurrence of HILP [36]. The RAW metric is relevant for preventative planning and proactive measures before the occurrence of HILP events, given the objective of the authors to suggest network reinforcement strategies tailored towards various wind speeds employing this metric [46]. In contrast to the RAW metric, the SRI metric was developed to particularly address the dynamics that occur during the occurrence of an event. By concentrating on the event phase, the SRI metric provides valuable insights into the resilience performance of the system during critical periods [28].

A separate significant study examined the post-conflict discourse surrounding bridge targeting and resilience evaluation, emphasizing a cost-based resilience metric for traffic. The inclusion of the period between the attack's aftermath and the initial phase of the reconstruction process was a distinctive aspect of this investigation. By considering this temporal aspect, the researchers gained valuable insights into the dynamics of bridge resilience and the effects on traffic flow [39].

In [65], a combined metric encompassing total energy shedding, maximum power loss during performance degradation to its minimum amount after the event, and maximum power loss until

Table 5: Summary of metrics associated with uncertainty aspects.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[28]	Captures the system conditions during HILP.	O	-	G	Dur (Res)	S/R	-	-
[29]	The cascading caused by thermal overloads.	O	-	G	Dur (Res)	S/R	-	-
[46]	Ranking circuits based on EENS	O/P	-	F	Pre	R	✓	-
[43]	CEEENS is considered as a resiliency metric.	O/P	-	F	Pre	R	✓	✓
[54]	Conditional Value at Risk of EENS.	P	-	F	Pre	R	-	-
[47]	Power loss in MW (EDNS), maximum ((VaR$_a$) and average (CVaR$_a$) power loss with a specified degree (a) of assurance.	O	-	F	Dur	S/R	✓	✓
[55]	Minimizing expected loss and CVaR of the loss's distribution.	P	-	G	After	R	-	✓
[61]	Resistancy: quantifies the system's ability to withstand the event and prevent its propagation.; Recovery: denotes the ratio of expected recovered interrupted loads to the sum of the total energy of interrupted loads; and Resiliency: represents the ratio of expected supplied energy to the total energy of the loads.	O	-	G	Dur	S	-	✓
[49]	Energy not served, total loss of utility revenue, total outage penalty cost, total avoided outage cost by employing demand response, and resiliency index of the network.	O	-	G	Dur	S	✓	✓
[59]	Treating metrics as a distribution instead of single numbers.	P	-	F	Pre	S	✓	-
[60]	The area under the performance curve.	O	✓	F	Dur	R	-	-
[56]	Capturing the changing climate effect on the system.	P	-	-	Pre	R	-	-
[58]	The area under the curve of damage grid to intensity of the event.	P	✓	G	Pre	R	-	-

Table 6: Summary of metrics associated with temporal aspects.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[65]	Resist/recovery ratio (R^s), Total energy shedding (E^{shed}), peak load power shedding (P^{peak}), time of degradation (T^D), time to restore system from the beginning of event (T^R)	O	✓	F	Pre/Dur	D	-	✓
[66]	Load shedding, Failure of components, System's islanding possibility, Maximum generation and transmission capacity, Repair time, Real-time assessment of load loss, Generation and transmission insufficiency, Average falling speed of the system performance, Ratio of restored load and generation, Restoration speed and efficiency of system, Economic cost of the repair	O	-	F	Pre/Dur/After	D/S/R	✓	✓
[64]	A code-based resiliency metric incorporates the temporal aspect of different operational stages	O	-	F	Dur	D	-	✓
[26]	Assessing vulnerability and restoration rate of the system	P	✓	F	Pre/Dur	D	-	-

full recovery has been proposed for incorporation in optimization and mathematical modelling. This metric proves valuable when the operator lacks access to the resiliency trapezoid and shares the same unit of MWh by normalizing the total energy shedding term.

A comprehensive study presented various metrics for evaluating resilience at different stages, including before, during, and after disturbances [66]. The pre-disaster evaluation centred on quantifying the robustness of power systems against prospective disasters. The during-disaster assessment involved calculating the system's resistance to disturbances in real-time through state estimation. Using sequential Monte Carlo simulation, the post-disaster evaluation of restoration capability considered response capability, restoration efficiency, and restoration economy. This study proposes several metrics to assess the pre-disturbance situation, including the ALRIL, PCFD, Possibility of System Islanding (PSI) and PIN, GMA TMTS, failure rates of transmission lines, conditional risk probability, and repair rate model of transmission lines. For the during-disaster situation, the study introduces three metrics: CLLP, ATCS, and APDA. In the aftermath of a disaster, the resiliency of a system is measured using the following metrics: PLLP, AFS, RLRO, ARSS, REI, and RES.

By precisely modelling the distribution system's overhead lines and poles, reference [26] intended to provide an overall timeline for the power system's resilience. The vulnerability rate illustrates the system's degradation during an unreliable state, while the restoration rate demonstrates the system's improvement during the recovery state. In Table 6, metrics associated with temporal aspects are summarized.

3.5. Performance evaluation

Resilience metrics consider various concepts in the power system as a performance. LOLE, LOLF, and EENS metrics respectively represent the average hours that customers are in an outage, the frequency of outages, and the energy not distributed [36, 46]. Due to its normalization, EIU is a more accurate indicator of unsupplied energy in cases of resiliency, as it clearly distinguishes between reliable and resilient systems. This is because its amount is negligible in normal events, but high in extreme events that happen in resiliency. In addition, LOLF has been utilized as a performance indicator to demonstrate the impact of increasing storm frequency and intensity [38]. Although there is a linear relationship between the increase in storm frequency and LOLF, there is an exponential relationship between the increase in storm intensity and LOLF. The effect of flood on CVaR of EENS has been investigated in [54]. Two resiliency metrics, namely average lost load and normalized cascade size have been proposed to assess the impact of cascade failures during islanding [67]. The SRI metric considers the amount of load shedding required to reach the stable state of the system as a criterion [28]. The maximum Loss of Load ($LOL^{\max}$) is used as part of the load constraints to limit the load shedding ratio[68].

The FLEP metric, aiming to be a comprehensive resilience measurement tool, acknowledges the distinct nature of system performance in both operational and planning contexts. Notably, the performance aspects concerning online transmission lines, connected production capacity, load connection, and the number of disconnected lines, among others, exhibit notable variations depending on whether the focus is on operational or planning considerations [42]. To evaluate resilience, four metrics, including LOLP, EDNS (classic metrics), the expected number of line outages (K), and the difficulty level of grid recovery index (G), were employed [44]. The value of K is derived from the fragility function, whereas G estimates network performance by employing a weighted combination of five elements: extreme event severity, power infrastructure damage, transportation infrastructure damage, cyber infrastructure damage, and the unavailability of human and material resources. It is noteworthy to mention that G integrates the conventional concept of Mean Time to Repair (MTTR) within its formula. Reference [69] incorporated the four metrics from the prior reference and added the system weakness metric to the resiliency metric's vector. The latter metric calculates the deviation from the nominal value of the system components that have not experienced failure yet. Furthermore, it has been demonstrated that the existence of a microgrid prolongs the grid's degradation process during HILP events. The suggested metric in [70], in contrast to EDNS, represents the amount of power available during the severe event.

