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Metrics and enhancement strategies for grid resilience and reliability during natural disasters

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ABSTRACT

The rise in power shutdowns triggered by severe weather due to deteriorating climate change has expedited the research in enhancing community resilience. Several researchers and policy-makers have contributed to the characterization and parameterization of energy resilience and reliability in particular, which requires accumulated and coordinated studies to underline the outcomes and reflect those in future works on grid resilience and reliability enhancement. The concept of both the resilience and reliability of the grid systems should be defined and distinguished so that the systems can be clearly comprehended, assessed, and operated to maintain flawless operation and ensure environmental sustainability. This paper meets the mentioned objectives to discuss grid resilience and reliability, their quantification metrics, and their enhancement techniques in detail. The paper also categorizes the United States into four tiers based on grid reliability and grid resilience using Monte Carlo Simulations and the discussed metrics. Two novel terminologies named resilience risk factor and grid infrastructure density are propounded in this work, which will serve as vital parameters to determine grid resilience.

1. Introduction

The electricity grid is undoubtedly the largest energy system, where an energy system is defined as a system responsible for the generation or production, conversion, transmission, distribution, and consumption of energy. The electric power grid, heating and cooling networks, fuel supply systems, gas pipelines, carbon dioxide pipelines, fuels for transportation, etc.- all comprise energy systems. One plausible and feasible method of decarbonizing, and therefore "cleaning", the human energy consumption is to shift all forms of energy consumption to electricity. With the unprecedented progress of technology, electrifying our energy sources is definitely possible, hindered only by a span of time, joint efforts, and voluntary investment. To do so, the electricity grid needs to be made more robust, resilient, and reliable. However, the unobstructed operation of the electricity grid is often hindered due to technical faults, manmade factors, natural disasters, etc. This is highly concerning, especially when all human energy consumption is about to rely completely on electricity. The subsequent rise of power outages due to various national level natural catastrophes has been a matter of significant concern for the research community and policymakers for a long time. The increasing dependency on electricity has made the intermittency an urgency to solve [1,2]. To tackle such a situation, several studies have demonstrated a system of threat-based decision assistance to support local and national managers and supervisory parties in promoting service capital investment that minimizes harsh weather risks in the utility sector. With deteriorating climate change and increasing global temperatures, disasters have become more frequent and severe. Various natural disasters such as ice storms, hurricanes, droughts, solar storms, earthquakes, heatwaves, wildfires, etc. can cause severe power outages [3]. The impacts induced by national level catastrophes can be so critical that power recovery to the pre-catastrophe state may take years [4]. The present sophisticated and interdependent grid infrastructures are complex, where monitoring, sensing, control, and communication are compounded in a single system. So, a failure at one point may lead to a cascading failure of several other parts [3]. For such reasons, the existing U.S. grid is deteriorating and experiencing constant under-investments. Various past incidents have indicated the vulnerabilities of the existing electric grid worldwide, such as the U.S. eastern blackout of August 2003 and India blackout of July 2012 [5,6]. In the U.S. eastern blackout, almost 50 million consumers had lost electricity in more than eight states [7]. The grinding energy outage which occurred across 17 states in the U.S. in superstorm Sandy of 2012, left more than 8.1 million homes affected. In fact, disaster

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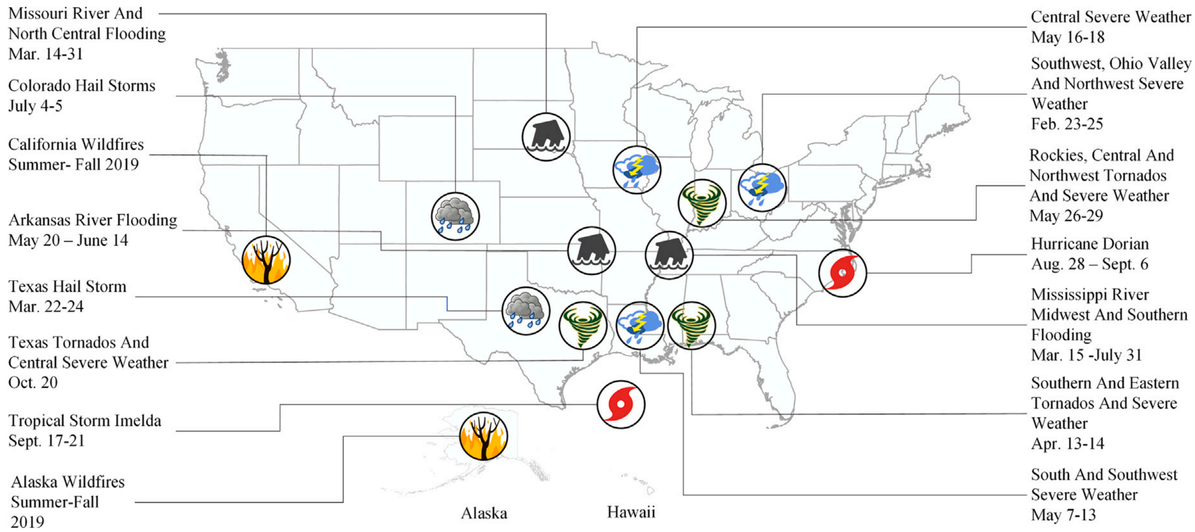

Fig. 1. The location of U.S. disasters occurring across the U.S. in 2019. Most of these disasters have occurred in mid and south-eastern states and led to disruptions in the power grid.

and climate-related power outages are on the rise since the past two decades [8].

A single interruption in the power distribution system (PDS) can leave millions of people out of power for days. Such events motivated researchers and engineers to improve grid resilience and redesign the entire grid infrastructure [9,10]. The state- and federal-level reliability index currently employed in analysis for the transmission and distribution (T&D) infrastructures do not guarantee any effective mechanism for the grid to withstand natural disasters and enhance grid resilience [11,12]. Although several researches on optimization, simulation, or empirical analysis of the grid network are being performed to solve these issues, there are still substantial information gaps in theory and practical approaches.

Existing researches primarily investigate the aftermath of a particular disaster on the grid. Several studies extensively analyze post-catastrophe recovery planning and the impacts of hurricanes, wildfires, or ice-storms [13,14]. For instance, Ref. [15] has proposed a proactive model for resource allocation to repair and restore the grid to pre-hurricane state. Using the standard IEEE 118-bus system, the paper has developed an efficacious infrastructure to reduce damages caused to the grid by natural disasters. The impact of severe earthquakes on the power grid has also been studied [16,17]. Other disasters, such as heavy rain, wind, or thunderstorms, have also been addressed and evaluated in recent studies [18,19]. Fig. 1 demonstrates the locations of major U.S. disasters that occurred in 2019. However, the 'disaster-specific' analysis of danger neglects the expansive aspects of multi-disaster danger assessments and may lead to siloed strategies, replicated interventions, and short-sighted alleviation techniques that can make the arrangement more vulnerable to a broader range of dangers [20,21]. These analyses lacked extensive and accurate data on failures, recovery, and their analogous mathematical model. Besides the granularity of data, previous studies were hindered by a dearth of regional-scale covering varied service regions. The need to collect large-scale data and high-resolution on failure sits a methodological hurdle for scrutinizing resilience [22,23]. Historically, the data on restoration and failure is mainly collected for reporting purposes [24,25], gathered within particular geographic areas, operated by the distribution system operators (DSOs), and not disseminated across other geographic regions. Data accumulated on a daily or an hourly basis contain too simplistic information to conduct researches on infrastructure and services resilience. Consequently, a limited quantity of studies uses fault data from individual service areas [26,27].

This review work contributes to the clear description of grid resilience and grid reliability along with their comparison, quantification, enhancement strategies, challenges and research gaps. As a novel contribution, this paper analyzes the U.S. grid infrastructure with its resilience and reliability assessment, and provides a map to distinguish the states based reliability and resilience indices. Two novel terminologies – grid infrastructure density and resilience risk factor – have been proposed and defined in the effort to categorize the U.S. states.

The rest of the sections of the paper are organized as follows: Section 2 explores the general description of grid resilience and reliability, and compares them in brief. To quantify a grid or to compare two grids, proper metrics are needed, and Section 3 provides the required quantification for this purpose. Section 4 sheds light on the resilience and reliability scenario of the U.S. electricity grid. In Section 5, several strategies of grid reliability enhancement have been chalked out, which will be a cornerstone in the development of further studies. Section 6 talks about different techniques for the enhancement of grid resilience. Apart from some recent studies, there are many cryptic points for achieving a state-of-the-art practical resilient and reliable grid; in Section 7, the possible challenges and future research needs are summarized. Section 8 lists out the overall outcomes of this work. Finally, the paper concludes in Section 9.

2. Grid resilience and reliability

Electricity grids are expected to be both resilient and reliable. Reliability of the grid is achieved if it is resilient. The study of grid resilience and reliability seeks to clearly define grid resilience and grid reliability with relevant introductory ideas and precise comparison between the two.

2.1. Grid resilience

Grid resilience finds its roots in the need to identify values and acts to protect the grid from disasters and stress, and develop plans to overcome contingency. Grid resilience refers to the grid's ability to endure grid disruptions and spring back to normal operating conditions without or with minimal external interference or to adjust with the pressure to alleviate compromise by graceful degradation. Presidential Policy Directive (PPD) 21 defines grid resilience as the ability to rapidly plan and adapt to severe conditions and resist and recover from disturbances. Resilience comprises the capacity to survive and recover from naturally occurring disasters or direct artificial threats. The Electric Power Research Institute (EPRI) defines resilience in three respects: prevention, regeneration, and sustainability. Resilience is a

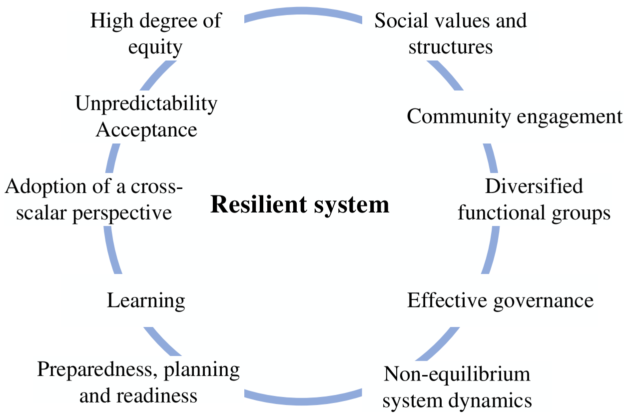

Fig. 2. The 10 interdependent characteristics of a resilient system.

joint mission for those who deal with disasters, conflict, and economic, financial, and climate change challenges. Therefore, all energy systems aim to ensure that shocks and stresses do not lead to a long-term failure [28,29]. Improving resilience includes the application of policies that compensate for all forms of resilience, so as not to increase one variable at the cost of another. The resilience concept is getting more flashlight day by day for the increasing magnitude and severity of disasters. For instance, in the year 2019 alone, 90 different disasters, including thunderstorms, cyclones, wildfires, flash floods, earthquakes, etc. have vandalized the U.S. and claimed over 180 lives, and incurred a loss worth almost US$ 50 million [30].

Dimensions and characteristics of resilience. Resilience is characterized by situation assessments, rapid reactivity, and successful recovery strategies. Successful recoveries are ensured if a declining probabilistic collapse, reduced effects, and shorter recovery time is recorded. Besides, system robustness, redundancy, resourcefulness, and rapidity, referred as 4 'R's, can also characterize the resilience of both social and physical structures. A resilient framework has ten fundamental, interdependent aspects [31,32] . Fig. 2 depicts the cycle of a resilient system ensuring all the 10 interdependent characteristics.

Factors of grid resilience. The resilience of a power grid depends on the system's ability to sustain a constant supply of vital loads in High-Impact, Low-Frequency (HILF) contingencies cases. In case of any disruptions in the system, a resilient system must be able to return to the original state within the shortest time. There are several methods to facilitate grid resilience, such as infrastructure storm-hardening and more sophisticated control algorithms being applied. In addition to a mixture of these variables, enhanced system stability control would be vital to improving the resiliency of a PDS. The factors of grid resilience are denoted with their definition and relevant equation in Table 1. The resilience metrics suggested in this paper are based on the assumption that the variables listed in the table are closely associated with other factors to improve resilience. The power grid is viewed as a graph with n nodes and e branches for the subsequent interpretations.

Classification of power sector resilience. The basic perspective of resilience is roughly divided into three segments — hard, soft, and mixed. Hard resilience refers to the physical elements of functionality such as engineering and ecological systems. Soft resilience is the humane and social network such as culture, governance and social patterns, which are crucial to understand the impacts of disasters and the feasibility of the emergency management schemes [33]. Mixed resilience combines different infrastructures from hard and soft resilience to understand the systems. Grid resilience can further be categorized based on their performance, implementation, temporality, interdependency, and occurrences of events. The broad classification of resilience is summarized in Table 2.

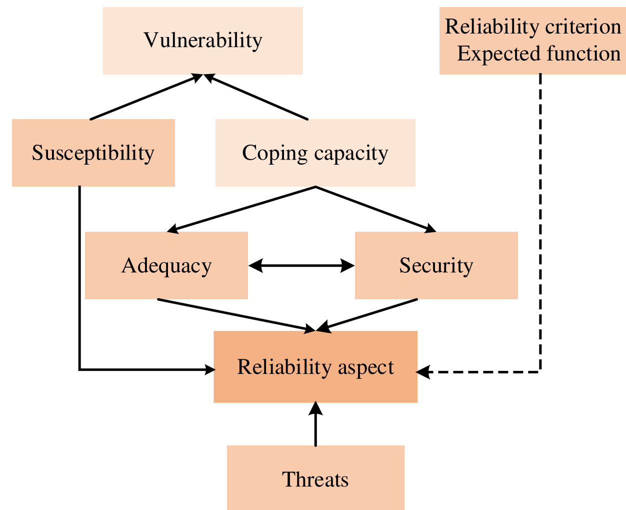

Fig. 3. Interaction between different aspects which determine the reliability of power systems [38]. The color box intensity demonstrates the degree of relationship in reliability aspect.

2.2. Grid reliability

The probability of an object or device to operate under certain fixed operating conditions without a loss for a certain period can be described as reliability. Grid reliability is the degree of power delivered to consumers within the accepted standards as required by the performance of the system's elements. The reliability level can be measured according to the duration, frequency, and scale of adverse effects on consumer service. Reliability assesses a power grid's capacity to provide sufficient electrical power supply meeting customer demands with minimal interruptions for a prolonged period [34]. It involves two essential technical elements of the power systems — adequacy of supply and uninterrupted operation [35].

Dimensions of reliability. Reliability analysis incorporates various techniques applied in numerous purposes in engineering design analysis [36]. Reliability analysis involves failure characterization, analysis of failure criticalness, analyzing the root cause of failure, analysis system threats, and study of failure elimination.

Classification and factors of reliability. Reliability can be classified into four principal classes based on a system's coherence [37], such as test–retest reliability, inter-rater reliability, parallel forms reliability, and internal consistency. The vulnerability of a power grid is its incapability of maintaining operation if a threat leads to an unexpected event or a system restart after the event. The system's reliability is determined by its weakness, risks, and redundancy criteria it imposes. The interlinking factors which decide the degree of reliability of the system are indicated in Fig. 3. Reliability focuses primarily on interruptions to customers and is, therefore, a power quality subset. Availability is interpreted as the voltage source uninterrupted for the percentage of the time. Its extension, unavailability, is the voltage source disrupted by a percentage of the time. Although the frequency and duration of interruptions are specifically discussed, they are categorized as a reliability subset (Fig. 4).

2.3. Comparison between grid resilience and grid reliability

If a grid is unreliable, it is not considered resilient, and the grid reliability can be enhanced by a resilient grid [40]. Reliability is a subset of grid resilience, since reliability is only achieved if a grid is resilient to disasters. The distinction between the definitions of grid resilience and reliability is clearly established in recent works, where researchers

Table 1
Factors of grid resilience. These factors play a direct role in determining the resilience of the power grid against disasters.

Factors	Description	Equation
Branch Count Effect (BCE)	Ratio of total number of attached branches to number of all loads for each Path Combination Without Loop (PCWL) in a Possible Network (PN)	$BCE_q = \frac{1}{N_q}\sum_{k=1}^{N_q} \frac{Nodes\ in\ PCWL\ \ for\ kth\ PN}{Number\ of\ loads\ in\ kth\ PN}$
Overlapping Branches (OB)	Total number of common branches in each PCWL in a PN	$OB_q = \frac{1}{N_q}\sum_{k=1}^{N_q}\ Common\ branches\ in\ the\ kth\ PN$
Switching operations	Total number of switch status changes, creating different PNs without any loop and connecting all loads to the source.	N/A
Repetition of sources	Ratio of the number of available sources used for supplying all loads in each PN to the number of all loads.	N/A
Path Redundancy (PR)	Total number of available paths to the total number of loads in each PN	$PR_q = \frac{All\ paths\ from\ load\ to\ sources\ in\ the\ qth\ FN}{Number\ of\ all\ loads\ in\ the\ qth\ FN}$
Probability of Availability and Penalty Factor (PoA & PF)	Based on reliability or likelihood of source availability, and the distribution of PF losses.	$PoA\ \&\ PF_q = \frac{1}{N_q}\sum_{k=1}^{N_q}\ PoA\ \times PF\ for\ kth\ PN$
Aggregated Central Point Dominance (ACPD)	Captures the data about the node's significance to the specified topology of the network.	$ACPD_q = \frac{1}{D_q}\sum_{d=1}^{D}\ \Omega_d^q\ \times C_B(d)$

Table 2
Classification of grid resilience. Power grid resilience can be classified on the basis of five prime bases. The temporality based classification is the most highly used.

Classification		Description
Performance-based	Active resilience Passive resilience	The resilience from direct threats on the system. The resilience from indirect threats on the system.
Implementation based	Planning phase Operational phase	Architecture adaptation, framework hardening, and the implementation of smart investment policies. Control strategies and policies.
Temporality-based	Before threat During threat After threat	Ability to anticipate, mitigate, and reduce the threat before the disaster System's capacity to confront, absorb, and endure a hazard. System's recovery, restoration, reconfiguration, and repair after the threat.
Interdependent systems	Economic resilience Human resource resilience Supply chain resilience	Community's ability to predict, adapt to, and take advantage of changing conditions. Human factors associated with grid resilience. The supply chain's capacity to prepare itself for unanticipated threat circumstances.
Event-based	Physical resilience Cyber resilience	The physical and environmental hazards created by humans. Cyber threats or attacks.

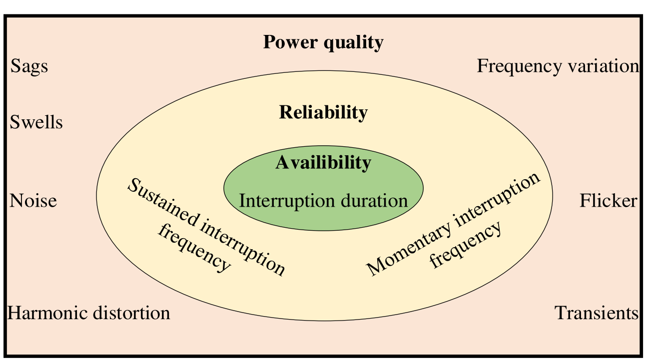

Fig. 4. Availability is a reliability subset, and reliability is a power quality subset. Power quality tackles any divergence from an ideal supply of sinusoidal voltage. Reliability addresses outages [39].

claim that grid reliability addresses low impact high frequency (LIHF) events, while grid resilience traffic with high impact low frequency (HILF) events [41]. For instance, blackouts are more frequent in radial networks compared to meshed networks, but short blackouts last for 2 h in radial networks, and up to 8 h in meshed networks [42]. Therefore, short blackouts are LIHP events for radial networks, indicating a part of the reliability of the network; but they are HILP events for meshed networks, indicating a part of the network resilience. So, the same event might hamper the reliability of some networks and the resilience of some networks; it depends on the impact of the event on the network. Grid resilience also involves the infrastructure's failure cycle, while grid stability often takes network recovery time into account.

Reliability is described as the ultimate goal of the power grid with its focus on maintaining loads. The power grid must also be resistant to cyber incidents, which compromise the reliability. It is crucial to recover faster, learn from past mistakes, and adapt accordingly. While connected, a resilient grid may not be necessarily reliable, and a reliable may not be resilient. The multiplex correlation between resilience and reliability domain is portrayed in Fig. 5.

Under a resilient framework, rolling brownouts could be more acceptable as resilience allows for intermediary positions between on and off. This suggests that while a power grid's purpose may be reliability, resilience may be a pragmatic trade-off that reflects disasters' changing characteristics.

Nevertheless, reliability continues to be critical, as it is essential to provide power with as fewer disruptions as possible in a consistent way. Indeed, this suggests that resilience may be a compromise and a necessary component of reliability, but that reliability should remain a power system's ultimate goal. Table 3 represents the major contributions of grid resilience and reliability discussed in concurrent literature, with the technological readiness level (TRL) of each case, which is an indicator of the maturity of the technology.