Traffic network performance is evaluated by examining the traffic-to-population ratio to ensure a standard assessment. The resilience metric is further normalized by incorporating the reconstruction cost [39]. Considering the importance of various loads, a cost function has been introduced to the resiliency metric in the coordinated planning of the energy transportation network and power system to minimize load curtailment after the incidence of a severe event [71]. The Restoration Scheme Evaluation (RSE) metric is introduced, emphasizing the significance of rapid, efficient, and cost-effective restoration schemes [66]. This metric captures both the economic loss of load and the economic cost of repair works. Minimizing the number of de-energized zones through the implementation of a FLISR process using a binary variable is proposed as part of the proposal for a CRC [72].

In an innovative study [73], the CPARM metric was introduced, considering both the power

Table 7: Summary of metrics based on systems performance assessments.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[39]	Cost-based resilience index.	P	-	G	Dur/After	D	-	-
[38]	LLO, LLD, ENS, EENS.	P	-	G	Pre	D	✓	-
[72]	Minimizing de-energized zones	O	-	F	Dur(res)	D	-	✓
[68]	Using the maximum loss of load as a boundary of Objective Function	P/O	-	G	Pre/Dur	S	✓	✓
[71]	Minimize load curtailment.	P	-	G	After	D	-	✓
[67]	Average loss load and normalized cascade size.	O	-	F	Dur/After	D	-	✓
[44]	Number of line outages, the difficulty level of grid recovery.	O	-	F	Pre	S	✓	-
[69]	A vector comprising five resiliency indices.	O	-	F	Pre	S	✓	-
[70]	Capturing probability of each HILP event.	O	-	G	Dur	S	-	-
[73]	CPARM considers both power-side resilience and cyber-side resilience.	O	-	F	Dur	D	✓	-
[74]	Physical resilience consists of the penalty of generation and voltage violation, Cyber resilience metric considers the ratio of successful remote and local attacks to all of the attacks.	O	-	-	Dur	D	-	✓

and cyber aspects. The power part comprises conventional elements of resiliency, including load, reserve capacity, available line capacity, and reliability. Simultaneously, the cyber part aims to evaluate the maximum damage an attacker can inflict on the system. In a related study, a cyber metric was established, which considers successful internal and remote attacks in relation to all attacks [74]. Additionally, a physical metric was devised based on generation penalty and voltage violation.

In Table 7, metrics are presented based on performance assessments of systems.

3.6. Graph theory-based metrics

In the literature, power networks are modelled either traditionally as power flow problems or as a graph. Based on this, resilience quantification can be classified into two categories: graph-based and flow-based. Given that the majority of metrics are employed in power flow problems, here our focus will be exclusively on graph-based metrics. The power network is conceptualized as a graph composed of nodes (vertices) and edges (links), forming the network structure in graph-based approaches. Notably, some nodes may possess specific attributes, including geographical location, and network links are established between pairs of nodes.

To assess the resilience of the system as a whole, which integrates cyber and physical layers modelled as a graph, LLP and NLP metrics were introduced for reflecting actual resilience in cascading failure [75].

Defense islanding was proposed by modelling the power network in [29] as a graph, which allowed SRI to determine whether or not to implement it. LOLF, LOLE, and EENS are applicable to flow-based and graph-based power networks [38]. Regardless of the underlying network representation, these metrics offer flexible tools for evaluating the performance and resilience of power systems. The modeling of network efficiency (NE) involves summing the distances of the shortest paths between nodes within the network, as suggested in [76]. This calculation considers the total number of nodes within the network, encompassing various energy sectors.

By applying a multicriteria-decision making approach, i.e. AHP, various topological metrics were incorporated as a resiliency vector in [77]. Additionally, the assessment of resiliency includes consideration of power flow feasibility. In a similar study, overall system resilience scoring has been proposed using a synthesis of positive effect criteria such as network topological robustness and recovery of critical loads and negative criteria such as the number of switching times and total power loss [78]. Algebraic Connectivity (AC), graph redundancy (GR), and ESPC as positive criteria and ABCC as negative criteria all contribute to Topological Robustness (TR). To capture various aspects of the network's behaviour, AC, grid sensitivity, and grid resistance metrics are presented [34]. AC quantifies the network's changes from its previous state; grid sensitivity measures the network's reactions to changes; and grid resistance evaluates the grid's resistance to changes in its elements. In another study, the AHP approach is employed to determine the weighting of resilience metrics [79]. These weights are derived from considering the risk associated with the geographic location of each path and measures implemented to enhance network resilience against storms. Additionally, the severity of events and the position of power system equipment (overhead or underground) are taken into account. The metric developed in this study incorporates critical loads and conforms to the requirements of the power system graph. Choquet Integral is used to integrate seven graph theory concepts: Branch Count Effect (BCE), Overlapping Branches (OB), Switching Operations (SO), Path Redundancy, Probability of Availability (POA), Penalty Factor (PF), and Aggregated Central Point Dominance (ACPD) [80]. As in the aforementioned studies, AHP is applied to weight graph theory concepts. These concepts were utilized to assess the resiliency of feasible networks, with a focus on critical load restoration and minimizing the number of switching operations. Although the proposed metric can be applied to both operational and planning contexts, it falls short of quantifying the network's ability to rapidly recover. In addition to the previous reference metrics, [81] introduced two physical metrics, LSI and PSI, to assess the resiliency of the proposed system. LSI encompasses right-of-way clearance, number of joints, line sag, and number of spacer units to evaluate the strength of lines. On the other hand, PSI considers pole sharing, pole deflection, pole corrosion, muffing status, guy wire, and pole material to assess the strength of poles. Derived from the foundational post-outage power flow matrix, a metric for microgrid graphs is introduced [82]. This metric incorporates vulnerability rank and degree, alongside criticality rank and degree. An overview of graph-based metrics is presented in Table 8.

3.7. Curve-based metrics

In this section, we will analyse the metrics represented by curves. Typically, these measurements were developed using the triangle, trapezoid, or other form specified by the articles on resilience.

The intensity of the incident and the quantity of damages were used to create a resilience graph in [57]. This graph served as the foundation for the introduction of the SI metric, which determines the smoothness of the graph by computing all its slopes. The difference between the minimum and maximum slopes of the resilience graph is equivalent to the inverse of this holistic metric. The

Table 8: Summary of graph-based metrics.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[75]	Node and load loss proportion	O	-	G	Pre	D	-	-
[78]	AC: connectivity status of a network GR: redundancy of backup lines ABCC: number of shortest paths passing through a node. ESPC: average length of the shortest paths between sources and critical nodes.	O	-	F/G	Pre/After	S	-	✓
[77]	Combination of topological resiliency metric with power flow feasibility	O/P	-	G	After	S	-	✓
[79]	Geodesic path of between a node and a generator, maximum of all path length, critical power demand, total power demand	O	-	G	Pre	D	-	-
[80]	Integrating different graph theory concepts to quantify resiliency of networks	O/P	-	G	Pre	S	-	✓
[81]	Taking into account two physical metrics for overhead networks' poles and lines alongside graph-based metrics.	O/P	-	G	Pre		-	✓
[34]	Both graph and operational metrics are considered.	O	-	G	Pre	D	-	✓
[82]	Using vulnerability rank and degree and criticality rank and degree to calculate the resiliency of the proposed microgrid.	O	-	G	Dur	S	-	✓

CVaR index for CENS is used in this instance to quantify the number of losses, demonstrating the suitability of this metric for risk-based studies. Since the incident's severity might vary, the hurricane's speed is taken into consideration in this article.