3. Quantification of grid resilience and reliability

The analysis of grid resilience includes quantitative metrics which can be used in any power grid. The metrics are employed to assess grid efficiency, parallel two or more grids, and develop effective strategies for improvement. The right metrics must possess some definite requirements, such as quantifiability, comparability, and repeatability [58]. Electricity generation from oil, gas, and nuclear energy are particularly hazardous industries since they are very prone to high-impact accidents that may pose long term consequences. Resilience is, therefore, a crucial safety criterion in such industries. Bayesian network is an analytical cool deployed in the assessment of risk, resilience, and reliability of such hazardous electric power grids for their high probability of uncertain future events [59]. Traditionally, for quantitative risk analysis

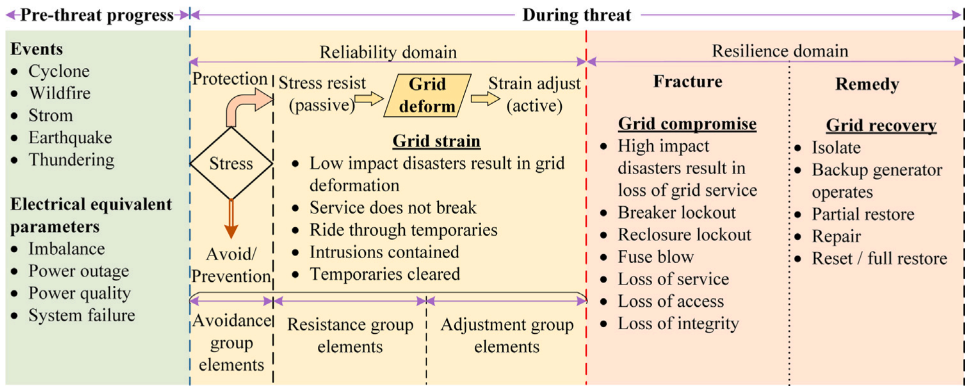

Fig. 5. Relationship between resilience and reliability [43]. Resilience focuses on high impact events and reliability deals with low impact events. Here, avoidance group elements avoid the introduced stress, such as river embankment to prevent flooding, sensory and forecasting systems. Resistance group elements resist the induced stress on grid, such as instrument transformers, relays, circuit breakers, etc. Adjustment group elements return the grid to the previous state, such as repair crews, replacement and repairs, vegetation management, etc.

Table 3
Grid resilience and reliability in literature summary. The Technological Readiness Level (TRL) of each contribution is also included.

Resilience	Reliability	Contribution	TRL
✓		Operational and Infrastructure Resilience [44]	7
✓	✓	Availability-based engineering resilience metric [45]	8
	✓	Evaluating network resilience and operator flexibility [46]	5
✓		Low-latency communications in resilience microgrids [47]	6
	✓	Operational reliability of multi-energy customers [48]	8
	✓	Reliability and the economic and environmental advantages of utilizing diesel generators [49]	7
✓		Spatial risk analysis of power systems resilience [50]	4
✓		Intentional islanding to prevent cascading faults [51]	5
✓		Resilience diversity in smart homes [52]	6
✓	✓	Efficient optimization process of studying the feasibility and economic aspect of microgrids [53]	5
✓	✓	Risk-based indicators to identify the necessary enhancements [54]	4
✓		Proposes an assessment process and a metric for uncertainties [55]	7
✓		Cyber–physical system which is diverse in organization and technologically advanced [56]	8
✓		Networked microgrids [57]	8

event tree and bow-tie model was used; recently researchers have shifted their focus on object-oriented Bayesian network. This system considers failures caused by very common causes and is extensively used in the risk assessment of offshore flaring systems [60], storage tank [61], and offshore drilling operations [62]. The grid stability quantification has been developed depending on the duration and frequency [63,64]. No individual index has been standardized yet to accurately quantify the resilience and reliability of an electrical grid. In the following two sections, the various metrics for grid resilience and reliability are described in detail.

Table 4
Various resilience metrics. Italic font denotes system characteristic-based resilience metrics, whereas normal text denotes resilience index based on performance.

Resilience metrics	Advantages	Disadvantages
Resilience triangle	Simple	Failed to encounter post-threat degraded state
Availability	Accounts redundancy and reparation rate	High error margin
Social welfare-based	Accounts population exposure to power	Failed to capture complexity of multi-dimensional power system
Resilience trapezoid	Infrastructure and operational resilience are separated.	Failed to indicate Postrestoration state
FLEP metrics	Numerical based	Failed to indicate Postrestoration state
Resilience Curve	Considers Postrestoration state	Computational complexity high
MCDM technologies	Considers several variables	Requires careful selection and respective weighting of variables
Explicit methods	Graph-theoretical metrics	Computational complexity high
Based on ENS and EIU	Considers adaptation analysis	Generalizes all threats

3.1. Resilience metrics

Grid resilience is not only a qualitative parameter, but it can also be quantified on the basis of some definite metrics. Grid resilience is an evolving field of study, and the resilience metrics proposed so far are very recent, and all of them are still under extensive research. There are several resilience metrics proposed in several works, and many groups are working to develop more efficient metrics to quantify grid resilience. However, one common limitation of all the works published so far is the absence of the numerical values of those metrics. The works propose brilliant ideas to quantify grid resilience, but do not actually demonstrate numerical values to those metrics. Table 4 outlines all the resilience metrics that are detailed in this section, along with their advantages and disadvantages.

3.1.1. Resilience index based on performance

Resilience index analysis takes different factors into consideration, which can typically be construed as having a quantifiable way for integrating several data points such as climate, power system limitations, cyber threats, and network strength. Resilience strategies are defined in many forms; for instance, the use of incremental resilience series illustrates the space–time effects of a significant event on system

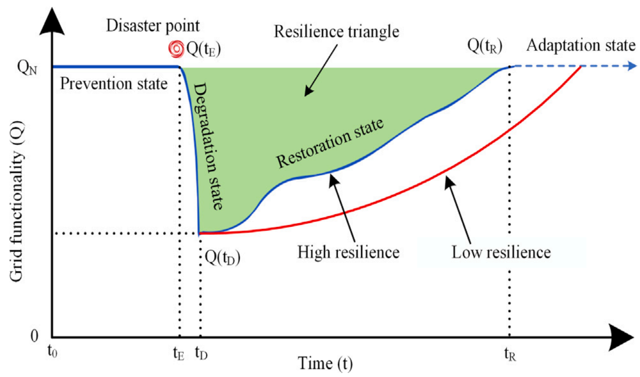

Fig. 6. Resilience triangle with 4 stages during a natural disaster. Also a comparison between high and low resilience is labeled here by different color of lines.

resilience. A basic resilience definition, Eq. (1), relates efficiency as a system uptime ratio to a total of downtime T_d and uptime T_u [45].

$$R = \frac{T_u}{(T_u + T_d)}. \tag{1}$$

This principle is convenient because it considers the functional efficiency of the system's conduct. Nonetheless, this can be unclear from an operational and strategic point of view when incorporating hardening strategies and algorithms for control. Recent researches have dived into the dynamic characteristics of system resilience comprising different weather factors on system failure nodes. This type of studies gives a detailed scenario of time dependent analysis of performance measures along with safety control [65].

Resilience triangle. Bruneau proposed the theory of the resilience triangle [66]. The resilience triangle describes the deterioration of a specific asset's functionality over the event timeline [67]. It is the foundation for empirical resilience assessment. Moreover, the term has been applied to trapezoidal resilience to take into account the deteriorating situation when there are no efficacious steps for restoration of threats [68,69]. Tierney proposed that a system's resilience can be calculated after the disaster by the state of operation and the required time to return previous state [70]. The efficiency of each device is measured as a single point in a multidimensional space for calculating results. The result can possibly be changed deliberately or accidentally, abruptly, or gradually over time and can be improved or diminished. The sudden and unexpected decrease in system performance is considered a fundamental concern for resilience.

The basic theory of the resilience test, that can be implemented in any subject area of concern, inclusive of the grid, was explained in their study. Further, the resilience triangle in the field of civil infrastructure was analyzed by Bocchini [71]. They construed that the triangle's three legs had a particular essence. The y-axis quantifies the capacity, x-axis communicates the overall rehabilitation time or speed, and the hypotenuse describes the functionality of recovery route approximation (Fig. 6). The resilience experts D'Lima and Medda diversely suggested that the network's stability depends on the speed at which the x-axis responds in the resilience triangle [72]. They adopted Uhlenbeck's mean-reversion model to analyze the recovery rate [73]. The effect can be calculated by measuring the difference in the grid functionality between normal and abnormal conditions during the case, according to Bruneau [66]. It is the region of the triangle of resilience, and the following equation mathematically represents the impact.

$$I = \int_{t_E}^{t_R} [Q_N - Q(t)]dt, \tag{2}$$

where t_R is the time of completion of the restoration, t_E is the starting time of the event, and I reflects the impacts of severe weather incidents. At time t, the complete grid normal functionality is Q_N, and the given time grid functionality is $Q(t)$. With Eq. (3), it is evaluated.

$$Q(t) = \sum_{n}^{N} [(\rho_n \times q_n)], \tag{3}$$

where q_n is the responsibility of the service for node n, this is measured by its loading capability. At the time t, ρ_n is the node's status, either regularly performed or flunked. The physical failure's risk of the grid segments builds upon their layout and is fundamentally lognormal distribution [74,75]. Eq. (4) expressed all these.

$$P(t) = \phi \left[ln\left(\frac{S(t)}{\theta}\right)/\omega \right], \tag{4}$$

where $S(t)$ is the disaster severity for the period of concern, $P(t)$ is a probability of a physical component failure, ω and θ are, respectively, both are the standard deviation and the normal logarithm median of the engineering parameter at which the portion crosses the danger phase thresholds. ϕ is the cumulative distribution function (CDF) of standard normal distribution. Grid resilience triangle can be divided into 4 phases. These phases change with the progress of disaster with time.

Phase A: Prevention State In order to mitigate the implications of a potential adverse weather occurrence, the grid requires periodic assessments and fast planning. Grid control is key to improving the grid resilience in the prevention state [68]. In this step, the prediction of potential grid conditions is used in different scenarios. The grid calculation can be generated using precedent, historical data for forecasting damage, such as the statistics of faults in the system, the number of consumers involved, and the damage duration [76]. The assessment findings will help mitigate or reduce extreme weather events by applying mitigation strategies. For instance, steps such as the implementation of water barriers or flood dams, installation of a water-resistant box for the grid portion, or the construction of a mobile transformer can be taken when high precipitations are expected early [77].