By introducing an extension to the resilience triangle, [42] made a significant contribution to the field of resilience research. This expansion included the incorporation of the FLEP metrics and the resilience trapezoid framework. These metrics investigate the resiliency of a system based on how quickly (ϕ-metric) and how drastically (Λ-metric) its resilience decreases, for what duration (E-metric) the post-event degraded state lasts, and how rapidly (Π-metric) it returns to its pre-event state. In another study, the performance drop during a disturbance is divided by the performance level expected under normal operating conditions to determine a resilience metric [76]. In [83], the authors sought to maximize resilience by minimizing the upper part of the operability trajectory, also known as the other side of resilience. In the presented diagram, higher robustness is indicated by lower performance loss at the moment of occurrence, while greater resilience in general is reflected by a larger area under the diagram. By employing a straightforward resilience metric defined in [84], the objective function is introduced as the minimization of the surface area under the system performance curve. The assessment of system resilience performance, which included MGs, utilized four normalized indicators [85]: VI, DI, REI, and MRI. The MRI metric is specifically tailored to assess the MG's restoration performance while ignoring the time required for infrastructure recovery to restore the system to its initial performance. The MG resilience index is calculated by combining four resilience metrics: FI, REI, MVI, and LLI [27]. The first two metrics are associated with MG performance curves, while the other two pertain to network technical metrics. Also, FI essentially shares similarities with the DI index but takes scenarios into consideration.

The resilience metric, as outlined in reference [86], is derived from the social welfare system's performance graph. Social welfare is obtained by employing the satisfaction function, which represents the accessibility of loads to power and water. This metric measures robustness by considering the minimum performance value and quantifying the ability to recover via the area under the social welfare graph. Additionally, it contributes to system recovery's rapidity.

Compared to other visual-based resiliency metrics, the RCID metric takes two additional factors into account [63]:

1. The system's initial resistance at the time of the catastrophe.
2. The effective duration of the event's impact, which is shorter than the time taken to reach the initial performance.

Adopting an alternative methodology, utilizing data sourced from the EAGLE-I, new resiliency metrics rooted in PDFs were introduced [87]. These metrics encompass the recovery rate, impact rate, and the recovery-to-impact ratio, all derived from the number of consumer outages in HILP events. The number of outages during HILP events exhibits a shape remarkably similar to the standard resilience curve, if one inverts the graph on the time axis. Consequently, the inverted curve can be regarded as the genuine representation of the resilience curve (see Figure 10).

The evolution of resilience curves is depicted in Figure 9. As illustrated, initial articles employ a basic resilience triangle approach (Figure 9a), which subsequently progresses to a refined resilience trapezoid (Figure 9b). In the final diagram (Figure 9c), a composite representation of suggestions from various articles is integrated to formulate a holistic resiliency curve. Primarily, the performance of the system has consistently evolved, generally improving. However, after resilience actions, the outcome can either maintain the existing level, exhibit enhancement, or experience deterioration. Secondly, it is important to account for the influence of flexibility options, such as microgrids. In the initial hours of an event, the system may uphold its performance through their assistance. Thirdly, proper consideration should be given to the consequences of multiple failures that occur after the initial incident. Finally, the presented curve should distinguish between operational and structural recovery. Operational recovery can be achieved within a relatively brief time-frame, while structural recovery demands a more extended period.

In Figure 10, we conduct a comparative analysis between the proposed resilience curve and real data sourced from the EAGLE-I database, specifically focusing on Hurricane Harvey's impact on Jefferson County, Texas, to assess the curve's utility. For a resiliency curve RC we define the cumulative impact $\mathcal{I}_{RC}$ as:

$$\mathcal{I}_{RC} = \int_{t_d}^{t_e} RC(t)dt. \tag{9}$$

It quantifies the total impact of the event, in $outages\,hour$. Not that the integral is defined between t_d the beginning of the degrading phase, and the end of the event t_e. Practically, it is hard to identify the event in real life before the actual cascades happening during the degradation phase. The deviation from the baseline (the real outage) indicates how well the resiliency curve captures the entire event.

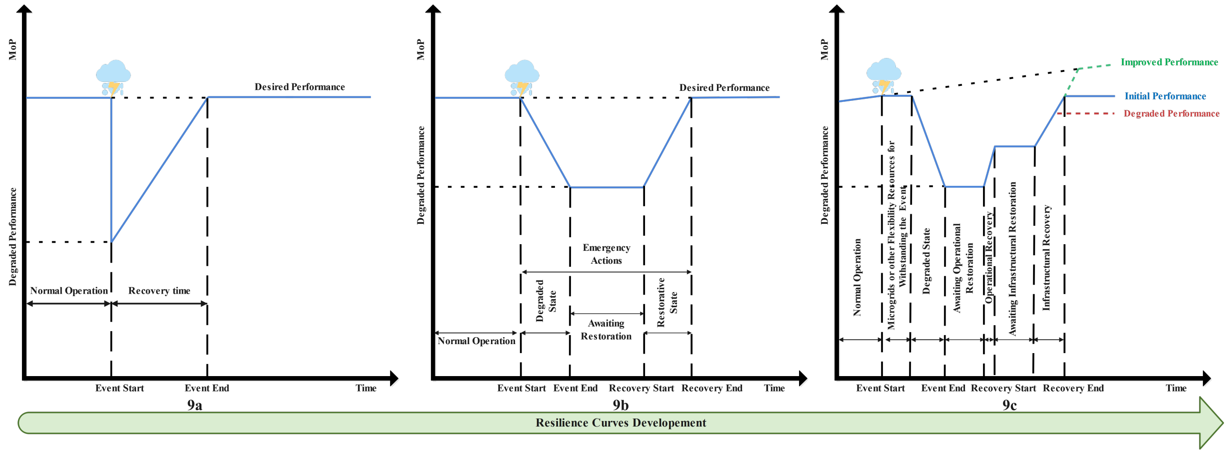


Figure 9: Evolution of resiliency curves.

Table 9: Comparison between resiliency curves with real HILP event (Hurricane Harvey) using the cumulative impact I_{rc} $(outages\ hour)$ defined in Eq. (9). Errors are calculated with respect to the real outage, used as the baseline.

Resiliency curve	cumulative impact I_{rc}	errors
Real Outage	2,090,939	-
Resilience Triangle	2,556,000	22.2%
Resilience Trapezoid	2,358,976	12.8%
Holistic Resilience	2,244,064	7.3%

Results can be found Table 9. The holistic model demonstrates an accuracy that differs from the baseline by only 7.3%, surpassing the trapezoid model, which deviates by 12.8% from the baseline. The resilience triangle, on the other hand, has the highest errors, culminating at 22.2%, highlighting that the holistic model performs better in representing real-world scenarios.

Our observations reveal that each HILP event possesses distinct characteristics. While a simple resilience triangle may suffice for modeling hurricane events, our proposed curve provides a more detailed representation. Similarly, during the first and second winter storms and associated cold waves, which resulted in power outages for over five million residents across the US (with Texas alone accounting for 4.3 million affected customers), the event's features can be approximated with a resilience trapezoid. Nevertheless, the comprehensive resilience curve introduced in this article offers a more intricate portrayal of these events. An overview of curve-based metrics is presented in Table 10.

4. Evaluating resilience metrics and recommendations

In section 3, metrics were categorized into seven distinct categories, each with its associated merits and limitations. Given the multifaceted nature of HILP events and their impacts on power grids, proposing a singular metric may not suffice as a comprehensive solution. Thus, we recommend the usage of a vector-based metric for evaluating system resiliency. This vector should

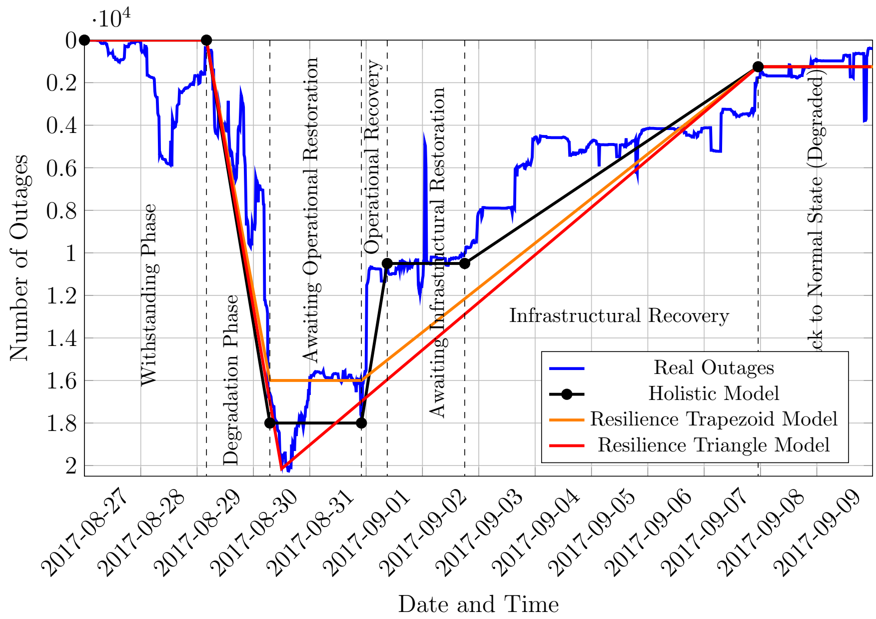


Figure 10: Comparison of the proposed resiliency curve with real HILP event (Hurricane Harvey).

Table 10: Summary of curve-based metrics.

Ref	Brief Description	P/O	V	F/G	Pre/Dur/After	D/S/R	Re	DER
[42]	How fast and low resilience drops, post disturbance duration, network recovery speed	O/P	✓	F	Dur (DP, Deg, Res)	D	-	-
[57]	The smoothness of resiliency graph based on the intensity of the event and number of damages	O	✓	F	Dur	R (CVaR)	-	-
[76]	Ratio of disturbed performance to undisturbed performance, Network efficiency	O	✓	G	Dur	D	-	✓
[83]	This metric demonstrates the operability of power system infrastructure	O	✓	G	Dur	S	-	-
[86]	Robustness, recoverability, and rapidness are combined in this metric.	P	✓	G	Pre	D	-	✓
[63]	Considering initial resistance and effective duration of extreme events in the resiliency metric.	O	✓	F	Dur	S	-	-
[85]	VI, DI, REI, and MRI are defined to measure degradation level, temporal degradation, restoration efficiency, and microgrid resilience, respectively	O	✓	F	Dur	D	-	✓
[84]	Normalized area under the system performance curve	O	✓	G	Dur	D	-	-
[27]	VI, DI, REI, and MRI are defined to measure degradation level, temporal degradation, restoration efficiency, and microgrid resilience, respectively.	O	✓	F	Dur	S	-	✓
[87]	Impact rate and duration, the recovery rate and duration, and the impact level. (PDF for each metric is also provided)	P	✓	F	Pre	S/R	-	-

encompass components addressing the degree of uncertainty, whether it is intended for operational or planning use, the temporal scope of events considered, the physical interpretation of the metric, the presence of a curve representation, and whether it is based on graph or power flow principles. Furthermore, it is crucial to explicitly identify the HILP event that is being discussed. To address these challenges and enhance the interpretability of metrics for researchers, we propose a code-based vector for resiliency metrics as expressed in Eq. (10):

$$\vec{\mathcal{R}} = [\mathcal{R}_1, \mathcal{R}_2, \mathcal{R}_3, \mathcal{R}_4, \mathcal{R}_5, \mathcal{R}_6, \mathcal{R}_7]. \tag{10}$$

Here, $\mathcal{R}_1$ represents whether the metric is used in operational (O_1) or planning (P_1) contexts. $\mathcal{R}_2$ identifies the temporal aspect assessed, with components for pre-event (Pr_2), during event (D_2) comprising Disturbance Progress (*DP*), Degraded state (*Deg*), and Restorative State (*RES*), and post-event (Po_2) phases. $\mathcal{R}_3$ describes the mathematical formulation of the resilience metric. $\mathcal{R}_4$ indicates whether the metric is based on a resilience curve (C_4) or not (N_4). $\mathcal{R}_5$ denotes the level of uncertainty in the metric, with D_5 representing deterministic, S_5 representing stochastic, and R_5 representing risk-based metrics. $\mathcal{R}_6$ reflects the modelling approach used, distinguishing between power flow (P_6) and graph-based (G_6) methods. Lastly, $\mathcal{R}_7$ specifies the type of event impacting the system, differentiating between cyber-attacks (Cy_7) and natural disasters (Na_7), with natural disasters explicitly stated to clarify their distinct effects. By reformulating Eq. (10), we can express Eq. (11) as follows:

$$\begin{aligned} \vec{\mathcal{R}} = [&O_1/P_1, \mathrm{Pr}_2/D_2(DP, Deg, Res)/\mathrm{Po}_2, \\ &\mathcal{R}_3 = \mathit{Formula}, C_4/N_4, D_5/S_5/R_5, P_6/G_6, \mathrm{Na}_7/\mathrm{Cy}_7]. \end{aligned} \tag{11}$$

As an illustrative example of how this vector can provide clarity for researchers, we applied it to the cybersecurity metric proposed in Article [74]. Eq. (12) below represents this metric:

$$\begin{aligned} \vec{\mathcal{R}} = [O_1, D_2(Deg), \mathcal{R}_3 = 1 - &\left(\sum \Theta^{\text{successful}}_{\text{remote}} + \sum \Theta^{\text{successful}}_{\text{local}}\right) / \\ &\left(\sum \Theta_{\text{remote}} + \sum \Theta_{\text{local}}\right), N_4, D_5, P_6, \mathrm{Cy}_7]. \end{aligned} \tag{12}$$

Eq. (12) means that the deterministic resilience metric is utilized during the operational stage of the degradation state. It lacks a visual representation and does not employ graph theory for representing electricity networks. Furthermore, the associated events possess a cyber nature, leading to the formulation of the resiliency metric through the application of the $\mathcal{R}_3$ formula.