Phase B: Degradation State The degradation process begins when a severe disaster hits at time t_E, and terminates when the grid reaches its most critical state in the time t_D, as shown in Fig. 6. This process demonstrates the effects of extreme weather catastrophes. It also reveals the grid's physical strength , which increases overall functionality loss. When no maintenance steps are taken after the accident, the grid's operability remains compromised. The effect of the deterioration process can be calculated by measuring the loss of the grid during the catastrophe. A physical defect or a cascading malfunction determines the malfunction status of the grid components. There is a physical failure if the gravity of extreme climatic conditions exceeds the grid's resistance. The damaged component may result in cascaded failures, since additional loads can be a burden for the other sections of the grid [78,79].

Phase C: Restoration State The process of restoration is a transition from the damaged situation to the pre-event state of the system. It starts with t_D when a replacement activity is introduced and terminates when the grid functionality enters the pre-event level. The grid is still in the maintenance cycle once this state starts. This process shows the nature of the impact of extreme warming and the dynamic response of the grid by evaluating the restored status of the grid components from the start of the recovery efforts. A restoration can retrieve a 100% or a certain percentage of grid features. A deficiency in a substation, for instance, can cause power loss to consumers in connection with a substation and cannot satisfy all customers by using a mobile substation. Therefore, two variables determining the operating capacity of the grid are the restoration period and factor. The time needed for restore service is the restoration period, and the restore component is the percentage portion of grid activity that this operational intervention restores. All of these functions rely on network recovery services, including rehabilitators, repair components, costs, connectivity, transportation, and temporary control. Consequently, in the restoration process, the goal of improving grid resilience is to increase operational readiness and restoration time.

Phase D: Adaptation State The recovery phase is a fully restored period until the next extreme weather disaster happens. The need to analyze this and the recovery process separates the grid stability analysis from the network's efficiency. This starts as soon as the grid is in its pre-event state and stops when the extreme disaster comes in. It can be considered a long-term mitigation process to analyze recent accidents, define grid vulnerabilities, and incorporate long-term improvement plans. The grid resilience analysis needs this process to be considered because it includes the grid's ability to face similar future events or even more severe weather events.

A limitation of the resilience triangle is that it does not take into account the degraded state that immediately follows the degradation state. For instance, if a blackout occurs due to a cyclone, it is not possible to immediately restore the system to normal after the disaster. It takes time to start the recovery process. This limitation is solved by the resilience trapezoid, which considers a post-threat degraded state after the occurrence of the disaster or threat.

Availability as resilience indicator. Based on availability, Cai implied an engineering resilience metric. The paper displays that the device will perform the required task within a defined interval of time of an engineering system's availability function [45]. The two transient cases are available vs. shock (blue line), and performance vs. deterioration (red line). From the initial availability of 100%, the performance of an infrastructure device continuously declines to achieve a stable state A_1 output in stable state t_1. This change is due to device deterioration and machine repairs every day. Assuming that an external shock is triggered on t_2, the usability decreases automatically to the A_2 functionality of the after-shock transient state and rises to a new A_3 balance state. This progress is often triggered by an emergency shock repair and part deterioration. The blue line in Fig. 7 reflects the quality without external shocks, despite the deterioration of materials, and the red line indicates the efficacy of emergency replacements aftershock and device deterioration. The steady-state availability A_1, transient-state post-shock availability A_2, steady-state post-shock availability A_3, steady-state time t_1, and static post-shock time $(t_3 - t_2)$ is measured by the engineering system structure and maintenance asset. It includes redundant configuration, failure rate, and repair rate. High redundancy, low fault, or high reparation rate contribute to high stability and fast, stable availability period before and after shocks. The resilience concept and function fits the state. Consequently, constant availability and a low steady-state time can demonstrate engineering resilience's efficiency and time-dependent characteristics. The resilience value increases with a rise in the availability of A and a reduction in restoration time t. Then $A/ln(t)$ is employed to define the resilience point. The natural logarithm $ln(x)$ function is employed to balance the degree of consequences among the availability of A and time t for recovery. The resilience metric is analyzed before and after external shocks to be the product of $A/ln(t)$. Therefore, the ultimate perfected resilience index is provided as follows:

$$\rho = \frac{A_1}{n\, ln(t_1)} \sum_{i=1}^{n} \frac{A_2^i A_3^i}{ln(t_3^i - t_2^i)}, \tag{5}$$

where for $i\ \epsilon[1, n]$, n is the number of shocks. Since the external determinants are unpredictable and random, they neither determine resilience nor engage in the resilience index.

Social welfare-based resilience index. Hoffman reported that there has been some research that quantifies a system's resilience based on enhancing social services to improve grid resilience [10]. Najafi introduced a metric resilience that will take into account population exposure to power and energy, the interdependence between energy and PDS, based on the social welfare indices of hurricanes [80]. Such a 1-dimensional analysis does not determine the complexity of multi-dimensional power grid resistance.

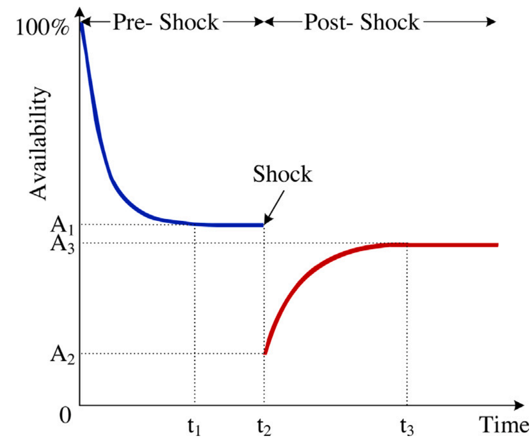

Fig. 7. Availability based resilience metrics. The blue line represents the quality without external shocks and the red line indicates the efficacy of emergency replacements aftershock and device deterioration [45].

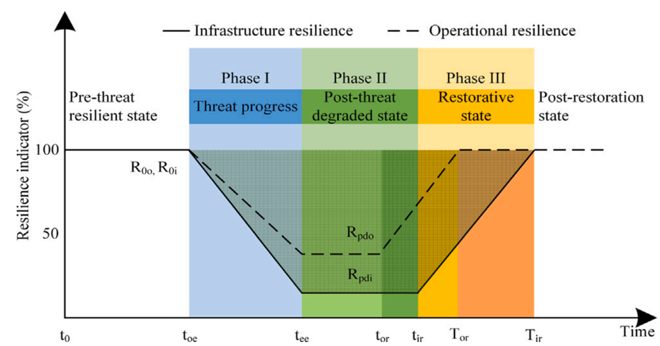

Fig. 8. Resilience trapezoid with different stages during a natural disaster [44,68]. The green box marked area represents the resilience trapezoid, the smaller the area gets; the more resilient grid will be.

Resilience trapezoid. The expansion of the resilience triangle is a trapezoid resilience feature that acknowledges the appearance of corrective action to expand the existing resilience evaluation as the triangle. A resilience index named *ΦΛΕΠ* is suggested [68] based on the trapezoid properties of the strength, as shown in Fig. 8.

The resilience metrics in the case of a single metric are derived from the three phases of trapezoid resilience: stage I: progression of threat; stage II: deterioration of post-perturbance; and stage III: restoration step. Fig. 8 depicts these stages, the less the area will be for any given trapezoid, the more resilient the grid will be. While it is true that the area of the whole trapezoid is a matter of consideration to determine the grid resilience, but since resilience refers to how fast the grid can return to normal operating conditions from the post-threat degraded state, so, the green zone of the post-threat degraded condition is the determining area to compare the resilience of two grids. The smaller the green zone, the faster will be the transition from the post-threat degraded state to the normal state. Fig. 8 demonstrates a hypothetical multi-phase trapezoid resistance that indicates the state (or phase) of an external threat power grid [44]. Besides, organizational flexibility and infrastructure are represented and can be quantified with multiple metrics, as seen later. As the name indicates, the operational stability refers to features that will ensure operating intensity for a power grid, such as the ability to guarantee continuous customer supply or catastrophe generating capability. The systems' resilience refers to a power grid's physical strength to reduce the impaired, broken, or otherwise not functioning component of the system. The comprehensive, multi-phase resilience evaluation is visible in the three phases:

- *Phase I*: Threat progress; $t \in [t_{oe}, t_{ee}]$ - between the initiation of the event t_{oe} and the end of the event t_{ee},
- *Phase II*: Post-Threat Degraded State; after the end of the event and before restoration starts; $t \in [t_{ee}, t_{or}]$ for operational resilience and $t \in [t_{ee}, t_{ir}]$ for infrastructure resilience, and
- *Phase III*: Restorative State; $t \in [t_{or}, T_{or}]$ for operational recovery and $t \in [t_{ee}, T_{ir}]$ for infrastructure recovery.

In Phase I, the power system resilience falls from the pre-threat operational and infrastructure resilience, R_{0_o} and R_{0_i} respectively, to the post-threat levels R_{pdo} and R_{pdi} in Phase II, prior to the initiation of the restorative Phase III. R_{0_o} and R_{0_i} may be 100% or less, according to the conditions and configuration of the pre-threat system. R_{pdo} is system- and event-specific — it may be lower or higher than R_{pdi}, according to the system itself and the event severity.

Phases II and III are divided into two sub-phases:

- the operational and infrastructure degraded states $t \in [t_{ee}, t_{or}]$ and $t \in [t_{ee}, t_{ir}]$ respectively), and
- the operational and infrastructure recovery states $t \in [t_{or}, T_{or}]$ and $t \in [t_{ir}, T_{ir}]$ respectively.

Resilience index $\boldsymbol{\Phi \Lambda E \Pi}$. It is crucial to identify a group of metrics that measure the performance during the various phases of the robust trapezoid to calculate the durability of a power system [44]. Table 5 introduces the principal resilience metrics suggested here in order to classify the trapezoid resilience, precisely for what quickly (Φ) and how slightly (Λ) resilience dropped during step I; the degree of (E) the deterioration condition after the event (step II) and how promptly (Π). In this phase, a set of four parameters is described as the $\Phi\Lambda E\Pi$ ("$\Phi\Lambda E\Pi$" is pronounced as the "FLEP") metric.

- The Φ-metric is measured by calculating the slope of the resilience deterioration throughout the incident (where $t_{ee} - t_{oe}$ is the period of the disaster).
- The Λ-metric is determined by the degree of resilience deterioration, i.e., $R_{0_i} - R_{pdi}$ and $R_{0_o} - R_{pdo}$ for the system and organizational resilience, respectively.
- The E-index determines the duration of the post-threat degraded state (phase II) and is provided by $t_{or} - t_{ee}$ and $t_{ir} - t_{ee}$ for the infrastructure and operational resilience, respectively.
- The Π-index is determined by the slopes of the infrastructure and operational recovery curves (phase III), which reflect both the initial pre-event resilience levels and the time needed for entering this resilience level.

The area of the trapezoid is used as a metric in addition to the $\Phi\Lambda E\Pi$ resistance metrics. As seen in Table 5, the area metric will, for the duration of the case, be expressed as the trapezoid integral, again taking into consideration the resilience of the operation and infrastructure. Piecewise linearity is acknowledged for the distinct stages of the resilience trapezoid (Fig. 8), which occurs in two right triangles for Phases I and III and one rectangle for Phase II. The areas resembling the three phases of the resilience trapezoid (I, II and III) can be determined as per the formula for determining the area of a triangle and rectangle. The cumulative area of the operational and infrastructure resilience trapezoid is yielded by the sum of the two triangles and one rectangle. The area index is reliant on the $\Phi\Lambda E\Pi$ index (particularly on the Λ and E index) described and mathematically signified in Table 5.

Although Ref. [44] deserves credit for introducing the $\Phi\Lambda E\Pi$ metric for quantifying the grid resilience, the limitation of their work is the absence of a proper explanation of how the metrics are used to measure grid resilience. The higher the value of the $\Phi\Lambda E\Pi$ metric, the better is the resilience of the grid, and vice versa. If we compare with the resilience trapezoid, a larger area of the trapezoid means less resilience, and therefore a higher value of the $\Phi\Lambda E\Pi$ metric. Thus, the correlation between the resilience trapezoid and the $\Phi\Lambda E\Pi$ metric is inverse.

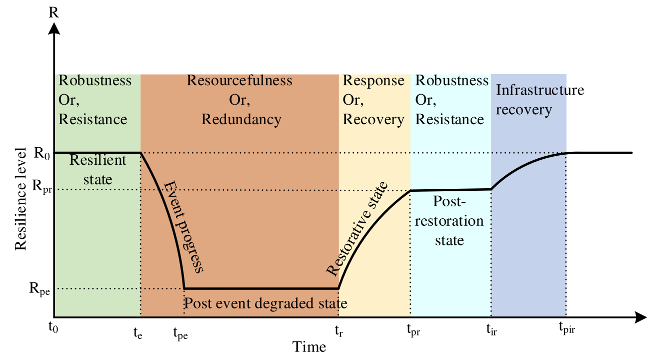

Fig. 9. Resilience curve. Different color shows the different phases of resilience during a disaster. Horizontal axis represents the time of disaster and vertical axis represents the resilience level or, grid functionality [41].

Resilience curve. The representative empirical resilience curve demonstrates the resilience degree concerning a disaster occurs as a function of time. Fig. 9 illustrates the primary resilience characteristics that must be developed by a power grid to deal with the changing circumstances associated with a disaster, such as an extreme storm heading across the grid successfully. In their analysis, the trapezoid was evaluated on how four stages of the resilience metrics are met: robustness, resilience, resources, and speed, as seen in this figure [81]. An empirical curve of resilience has been used to assist other resilience development strategies in recognizing the scheme's success before and after the incident [82,83]. As per the metric resilience method somehow denotes the level of degradation of resilience that progresses with the magnitude of the disasters and the worst case of the weather events. E refers to the post-disturbance deteriorated period; some refer to the recovery time. The PDS must be specified more precisely to lessen supply interruption to crucial loads to avoid the criticalness of elements. The most critical elements are loads that are typically marked as a priority by loads such as life-protection loads, such as clinics, hospitals, community centers, or the responsibility of public safety. This includes fire stations, military bases, police stations, and services for facilities such as data centers, contact centers, and water delivery centers. As shown in Fig. 9, the resilience curve can be divided into 5 regions, such as:

- Robustness or Resistance: Grid operates in normal condition.
- Resourcefulness or Redundancy: Disaster occurs; Post-event Degraded State occurs; Consumers out of power.
- Response or Recovery: Immediately post disaster, maintenance team works to restore power to affected consumers.
- Post-restoration State: An interim stability is achieved for power restoration; Full infrastructure recovery is still due.
- Infrastructure Recovery: Complete recovery of grid infrastructure; Grid returns to normal operation.

3.1.2. System characteristic-based resilience using impact factor

Resilience index using MCDM technologies. A multi-target problem of optimization that considers several variables that can lead to calculating device resilience is the next generation of resilience measurements. Metrics study explores the use of MCDM to calculate resiliency by using topological parameters to calculate resilience based on theory and the environment and the power system constraints [84,85]. Fig. 10 shows a framework for measuring strength measurements using the MCDM process. By choosing system variables that change over various situations and allocating appropriate weights on the basis of their effect on system resilience, a compound score can be determined. Such circumstances may be the network's condition during a case of danger or after the implementation of a resilience improvement program. It requires careful selection and respective weighting of variables, based on impact and elicitation, with operators and services.

Table 5
Details of $\Phi \Lambda E \Pi$ metric for quantifying the grid resilience. The phases and states are specified in term of the resilience trapezoid.

Symbol	Phase	State	Resilience metric	Mathematical expression		Measuring unit	
				Operational	Infrastructure	Operational	Infrastructure
Φ	I	Threat progress	How fast resilience drops?	$\frac{R_{pdo}-R_{0_o}}{t_{ee}-t_{oe}}$	$\frac{R_{pdi}-R_{0_i}}{t_{ee}-t_{oe}}$	MW/hours	Number of lines tripped/hours
Λ	I	Threat progress	How low resilience drops?	$R_{0_o} - R_{pdo}$	$R_{0_i} - R_{pdi}$	MW	Number of lines tripped
E	II	Post-threat degraded	How extensive is the post threat degraded state?	$t_{or} - t_{ee}$	$t_{ir} - t_{ee}$	Hours	Hours
Π	III	Restorative	How promptly does the network recover?	$\frac{R_{0_o}-R_{pdo}}{T_{or}-t_{or}}$	$\frac{R_{0_i}-R_{pdi}}{T_{ir}-t_{ir}}$	MW/hours	Number of lines restored/hours
Area		N/A	N/A	$\int_{t_{oe}}^{T_{or}} R_{op}(t)dt$	$\int_{t_{oe}}^{T_{ir}} R_i(t)dt$	MW $\times$ hours	(Number of lines in service) $\times$ hours

Table 6
Analytical metrics for quantizing grid reliability. The eight metrics are commonly used as a measure of the reliability of the electricity grid.

Analytical metrics	Definition	Equation	Parameters
System Average Interruption Duration Index (SAIDI)	Average duration of outage per consumer.	$SAIDI = \frac{\sum U_i N_i}{N_T}$	U_i = annual outage time, i = location, N_i = number of consumers, N_T = total number of consumers served
System Average Interruption Frequency Index (SAIFI)	Average amount of interruptions encountered by a consumer.	$SAIFI = \frac{\sum N_{ci}}{\sum N}$	N_{ci} = total number of customer interruptions, N represents total number of customers served.
Customer Average Interruption Duration Index (CAIDI)	Average outage time to a specific customer.	$CAIDI = \frac{\sum U_i N_i}{\sum \lambda_i N_i}$	i = location, N_i = the amount of consumers, λ_i = the rate of failure, and U_i is the yearly outage.
Customer Average Interruption Frequency Index (CAIFI)	Number of customers in the entire client base affected by interrupted consumer.	$CAIFI = \frac{\sum N_{ci}}{\sum N_{dc}}$	N_{ci} = total number of customer interruptions, and N_{dc} = number of distinct customers interrupted
Customer Total Average Interruption Duration Index (CTAIDI)	Cumulative average interruption period for clients with at least one interruption during the analysis phase.	$CTAIDI = \frac{\sum U_i N_i}{N_{io}}$	i = location, U_i = yearly outage time, N_i = the customers number, and N_{io} = the customers number that were interrupted.
Average Service Availability Index (ASAI)	Ratio of total number of customer hours of service availability at a given period to the total customer hours demanded.	$ASAI = \frac{\sum N_i \times 8760 - \sum U_i N_i}{\sum N_i \times 8760}$	i = location, U_i = the yearly outage in hours and N_i = the amount of consumers
Average Service Unavailability Index (ASUI)	Ratio of total number of customer hours of service unavailability at a given period to the total customer hours demanded	$ASUI = \frac{\sum U_i N_i}{\sum N_i \times 8760} = 1 - ASAI$	i = location, U_i = the yearly outage in hours and N_i = the amount of consumers
Momentary Average Interruption Frequency Index (MAIFI)	Cumulative interruptions experienced by a consumer in a definite span.	$MAIFI = \frac{\sum N_{ci}}{\sum N_c}$	N_{ci} = the total number of consumer interruptions less than the specified time, and N_c = the total number of consumers served.

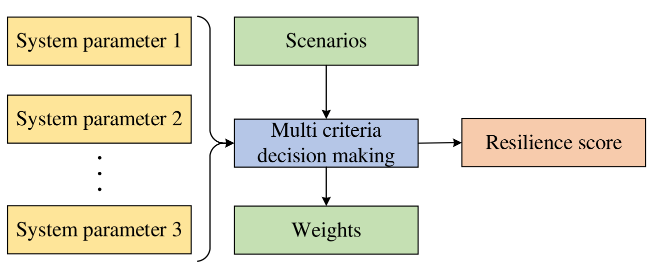

Fig. 10. Resilience metrics formation using MCDM techniques. MCDM is marked by blue box, takes multiple arguments and corresponding scenarios and weights, resulting in resilience score.

Threat modeling-based explicit methods. Durability assessment based on graph theory is the optimal test for the topology of the PDS. The distribution method is modeled on the diagram $G = (N, E, W)$ with a dividing and loading model (N), feeders are modeled as borders (E), critical generators and loading priorities (W). The distribution method is modeled on $G = (N, E, W)$. Kim analyzes the graph-theoretical metrics of the Korean power grid [86]. The reliability analysis for error and attack tolerance, cascading failures, and recovery analysis is performed on the basis of the network and node index of the graph similar to the Korean power grid. Graph-theoretical research can also be used to determine the degradation of the system as a geospatial risk. The resilience R metric implied that the distribution system's topological resilience included graphical–theoretical components, including the centrality of betweenness, algebraic connectivity, device factors like the equipment failure rate and the non-loss critical load and weather impact factor [87]. Threat impact boundary in basecase system model derives the degraded system model (Fig. 11). As a decision matrix,

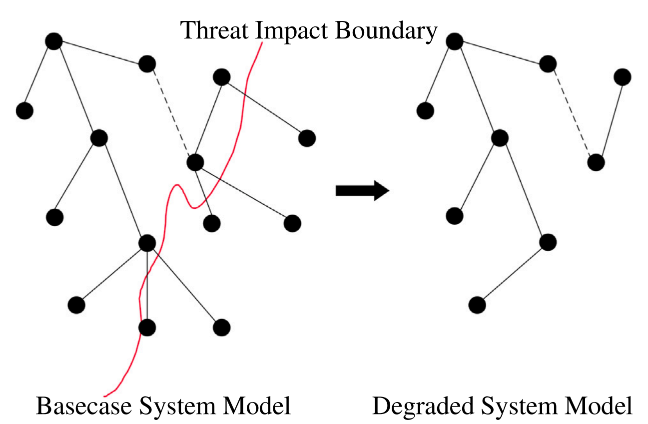

Fig. 11. Threat modeling using explicit methods. The threat impact boundary is denoted by a red curved line, which is the demarcation line of two sequential operation at pre- and post-disaster stages. The threat impact boundary segments up the basecase system model and results in degraded system model.