Furthermore, an ideal resilience metric for power systems should possess key attributes, including scalability, comparability, interpretability, quantifiability, and the ability to capture HILP events, as well as uncertainty. This ensures that the metric aligns with the comprehensive concepts outlined in the resiliency framework presented in Figure 6. This section proceeds by conducting a comparative analysis of six key types of metrics—reliability-based, risk-based, graph-based, cyber-based, curve-based, and FLEP metrics—utilizing a spider diagram (Figure 11).

Metrics associated with cybersecurity hold the potential to encompass HILP events stemming from human factors. However, within the existing body of power system literature, the incorporation of these metrics is still in its early stages. Graph-based metrics, rooted in the principles of graph theories, provide a means to comprehend the idea of resilience through analysing network

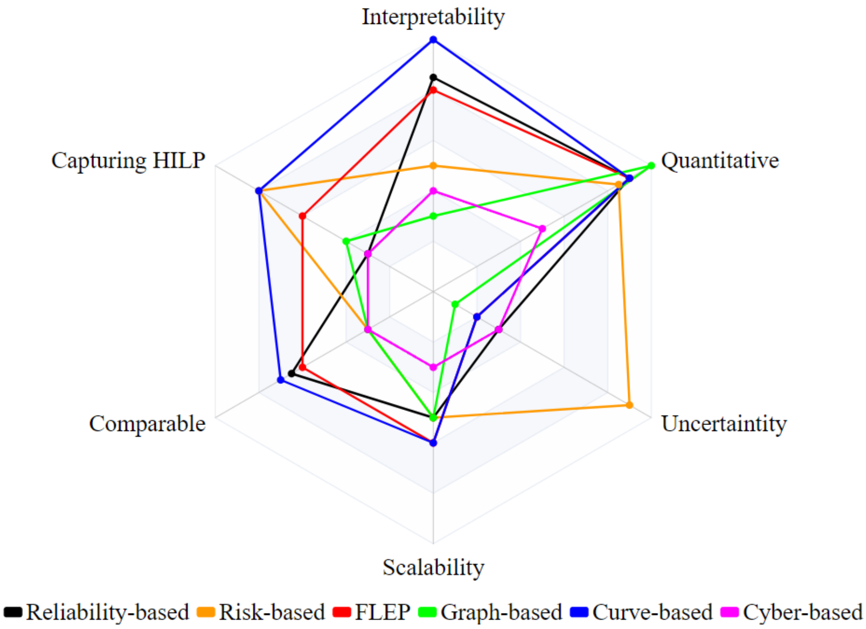


Figure 11: Evaluation of key metrics based on essential attributes of an optimal resilience metric.

topologies. While they serve as effective representations of resilience in networks, they fall short in terms of tailored inclusivity for capturing HILP events and their inherent uncertainties. Moreover, their comparability is hindered, and their physical meaning remains elusive.

Reliability-based metrics, on the other hand, present straightforward interpretability and comparability, although endeavours to adapt them for HILP events and uncertainty encapsulation have not been optimal. Conversely, risk-based metrics, with their capacity for embracing HILP events and their associated uncertainties, are purposefully designed to do so. However, their complexity hinders ease of comparison across systems.

The combination of metrics in the FLEP metric, which uses four different metrics, shows competence in many areas, except for being able to measure uncertainties. Comparatively, curve-based metrics exhibit advantages over FLEP metrics, particularly evident in the context of the EAGLE-I article [87], albeit their capacity to gauge uncertainties remains limited.

Based on the aforementioned comparisons, it becomes apparent that introducing a curve-based metric, such as the FLEP metric, which comprehensively accounts for all temporal aspects of HILP events, including uncertainty and risk similar to risk-based metrics, while also maintaining the ease of comprehension found in reliability-based metrics, can offer a promising solution to the emerging field of resilience metrics. Additionally, recognizing the importance of a HILP event's location in assessing resiliency, it is feasible to incorporate this aspect by employing a system modeling approach based on graph theory.

Ultimately, we propose the adoption of a comprehensive metric that encompasses the six identified key attributes. A combination of risk-based and curve-based metrics is deemed adequate, ensuring coverage of all essential attributes for an ideal resilience metric for most stakeholders. Furthermore, additional research is required to establish connections or formulate metrics related to cybersecurity, interdisciplinary considerations, and multi-energy carrier considerations, alongside the integration of machine learning methodologies in resilience studies.

5. Conclusion

This review thoroughly investigates the latest developments in quantitative resilience metrics in the context of electrical power systems, by examining a selection of articles mainly published between 2019 and 2023,

An extensive collection of quantitative resilience metrics was collected, with a categorization based on fundamental characteristics including operational or planning focus, visualization capabilities, reliance on flow or graph-based modelling, temporal characteristics, physical interpretations, treatment of uncertainties, connections to reliability metrics, and integration of distributed energy resources. Subsequently, a realistic representation of resilience in power systems was achieved by synthesizing resilience curves from various sources. We have compared the holistic curve produced by this approach to actual extreme event data for Hurricane Harvey from the EAGLE-I Database. This study provides a deep understanding of HILP event dynamics.

Additionally, an in-depth comparison was conducted on assessing resilience metrics, employing a spider diagram, as an illustration, to compare their performance across key features of a desirable metric. The comparative analysis allows for the identification of strengths and weaknesses of existing resilience metrics, which facilitates making informed decisions about practical applications. Recognizing the multifaceted nature of HILP events, we also introduce a code-based vector of resilience metrics. This vector aims to effectively tackle the widespread confusion found in existing literature. By offering an organized framework, it supplies researchers with a clear structure to work with, which ultimately enhances the interpretability and practicality of resilience measurements.

According to the findings, the following research gaps and recommendations are outlined.

- **Interdisciplinary Collaboration:**
  The resilience of power systems requires an interdisciplinary approach. To address cyber-physical threats to power grids, collaborations among power systems experts, data scientists, resilience specialists, and cybersecurity specialists are necessary. The emergence of holistic and ideal resilience metrics can be achieved through this approach.

- **Cybersecurity Measures:**
  While the cybersecurity measures aspect is in its initial stages, its significance in protecting power systems from cyber-attacks cannot be underestimated. Developing robust cybersecurity strategies and frameworks adapted to power systems will be essential to ensure their continued reliability and resilience in the face of evolving cyber threats.

- **Uncertainties and Machine Learning Solutions:**
  A prominent challenge in resilience metrics involves addressing system uncertainties, such as those encountered in renewable energy production, load consumption, and the impact of HILP events on power systems. Leveraging machine learning techniques as powerful tools to mitigate these uncertainties holds promise for enhancing resilience across various domains, including outage forecasting, stability assessment, control, and restoration.