RR^T is formed. A hierarchical analysis approach is applied to measure the relative value of each RR^T term, and the weighted sum of the single metric determines a single resilience metric. Expected Energy Not Supplied (EENS) typically expresses the extreme event's effect in order to calculate the share of critical loads not supplied.

Resilience metrics based on ENS and EIU. Espinoza defined another form of resiliency metrics which do not employ MCDM technologies, as an example to measure resilience by using existing reliability metrics [88]. It is worth noting that ENS, EENS, EIU, and loss of expected energy are still reliability metrics, but can be explicitly used

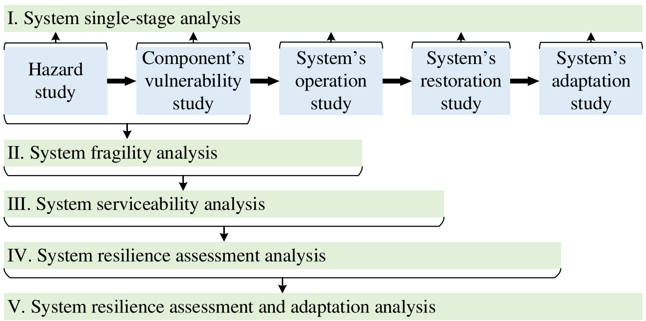

Fig. 12. Resilience metrics formation on energy not supplied and energy index of unreliability [88]. In this method, the last step of resilience is system resilience assessment and adaptation analysis. The sequential operations are marked by blue boxes and occur one after another.

for critical loads to catch resilience. In this work, the authors implied a 5-stage approach, risk characterization, vulnerability of elements, system services, system restoration, and adjustment strategies in order to counter various levels of threats. This scheme also includes the northern Chilean energy network. In Fig. 12, the complete framework for the establishment of resilience metrics based on reliability metrics such as ENS and EIU is manifested.

3.2. Reliability metrics

The IEEE Standard 1366 sets out a consensus-based diagnosis of basic reliability concepts. As a temporary break of 5 min or less, IEEE Standard 1366 – 2012 specifies a temporary interruption and a permanent interruption as any break which does not constitute a momentary break and defines interruptions persisted for five minutes. In 2017 the average interruption for electricity for U.S. consumers was 7.8 h (470 min), almost twice the average cumulative interruption period in 2016. In 2017 there were more critical incidents such as hurricanes and winter storms, and the total intermediate duration of major incidents was longer. The average duration of interruptions in 2016 and 2017 was almost identical, except for significant events, at approximately 2 h in both periods. In 2017, 1.4 interruptions occurred for the average consumer, including significant events and 1.0 interruption, excluding significant events. It offers an insight into the network state and the probability of major incidents and the grid's ability to avoid incidents. These two variables are adopted to assess grid reliability because they can be measured and enrolled for several years in the electrical industry. By using these variables, improvements, or damages in the reliability of a system can be manifested [89,90]. The metrics for measuring reliability of a grid may be analytical or probabilistic. An overview of eight analytical metrics is provided in Table 6. SAIDI and SAIFI are two of the most prominent analytical metrics for quantifying grid reliability. Fig. 13 exhibits the SAIDI and SAIFI value for the top and bottom 5 states of U.S. This figure considers the effect of both the major and non-major events throughout the year 2017 on grid infrastructure.

Five probability based metrics for quantizing grid reliability are discussed in this the paragraphs that follow.

Loss of load probability (LOLP). The probability in an electric grid of the load exceeding the generation is known as the LOLP, also abbreviated as LLP. It is ordinarily manifested as a percentage of time per year, hours per day. When the expected cumulative period in which a power shortage occurs is described, the measure is called the loss of load expectations more correctly. The initial introduction of the LOLP measure was by [91]. It has been used for a self-scheduling operational model for multiple users [48]. The LOLP is obtained by combining each capacity part's availability with the load duration curve. A load duration curve is defined as a function whose horizontal axis specifies the time interval, usually, the number of hours a year, in which the client's (peak) power demand (D) is equal to or outperforms the corresponding accessible capacity level of the ordinate (K^A) (Fig. 14). This confers the time for load loss for $(D \geq K)$ by a fault of the capacity outage. The value can be exercised as the cumulative probability of a load greater than or equal to the corresponding load $(D \geq K)$. The time variable is normalized as a balance of the total at any stage on the horizontal axis. The function can be reversed to achieve the proportion of this time interval because of its monotonicity and continuity. The reverse function can be translated as the cumulative distribution complementary function for the customer's query. As shown in Fig. 14, with a regular peak load curve can be used to calculate the loss of load probability. For jth system outage, O_j is the magnitude, P_j is the probability of a power outage, and t_j is the number of days that an outage would cause a loss of load in the system [92]. If the capacity breaks down below the reserve, this will not lead to load loss; an inevitable power failure higher than the reserve adds to the total risk $(P_j t_j)$. Furthermore, for the cycle, the system LOLP is:

$$LOLP = \sum_j P_j t_j. \tag{6}$$

The 0.0236 LOLP for Tier 4 states means, for example, that the loss of load in total for forced outages is about 2.36% of the time. The estimated load loss annually amounts to 8.61 days in one year, the average period accrued over which the output is equivalent to the capacity available or exceeds that due to induced load losses. Details of the LOLP calculation has been discussed in Section 4.1.

Loss of load expectation (LOLE). The LOLE implies the number of days (hours) in a predefined span wherein the regular peak load exceeds the generated power [93]. LOLE is a metric for calculating energy supply protection and establishing a level of efficiency for each country's regulatory authority. By using Eq. (7), the LOLE value can be calculated [94].

$$LOLE = \sum_{k=1}^{n} P_k \times t_k, \tag{7}$$

where, for n number of aptitude outage phase above the reserve, P_k is the individual probability of capacity outage, and t_k is when the loss load transpires. The Eq. (7) can further be transformed by utilizing the cumulative probability, as manifested in Eq. (8).

$$LOLE = \sum_{k=1}^{n} P_k \times (t_k - t_{k-1}), \tag{8}$$

where, for capacity outage, P_k is the cumulative power outage probability.

Expected energy not supplied (EENS). The anticipated unsupplied electricity in a year due to power generation inadequacy or unavailability or lack of fundamental power is termed EENS. The interruption with a probability P_k generates an energy curtailment of E_k as manifested in Eq. (9) as [93]:

$$AC_{loss}^{load} = \sum_{k=1}^{n} P_k \times E_k, \tag{9}$$

Annual cost of load loss. The corporation and the energy regulatory committee use the annual cost of load interruption to monetize the power interrupt's impact [49]. It provides consumers with valuable financial statistics on the expense generated over the rising electricity demand cycles where the utilities cannot satisfy. This shows that the provider will use the average load failure rate to determine their network's economic performance and reliability.

The cost of consumer dissatisfaction, C_{loss}, depends on the origins of the consumer supporting consideration based on the span of an interruption, the time of day, the season of an interruption, and interruption frequency. C_{loss} is in the range of $5\ to\ 40$ $/kWh for industrial

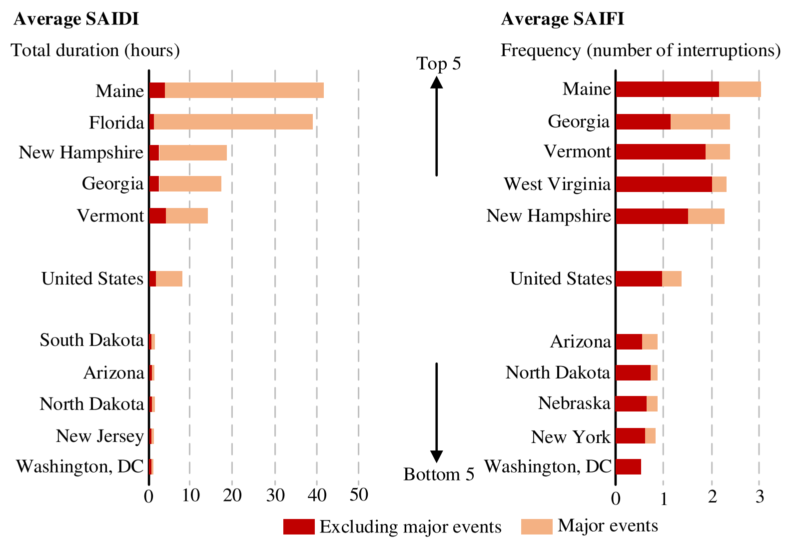

Fig. 13. SAIDI and SAIFI value for highest 5, lowest 5 states and average for U.S. For SAIDI major events have dominance whereas for SAIFI non major events.