- **Real-World Validation:**
  Future research must prioritize real-world validation of resilience metrics. While initiatives like the EAGLE-I database are valuable, obtaining precise, real-time data on power system topology and line outages during HILP events remains a critical challenge. Ensuring data accuracy is essential for practical resilience metric applications.

- **Multi-Carrier Energy Systems:**
  Future research should delve into the comprehensive study of multi-carrier energy systems, considering the complex interrelationships among power, gas, and water networks. Developing a unified metric that effectively evaluates resilience across these critical systems is vital. HILP events can disrupt all these domains, and a robust metric encompassing their complex interactions is important for enhancing overall system resilience.

Addressing the identified research gaps requires collaborative efforts, innovative methodologies, and a commitment to real-world validation. By prioritizing the outlined recommendations, researchers can significantly contribute to advancing the understanding and practical implementation of resilience metrics in the dynamic environment of electrical power systems, ultimately enhancing their reliability and resilience in the face of evolving challenges.

References

[1] A. B. Smith, Us billion-dollar weather and climate disasters, 1980-present (2022).

[2] M. H. Nejati Amiri, M. Mehdinejad, A. Mohammadpour Shotorbani, H. Shayanfar, Heuristic retailer's day-ahead pricing based on online-learning of prosumer's optimal energy management model, Energies 16 (3) (2023) 1182.

[3] O. S. Omogoye, K. A. Folly, K. O. Awodele, Review of sequential steps to realize power system resilience, in: 2020 International SAUPEC/RobMech/PRASA Conference, IEEE, 2020, pp. 1–6.

[4] I. Zunnurain, Y. Sang, P. Mandal, M. Velez-Reyes, J. Espiritu, Improving the resilience of large-scale power systems using distributed static series compensators, International Journal of Electrical Power & Energy Systems 145 (2023) 108702.

[5] J. Jasiūnas, P. D. Lund, J. Mikkola, Energy system resilience–a review, Renewable and Sustainable Energy Reviews 150 (2021) 111476.

[6] H. Silva, M. Vieira, A. Neto, Are safety-critical systems really survivable to attacks?, in: 2023 IEEE International Systems Conference (SysCon), IEEE, 2023, pp. 1–8.

[7] P. Kozak, I. Klaban, T. Šlajs, Industroyer cyber-attacks on ukraine's critical infrastructure, in: 2023 International Conference on Military Technologies (ICMT), IEEE, 2023, pp. 1–6.

[8] S. Afzal, H. Mokhlis, H. A. Illias, N. N. Mansor, H. Shareef, State-of-the-art review on power system resilience and assessment techniques, IET Generation, Transmission & Distribution 14 (25) (2020) 6107–6121.

[9] A. Stankovic, The definition and quantification of resilience, IEEE PES Industry Technical Support Task Force: Piscataway, NJ, USA (2018) 1–4.

[10] H. Raoufi, V. Vahidinasab, K. Mehran, Power systems resilience metrics: A comprehensive review of challenges and outlook, Sustainability 12 (22) (2020) 9698.

[11] Y. Xu, Y. Xing, Q. Huang, J. Li, G. Zhang, O. Bamisile, Q. Huang, A review of resilience enhancement strategies in renewable power system under hilp events, Energy Reports 9 (2023) 200–209.

[12] S. A. Mansouri, E. Nematbakhsh, M. S. Javadi, A. R. Jordehi, M. Shafie-khah, J. P. Catalão, Resilience enhancement via automatic switching considering direct load control program and energy storage systems, in: 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), IEEE, 2021, pp. 1–6.

[13] H. Saboori, Enhancing resilience and sustainability of distribution networks by emergency operation of a truck-mounted mobile battery energy storage fleet, Sustainable Energy, Grids and Networks 34 (2023) 101037.
[14] G. Liu, M. F. Ferrari, T. B. Ollis, A. Sundararajan, M. Olama, Y. Chen, Distributed energy management for networked microgrids with hardware-in-the-loop validation, Energies 16 (7) (2023) 3014.
[15] J. M. Home-Ortiz, O. D. Melgar-Dominguez, M. S. Javadi, J. R. S. Mantovani, J. P. Catalao, Improvement of the distribution systems resilience via operational resources and demand response, IEEE Transactions on Industry Applications 58 (5) (2022) 5966–5976.
[16] Y. Lin, Z. Bie, A. Qiu, A review of key strategies in realizing power system resilience, Global Energy Interconnection 1 (1) (2018) 70–78.
[17] A. A. Bajwa, H. Mokhlis, S. Mekhilef, M. Mubin, Enhancing power system resilience leveraging microgrids: A review, Journal of Renewable and Sustainable Energy 11 (3) (2019).
[18] M. Mahzarnia, M. P. Moghaddam, P. T. Baboli, P. Siano, A review of the measures to enhance power systems resilience, IEEE Systems Journal 14 (3) (2020) 4059–4070.
[19] A. Younesi, H. Shayeghi, Z. Wang, P. Siano, A. Mehrizi-Sani, A. Safari, Trends in modern power systems resilience: State-of-the-art review, Renewable and Sustainable Energy Reviews 162 (2022) 112397.
[20] V. Tansakul, A. Myers, S. Tennille, M. Denman, A. Hamaker, J. Huihui, K. Medlen, K. Allen, D. Redmon, S. Chinthavali, et al., Eagle-i power outage data 2014-2022, Tech. rep., Oak Ridge National Lab.(ORNL), Oak Ridge, TN (United States). Oak Ridge … (2023).
[21] M. Dilley, Natural disaster hotspots: a global risk analysis, Vol. 5, World Bank Publications, 2005.
[22] AON, Weather, climate and catastrophe insight — aon, accessed Sep. 13, 2023 (2023).
URL `https://www.aon.com/weather-climate-catastrophe/index.aspx`
[23] I. P. T. Force, A. Stanković, K. Tomsovic, F. De Caro, M. Braun, J. Chow, N. Äukalevski, I. Dobson, J. Eto, B. Fink, et al., Methods for analysis and quantification of power system resilience, IEEE Transactions on Power Systems (2022).
[24] J.-P. Watson, R. Guttromson, C. Silva-Monroy, R. Jeffers, K. Jones, J. Ellison, C. Rath, J. Gearhart, D. Jones, T. Corbet, et al., Conceptual framework for developing resilience metrics for the electricity oil and gas sectors in the united states, Sandia national laboratories, albuquerque, nm (united states), tech. rep (2014).
[25] S. A. Mansouri, E. Nematbakhsh, A. Ahmarinejad, A. R. Jordehi, M. S. Javadi, M. Marzband, A hierarchical scheduling framework for resilience enhancement of decentralized renewable-based microgrids considering proactive actions and mobile units, Renewable and Sustainable Energy Reviews 168 (2022) 112854.
[26] F. Dehghani, M. Mohammadi, M. Karimi, Age-dependent resilience assessment and quantification of distribution systems under extreme weather events, International Journal of Electrical Power & Energy Systems 150 (2023) 109089.
[27] A. Younesi, H. Shayeghi, P. Siano, A. Safari, H. H. Alhelou, Enhancing the resilience of operational microgrids through a two-stage scheduling strategy considering the impact of uncertainties, IEEE Access 9 (2021) 18454–18464.
[28] M. Panteli, D. N. Trakas, P. Mancarella, N. D. Hatziargyriou, Power systems resilience assessment: Hardening and smart operational enhancement strategies, Proceedings of the IEEE 105 (7) (2017) 1202–1213.
[29] M. Panteli, D. N. Trakas, P. Mancarella, N. D. Hatziargyriou, Boosting the power grid resilience to extreme weather events using defensive islanding, IEEE Transactions on Smart Grid 7 (6) (2016) 2913–2922.
[30] M. Lotfi, M. Panteli, B. V. Venkatasubramanian, M. S. Javadi, L. M. Carvalho, C. S. Gouveia, Quantifying the difference between resilience and reliability in the operation planning of mobile resources for power distribution grids, Findings (2022).
[31] H. Gao, Y. Chen, Y. Xu, C.-C. Liu, Resilience-oriented critical load restoration using microgrids in distribution systems, IEEE Transactions on Smart Grid 7 (6) (2016) 2837–2848.
[32] A. Hussain, A. O. Rousis, I. Konstantelos, G. Strbac, J. Jeon, H.-M. Kim, Impact of uncertainties on resilient operation of microgrids: A data-driven approach, IEEE Access 7 (2019) 14924–14937.
[33] D. Luo, Y. Xia, Y. Zeng, C. Li, B. Zhou, H. Yu, Q. Wu, Evaluation method of distribution network resilience focusing on critical loads, ieee Access 6 (2018) 61633–61639.
[34] P. Dehghanian, S. Aslan, P. Dehghanian, Maintaining electric system safety through an enhanced network resilience, IEEE Transactions on Industry Applications 54 (5) (2018) 4927–4937.

[35] J. Gui, H. Lei, T. R. McJunkin, B. Chen, B. K. Johnson, Operational resilience metrics for power systems with penetration of renewable resources, IET Generation, Transmission & Distribution 17 (10) (2023) 2344–2355.
[36] M. Panteli, P. Mancarella, Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events, IEEE Systems Journal 11 (3) (2015) 1733–1742.
[37] S. Espinoza, M. Panteli, P. Mancarella, H. Rudnick, Multi-phase assessment and adaptation of power systems resilience to natural hazards, Electric Power Systems Research 136 (2016) 352–361.
[38] G. Fu, S. Wilkinson, R. J. Dawson, H. J. Fowler, C. Kilsby, M. Panteli, P. Mancarella, Integrated approach to assess the resilience of future electricity infrastructure networks to climate hazards, IEEE Systems Journal 12 (4) (2017) 3169–3180.
[39] S.-A. Mitoulis, S. Argyroudis, M. Panteli, C. Fuggini, S. Valkaniotis, W. Hynes, I. Linkov, Conflict-resilience framework for critical infrastructure peacebuilding, Sustainable Cities and Society 91 (2023) 104405.
[40] S. D. Manshadi, M. E. Khodayar, Resilient operation of multiple energy carrier microgrids, IEEE Transactions on Smart Grid 6 (5) (2015) 2283–2292.
[41] M. Nazemi, M. Moeini-Aghtaie, M. Fotuhi-Firuzabad, P. Dehghanian, Energy storage planning for enhanced resilience of power distribution networks against earthquakes, IEEE Transactions on Sustainable Energy 11 (2) (2019) 795–806.
[42] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, N. D. Hatziargyriou, Metrics and quantification of operational and infrastructure resilience in power systems, IEEE Transactions on Power Systems 32 (6) (2017) 4732–4742.
[43] T. Lagos, R. Moreno, A. N. Espinosa, M. Panteli, R. Sacaan, F. Ordonez, H. Rudnick, P. Mancarella, Identifying optimal portfolios of resilient network investments against natural hazards, with applications to earthquakes, IEEE Transactions on Power Systems 35 (2) (2019) 1411–1421.
[44] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, Z. Bie, Microgrids for enhancing the power grid resilience in extreme conditions, IEEE Transactions on Smart Grid 8 (2) (2016) 589–597.
[45] H. Chen, C. Pilong, P. Rocha-Garrido, D. Frogg, M. Jayachandran, D. Manno, J. Sexauer, C. Callaghan, R. Dropkin, J. Mulhern, et al., Grid resilience with high renewable penetration: A pjm approach, IEEE Transactions on Sustainable Energy 14 (2) (2022) 1169–1177.
[46] M. Panteli, C. Pickering, S. Wilkinson, R. Dawson, P. Mancarella, Power system resilience to extreme weather: Fragility modeling, probabilistic impact assessment, and adaptation measures, IEEE Transactions on Power Systems 32 (5) (2016) 3747–3757.
[47] Y. Dai, R. Preece, M. Panteli, Risk assessment of cascading failures in power systems with increasing wind penetration, Electric Power Systems Research 211 (2022) 108392.
[48] H. Farzin, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, Enhancing power system resilience through hierarchical outage management in multi-microgrids, IEEE Transactions on Smart Grid 7 (6) (2016) 2869–2879.
[49] S. R. Osman, B. E. Sedhom, S. S. Kaddah, Optimal resilient microgrids formation based on darts game theory approach and emergency demand response program for cyber-physical distribution networks considering natural disasters, Process Safety and Environmental Protection 173 (2023) 893–921.
[50] P. Dehghanian, S. Aslan, P. Dehghanian, Quantifying power system resiliency improvement using network reconfiguration, in: 2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS), IEEE, 2017, pp. 1364–1367.
[51] H. Soualah, G. Jodin, R. Le Goff Latimier, H. Ben Ahmed, Energy not exchanged: A metric to quantify energy resilience in smart grids, Sustainability 15 (3) (2023) 2596.
[52] A. Kwasinski, Quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level, Energies 9 (2) (2016) 93.
[53] E. Rosales-Asensio, J.-L. Elejalde, A. Pulido-Alonso, A. Colmenar-Santos, Resilience framework, methods, and metrics for the prioritization of critical electrical grid customers, Electronics 11 (14) (2022) 2246.
[54] W. Li, E. A. M. Ceseña, L. S. Cunningham, M. Panteli, D. M. Schultz, S. Mander, C. K. Gan, P. Mancarella, Assessing power system resilience to floods: A geo-referenced statistical model for substation inundation failures, in: 2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), IEEE, 2022, pp. 1–5.
[55] A. Poudyal, S. Poudel, A. Dubey, Risk-based active distribution system planning for resilience against extreme