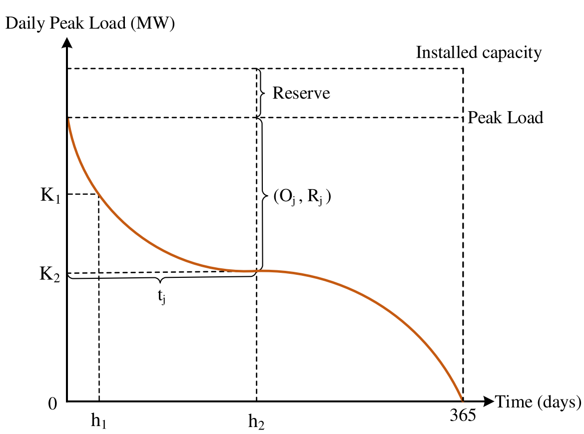

Fig. 14. Estimation of LOLP from load duration curve. Load duration curve is graphed from peak load margin leaving reserve power generation capacity. K_1 and K_2 represent the daily peak load at times h_1 and h_2, respectively. O_j refers to a decrease in the daily peak load after a certain time R_j.

consumers and 2 *to* 12 $/kWh for domestic consumers [95]. The AC_{loss}^{load} is a product of EENS and C_{loss}, as manifested in Eq. (10) [49]:

$$AC_{loss}^{load} = \sum_{i=1}^{n} EENS_i \times C_{loss,\ i}. \tag{10}$$

Forced outage rate (FOR). The FOR is one of the most critical ingredients needed in the reliability analysis of power generation adequacy [94]. FOR denotes the ratio of the number of hours a generating unit is out of service (due to any unexpected breakdown or shortage) to the number of total service hours. Eq. (11) stands the FOR equation.

$$FOR = \frac{\sum Down\ time}{\sum Down\ time + \sum Up\ time}. \tag{11}$$

4. Grid reliability and resilience assessment of the United States

The vast transmission line network in the U.S. creates a threat to the overall grid resilience and uses a large land area. The blackout in New York City and most of the Northeast in 1965 was the first blow to the golden age of the U.S. electricity grid. The designers and operators of power systems and managers realized that their systems could collapse extensively for the first time. In the U.S., local and national research on resilience has been inspired by the impacts of Hurricane Andrew in 1992, the Northridge Earthquake in 1994, the terrorist attacks on World Trade Center and Pentagon in 2001, Hurricane Katrina in 2005, Superstorm Sandy in 2012, Hurricanes Harvey, Irma, and Maria in 2017 [96,97]. In a worldwide aspect, the Italy L'Aquila earthquake in 2009, the New Zealand earthquake in 2011, central Italy earthquake in 2016 have urged resilience analysis. Thousands of power systems are being affected by natural disasters that are expected to rise as a result of climate change [98,99]. These events lead to costly power outages for many customers in the long term. For example, the U.S. economy has cost $ 20−55 billion a year in terms of storm-related outages [100]. Ref. [101] recommended an integrated strategy of the electricity and gas community to decide the optimum design and the project, considering a resilient scheduling strategy. Hurricanes can appear in enduring days or weeks of power outages. Hurricane Harvey, for example, triggered 14 days of power outage in Texas [102,103].

The various natural disasters and their impact on various critical power infrastructures are enlisted in Table 7. The number of stars and the color intensity — both are indicators of the level of impact on electrical grid infrastructure, such as hydropower plant, thermal power plant, nuclear power plant, solar PV panels, wind turbines, T&D lines, and substation. A higher number of stars or a darker shade of color denote higher impact, and vice versa. The most damaging natural disasters for the grid are earthquake and cyclone. Earthquake affects all levels of power sector infrastructure except solar power plants. Massive changes in technology, environmental, and economic policy change the supply of energy. In Table 8, different significant disasters in the U.S. history, categorization of grid history, periods, and available grid technologies at that time are presented with the number of consumers out of power and property damage cost. With the advancement of technology, the same scale disaster causes fewer customers out of power if the increase in consumer number is adjusted.

Load shedding is a good way to restore system reliability to the acceptable levels [104]. There have been numerous discussions pertaining to electricity pricing in the U.S. over the concerns about grid reliability [105] and resilience. However, very few studies have dissected the U.S. grid to get a clear insight of the actual scenario of the reliability and resilience of the U.S. national grid. To bridge this knowledge gap, this section quantifies the resilience and reliability of the U.S. grid and categorizes the states.

Table 7
Power infrastructure vulnerability for different types of natural disasters. A darker shade of color shows more impact on a particular infrastructure, which is also represented by a higher number of stars. More stars and darker color represent more impact on infrastructure.

Type	Earthquake	Cyclone	Flood	Tsunami	Wildfire	Drought	Extreme Heat
Thermal	****	****	***	****	N/A	****	***
Hydropower	****	**	***	**	N/A	****	***
Nuclear	****	***	***	****	N/A	****	***
Solar (PV)	**	****	***	***	N/A	***	*
Wind	****	***	**	***	N/A	*	*
Gas	****	***	**	****	N/A	*	***
Oil	****	****	***	****	N/A	**	***
T&D lines	***	****	**	***	****	***	***
Substations	****	****	****	***	****	**	***

Table 8
Significant disasters in the U.S. from 1980 to 2017, with estimated losses, and the present technology of power grid adopted after the said disaster.

Year	Disaster name	No. of people out of power in Million	Property damage cost in Billion USD	Present grid technologies
1980	Heat wave	0.034	20	DER, Renewables, SVC, SF_6 CB, HVDC, EMS
1992	Loma Prieta earthquake	1.4	6	SMES
1989	Hurricane Hugo	0.1	7	N/A
1989	Hurricane Andrew	1	25	TCSC
1994	Northridge earthquake	3.5	23	N/A
2005	Hurricane Katrina	3	125	STATCOM, UPFC, CSC, Microgrid
2012	Hurricane Sandy	8.1	75	High voltage AC CB
2017	Hurricane Irma	16	64.7	ESS, IoT
2017	Hurricane Maria	3.4	91.6	N/A
2017	Hurricane Harvey	0.2	125	N/A

4.1. Assessing the United States grid reliability

The reliability of the U.S. electricity grid can be assessed using two parameters, namely LOLP and the Frequency of Load Loss. These two parameters can be calculated using Monte Carlo simulations, which is based on imitating a physical structure's stochastic behavior, in this case, an electrical grid. MCS is exceptionally beneficial when the subject system exhibits random behavior in any form, especially when it becomes too complex to be evaluated through conventional analytical methods. Apart from strict application scenario of power system, MCS is also used for simulating cost–benefit analysis of remote offshore systems [106]. The electrical grid is divided into many smaller parts whose behavior can be predicted either by probability distributions or deterministic measurements to render such a simulation. These individual parts are then combined to get the total electric grid reliability, leading to a mathematical model. To get a better understanding of MCS, consider a system of two indispensable components. Initially, Component 1 is kept upstate. The time at which this element will fail is evaluated using a random number and the probability distribution of the uptime. Similarly, a potential repair period is developed. The history of the part developed in this way is one possible realization of the stochastic process. Component 2 realization is then built, and the simultaneous durations of the breakdown reflect the durations of system failure since all components are required for system performance. In this way, a variety of realizations of the grid history can be built, and the reliability metrics can be derived using statistical techniques from those realizations Algorithm 1 will find the LOLP and the Frequency of Load Loss of an electrical grid with the MCS to assess grid reliability. In Fig. 15 the U.S. map is shown by categorizing the states based on their LOLP value, which is calculated based on the federally accepted disaster data since 1953 [107,108]. Below are the assumptions for MCS assessment strategy of grid reliability:

1. The power generation unit's failure rate is considered as $0.1/24$ h, and the repair rate is considered $1/8$ h.
2. Weather is considered as a two-state component with a failure rate of $1/200$ and a repair rate $1/20$.
3. The failure and repair rate scheming is complicated and highly dependent on the transmission line's geographical location. So, these rates vary from state to state. The failure rate is calculated from the product of a state's annual average disasters and the average disaster duration in adverse weather.
4. The average disaster span is calculated with the weighted average method, the frequency of each disaster is considered as respective weights, and their period is value.
5. The failure rate in normal weather also maintains a close relationship with the failure rate in adverse weather. Based on historical data, this factor is rounded down to 2 [109].
6. The repair rate is estimated as constant for transmission lines, $1/8$ h.

The basic steps of the MCS-based grid reliability assessment technique are:

1. Determine time to next event (TTE).
2. If load was not served between the last event and this upcoming one, update running time of unserved load.
3. Make the next event occur by changing the state of the relevant component.
4. Update time.
5. Update TTE's for all other components.
6. Determine whether or not load is served.

4.2. Assessing the United States grid resilience

The U.S. states can be classified on the basis of population and gross domestic product (GDP) density. The GDP data per state is considered according to the data of 2019. The GDP density (per square mile) is assessed to establish economical uniformity for each state. Mile is the commonly used unit for measuring length in the U.S. Therefore, this section uses mile for maintaining consistency with the available data. A square mile is equivalent to 2.59×10^6 square meters. In urban areas, the population density and GDP density are much higher (population density is more than 500 per square mile), and so is the density of the grid infrastructure. The density of grid infrastructure is a novel terminology, which refers to the amount of grid infrastructure per

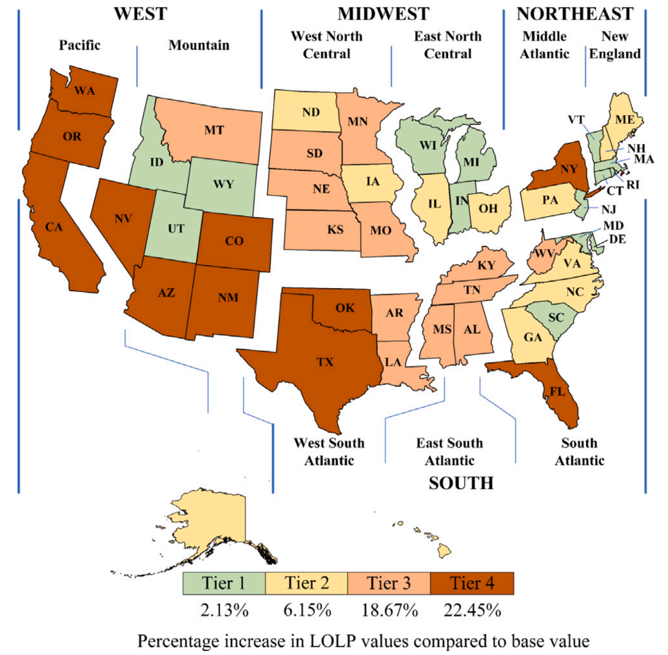

Fig. 15. The categorization of U.S. states, according to LOLP; calculated based on federally affirmed disasters since 1953 [107,110]. The LOLP value of Delaware is considered as the base value, as this state has the least LOLP among the U.S. states.

Algorithm 1: MCS finds the Loss of Load Probability and the Frequency of Load Loss of an electrical grid.