weather events, IEEE Transactions on Sustainable Energy 14 (2) (2022) 1178–1192.
[56] Y. Zhou, M. Panteli, B. Wang, P. Mancarella, Quantifying the system-level resilience of thermal power generation to extreme temperatures and water scarcity, IEEE Systems Journal 14 (1) (2019) 749–759.
[57] M. Mahzarnia, M. P. Moghaddam, P. Siano, M.-R. Haghifam, A comprehensive assessment of power system resilience to a hurricane using a two-stage analytical approach incorporating risk-based index, Sustainable Energy Technologies and Assessments 42 (2020) 100831.
[58] X. Lian, T. Qian, Z. Li, X. Chen, W. Tang, Resilience assessment for power system based on cascading failure graph under disturbances caused by extreme weather events, International Journal of Electrical Power & Energy Systems 145 (2023) 108616.
[59] E. L. Barrett, K. Mahapatra, M. Elizondo, X. Fan, S. Davis, S. Newman, P. Royer, B. Vyakaranam, F. B. Dos Reis, X. Ke, et al., A risk-based framework for power system modeling to improve resilience to extreme events, IEEE Open Access Journal of Power and Energy 10 (2022) 25–35.
[60] J. Kong, C. Zhang, S. P. Simonovic, Resilience and risk-based restoration strategies for critical infrastructure under uncertain disaster scenarios, Sustainable Cities and Society 92 (2023) 104510.
[61] S. Mousavizadeh, M.-R. Haghifam, M.-H. Shariatkhah, A linear two-stage method for resiliency analysis in distribution systems considering renewable energy and demand response resources, Applied energy 211 (2018) 443–460.
[62] M. A. Gilani, R. Dashti, M. Ghasemi, M. H. Amirioun, M. Shafie-khah, A microgrid formation-based restoration model for resilient distribution systems using distributed energy resources and demand response programs, Sustainable Cities and Society 83 (2022) 103975.
[63] Y. Yang, W. Tang, Y. Liu, Y. Xin, Q. Wu, Quantitative resilience assessment for power transmission systems under typhoon weather, IEEE Access 6 (2018) 40747–40756.
[64] S. Chanda, A. K. Srivastava, M. U. Mohanpurkar, R. Hovsapian, Quantifying power distribution system resiliency using code-based metric, IEEE Transactions on Industry Applications 54 (4) (2018) 3676–3686.
[65] Y. Yao, W. Liu, R. Jain, B. Chowdhury, J. Wang, R. Cox, Quantitative metrics for grid resilience evaluation and optimization, IEEE Transactions on Sustainable Energy 14 (2) (2022) 1244–1258.
[66] H. Zhang, H. Yuan, G. Li, Y. Lin, Quantitative resilience assessment under a tri-stage framework for power systems, Energies 11 (6) (2018) 1427.
[67] R. Ma, S. Basumallik, S. Eftekharnejad, Controlled islanding resilience with high penetration of renewable energy resources, IEEE Transactions on Sustainable Energy 14 (2) (2022) 1312–1323.
[68] S. Wang, R. Bo, A resilience-oriented multi-stage adaptive distribution system planning considering multiple extreme weather events, IEEE Transactions on Sustainable Energy 14 (2) (2023) 1193–1204.
[69] A. Younesi, H. Shayeghi, A. Safari, P. Siano, A quantitative resilience measure framework for power systems against wide-area extreme events, IEEE Systems Journal 15 (1) (2020) 915–922.
[70] N. T. Bazargani, S. Bathaee, A general framework for resiliency evaluation of radial distribution system against extreme events, in: Electrical Engineering (ICEE), Iranian Conference on, IEEE, 2018, pp. 1179–1184.
[71] T. Xu, C. Shao, M. Shahidehpour, X. Wang, Coordinated planning strategies of power systems and energy transportation networks for resilience enhancement, IEEE Transactions on Sustainable Energy 14 (2) (2022) 1217–1229.
[72] M. M. Hosseini, L. Rodriguez-Garcia, M. Parvania, Hierarchical combination of deep reinforcement learning and quadratic programming for distribution system restoration, IEEE Transactions on Sustainable Energy 14 (2) (2023) 1088–1098.
[73] A. Rahiminejad, J. Plotnek, R. Atallah, M.-A. Dubois, D. Malatrait, M. Ghafouri, A. Mohammadi, M. Debbabi, A resilience-based recovery scheme for smart grid restoration following cyberattacks to substations, International Journal of Electrical Power & Energy Systems 145 (2023) 108610.
[74] M. Mccarty, J. Johnson, B. Richardson, C. Rieger, R. Cooley, J. Gentle, B. Rothwell, T. Phillips, B. Novak, M. Culler, et al., Cybersecurity resilience demonstration for wind energy sites in co-simulation environment, IEEE Access 11 (2023) 15297–15313.
[75] H. Zhou, Z. Shen, Z. Li, Evaluating the resilience of cyber-physical power systems by weighted spectral analysis, Energy Reports 8 (2022) 111–120.
[76] N. Yodo, T. Arfin, A resilience assessment of an interdependent multi-energy system with microgrids, Sustain-

able and Resilient Infrastructure 6 (1-2) (2021) 42–55.
[77] S. Chanda, A. K. Srivastava, Defining and enabling resiliency of electric distribution systems with multiple microgrids, IEEE Transactions on Smart Grid 7 (6) (2016) 2859–2868.
[78] C. Qin, L. Jia, S. Bajagain, S. Pannala, A. K. Srivastava, A. Dubey, An integrated situational awareness tool for resilience-driven restoration with sustainable energy resources, IEEE Transactions on Sustainable Energy 14 (2) (2023) 1099–1111.
[79] S. Pandey, S. Chanda, A. K. Srivastava, R. O. Hovsapian, Resiliency-driven proactive distribution system reconfiguration with synchrophasor data, IEEE Transactions on Power Systems 35 (4) (2020) 2748–2758.
[80] P. Bajpai, S. Chanda, A. K. Srivastava, A novel metric to quantify and enable resilient distribution system using graph theory and choquet integral, IEEE Transactions on Smart Grid 9 (4) (2016) 2918–2929.
[81] B. R. Naidu, K. K. Saini, P. Bajpai, C. Chakraborty, A novel framework for resilient overhead power distribution networks, International Journal of Electrical Power & Energy Systems 147 (2023) 108839.
[82] A. D. Bintoudi, C. Demoulias, Optimal isolated microgrid topology design for resilient applications, Applied Energy 338 (2023) 120909.
[83] Y. Tan, A. K. Das, P. Arabshahi, D. S. Kirschen, Distribution systems hardening against natural disasters, IEEE Transactions on Power Systems 33 (6) (2018) 6849–6860.
[84] G. Li, G. Huang, Z. Bie, Y. Lin, Y. Huang, Component importance assessment of power systems for improving resilience under wind storms, Journal of Modern Power Systems and Clean Energy 7 (4) (2019) 676–687.
[85] M. Amirioun, F. Aminifar, H. Lesani, M. Shahidehpour, Metrics and quantitative framework for assessing microgrid resilience against windstorms, International Journal of Electrical Power & Energy Systems 104 (2019) 716–723.
[86] J. Najafi, A. Peiravi, J. M. Guerrero, Power distribution system improvement planning under hurricanes based on a new resilience index, Sustainable cities and society 39 (2018) 592–604.
[87] M. Abdelmalak, J. Cox, S. Ericson, E. Hotchkiss, M. Benidris, Quantitative resilience-based assessment framework using eagle-i power outage data, IEEE Access 11 (2023) 7682–7697.