Input: Generators, transmission lines failure rate and repair rates for both normal and adverse weather.
Output: Loss of Load Probability and the Frequency of Load Loss of an electrical grid.
Initialize: Two state component for disaster, loads and all other associated grid components.
while $i <$ 100000 **do**
  Sort: Components based on their time to event (TTE)
  if $delta <$ 0 **then**
    Raise: Value Error
  if $load\ not\ served$ **then**
    Log: The unserved load event.
    Update: Unserved time with given change in time.
  if $previous\ load\ served$ **then**
    Update: Loss of load counter if this is a loss of load event, but load was being served before.
  Toggle: State of the component and update it is TTE.
  if $time <$ 8760 **then**
    Update: Year counter and total time, reset time.
    Set: Unserved time in the array and reset it.
    Compute: The mean unserved time thus far, and append to the appropriate array.
    Compute: The estimated coefficient of variation.
    if $coefficient\ of\ variation <$ 0.05 ***and*** $year >$ 1 **then**
      Break: With statement.
  else
    Update: The time.
for $C \leftarrow$ ***in*** $components[1:]$ **do**
  Update: TTE for all other components.
Log: Disaster.
Compute: Load served.
Update: Initial counter.
return $Final\ statistics.$

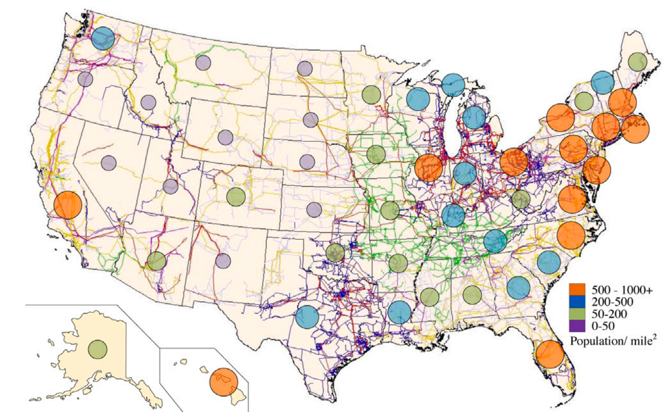

Fig. 16. Grid infrastructure density with population density in the U.S. Both densities are comparatively higher in east coast. [1 mile = 1609.34 m. 1 square mile = 2.59×10^6 square meters.].

unit area. Based on Fig. 16, the north-eastern and south-eastern part of the U.S. has greater density of grid infrastructure. A dense grid infrastructure implies a developed economy, a sophisticated grid, and readily available services to the grid. Therefore, a higher number of repair teams and services are provided to urban areas. For this reason, a crisis or power outage in urban areas is much simpler to solve.

The value of the load is another critical factor for a power outage. In rural areas, where the population density is much lower, the problem of power outages is unlikely to be addressed as quickly as in urban areas, leading to a more prolonged power outage for a single case. Another critical factor is the risk factor of a state and the infrastructure in urban and rural areas. In a given state, where high-impact disasters are less likely to occur, the investment in infrastructure to boost grid resilience would be more unlikely. The frequency of disasters is the average number of disasters occurring in a particular area per year.

$$RRF = Disaster\ frequency \times Resilience\ score. \tag{12}$$

A new terminology is proffered here, named Resilience Risk Factor (RRF), expressed as the product of the frequency of disaster and the resilience score. It is represented in Eq. (12). In order to estimate the RRF for a particular state, the frequency of disaster is obtained from the FEMA dataset. The number of disasters in each U.S. state has been recorded for each year since 1953. Then the number of disasters was divided by the number of years till 2020 in order to obtain the frequency of disaster. The resilience score is computed from the trapezoid of resilience. The trapezoid region is measured along with $\Phi\Lambda E\Pi$ metrics, which are often referred to as 'FLEP' metrics (initially suggested by [44]), to obtain a better understanding of the resilience trapezoid. Based on the RRF, the 50 states can be divided into four with 12 states in each tier – Tier 1, Tier 2, Tier 3, and Tier 4. Among them, Tier 4 is the most susceptible to disasters, followed by Tiers 3, 2, and 1. Therefore, the Tier 4 states deserve more resources allocated to improving the grid resilience. Table 9 demonstrates the assessment of the grid resilience of the U.S. states classified into 4 tiers according to the FLEP metrics. Some noteworthy observations from the resilience trapezoid are as follows:

- Within the states in the same tier, the resilience falls quicker than the recovery rate. The factor between these two rates varies from 1.5 to 4.
- A higher probability of disaster implies a much higher factor between the falling resilience and recovery rates.
- The states with a higher RRF have comparatively lower resilience during disasters.

Table 9
Grid resilience assessment of the U.S. states with FLEP index. Higher value indicates higher resilience, and vice versa. Tier 1 has the highest resilience, while Tier 4 has the least resilience.

Resilience metric	Phi, How fast resilience drops? (MW/hours)	Lambda, How low resilience drops? (MW)	E, How extensive is the postthreat degraded state? (Hours)	Pi, How promptly does the network recover? (MW/hours)	Resilience ×10 000
Tier 1	168	16	9	42	101.60
Tier 2	26.33	21	9	15.8	7.86
Tier 3	14.2	29	12	6.45	3.18
Tier 4	5.6	42	15	3.64	1.28

Table 10
Grid resilience assessment of the U.S. states with the proposed metrics of [111].

State tier	Absorptive capacity, Ab	Adaptive capacity, Ad	Restorative capacity, Res	Resilience
Tier 1	0.16	0.75	42	27.21
Tier 2	0.21	0.53	15.80	7.15
Tier 3	0.29	0.43	6.45	2.40
Tier 4	0.42	0.39	3.64	1.21

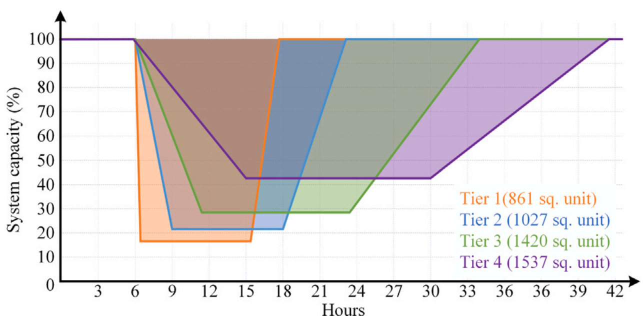

Fig. 17. Resilience trapezoid for different tiers of states. The less area trapezoid covers, the more resilient the system will be.

The resilience metric according to the resilience trapezoid can be explained in the light of Fig. 17. Tier 1 has a lesser area of the trapezoid. It has the highest resilience and lowest RRF. Since it is more resilient, it spends the least time in the post-threat degraded state, and quickly returns to full capacity. Tier 4 is at the other end of the spectrum, with the highest area of the trapezoid. It has the least resilience and highest RRF. Since it is less resilient, it spends the longest time in the post-threat degraded state, and slowly returns to full capacity. So, Tier 1 has the highest resilience, followed by Tiers 2 and 3, and finally Tier 4 has the lowest resilience. Accordingly, Tier 1 has the lowest RRF, followed by Tiers 2 and 3, and finally Tier 4 has the highest RRF.

The previously demonstrated FLEP metrics has been verified with the metrics proposed by [111]. To quantify resilience, a novel method has been proposed in [111] based on the Boolean relation among the absorptive, adaptive, and restorative capacities of the system. Eq. (13) can be noted according to their proposed metric, where RE = Resilience, Ab = Absorptive capacity, Ad = Adaptive capacity, and Res = Restorative capacity.

$$RE = Ab \vee (Ad \wedge Res) = Ab + Ad.Res - Ab.Ad.Res \tag{13}$$

This method directs on the residual capacity to absorb the interruption and its contribution to resilience. According to the metric proposed in [111], the resilience of the Tier 1 is the highest, and Tier 4 has the lowest resilience. Table 10 represents the results obtained by the use of this metric. A similar result is obtained from the FLEP metrics, shown in Table 9. Comparison of Tables 9 and 10 reveals that the tables concur with each other. Hence, both methods are acceptable and reliable indices of resilience assessment.

5. Grid reliability enhancement strategies

Besides high impact disasters, which is the study focus of resilience, different low impact disasters occur across the U.S., such as landslide, wildfire, or flood. Such disasters leave a low impact on human lives but can be devastating for grid infrastructure. Through the reliability index values, the power quality delivered by an organization is measured. For such reasons, several reliability enhancement techniques must be studied. These strategies may include infrastructure upgrades like distribution feeder reconfiguration or demand-side management. In recent times, ESS, annual energy management, smart grid, and microgrid are high-ranked to enhance grid reliability.

5.1. Distribution feeder reconfiguration (DFR)

A feeder line feeds electric power from the substations to the distribution lines. Owing to infrastructure faults, such as overhead and underground cable faults, historical anomalies suggest that a substantial part of service interruptions were triggered. Indeed, the optimum operating temperature for underground lines is specified and may create a problem with insulation if the device failure rates are exceeded. The resistive losses generated by a power cable generate heat in the feeder that proportionally increases the temperature to the square of the feeder's current capacity. Furthermore, the removal of moisture occurs quickly at raised temperatures. In comparison, the expected lifespan of the insulation declines exponentially with rising ambient temperature. Overhead cables may have similar consequences [112]. High currents make the overhead cables sag, thus decreasing ground clearance, and raising the chances of an electric split. Reduction of the branch currents positively impact system stability. DFR through readjustment of the network topology minimizes the magnitude of each branch current, thus significantly reducing the system's overall power loss. Furthermore, the detrimental temperature effects on the stability of the power systems are nearly moderated. By minimizing the system's overall power failures, the feeder's load capacity is increased to improve the system stability and reliability. DFR can decrease the temperature of the cables (by decreasing the current) and can thus be considered a technique for reducing the failure rate.

Before implementing DFR on a grid, a cable i has a fundamental failure rate of i^{init}. The lowest failure rate obtained for the ith cable due to current decrease, is interpreted as i^{best}. Therefore, a new failure rate is specified as Eq. (14) for any cable in the grid according to the current reduction percentage [113].

$$\lambda_i^{new} = \chi(\lambda_i^{init} - \lambda_i^{best}) + \lambda_i^{best}. \tag{14}$$

$$\chi = \frac{I^i_{R-new}}{I^i_{R-old}}. \tag{15}$$

Each feeder branch's failure rate is established with a linear relation to the compensation percentage. In Eq. (15), the vector χ is the compensation coefficient of the ith branch ith branch's compensation coefficient. The compensation coefficient is the ratio of branch current, after DFR is applied. It can be used as the coefficient of failure rate reduction before applying DFR to the same value. By introducing a DFR strategy, the power flow direction is modified to decrease the active/reactive portion of the feeder branch to a lower value as a direct effect.

5.2. Energy storage systems (ESS)

The employment of ESS plays a vital role in grid reliability enhancement. Effective planning of battery storage or water reservoir can reduce grid vulnerability and increase reliability in return. Nevertheless, the incorporation of ESS in the grid comes with a price tag. So effective planning to integrate ESS is essential. The main costs of the grid with ESS are ENS cost and the investment and operation cost of ESSs. If, in any given grid or grid segments, the cost of ESS investment and operation is less than ENS cost, ESS can be effectively incorporated. The ENS expense is surveyed fundamentally as the cost of the unsupplied loads over some time (usually one year). This expense is estimated annually in \$/year as the quantity of unsupplied energy ENS_t (kWh) at phase t multiplied by the penalty EC_t (\$/kWh) as in Eq. (16). T symbolizes the total number of days.

$$Cost_{ENS} = \sum_{t=1}^{T} (ENS_t \times EC_t) \quad (\$/year). \tag{16}$$

The investment cost of ESSs is proffered by Eq. (17) in \$/year. The term E_E indicates the installed ESSs, term IE_E attests the expense of ESSs (\$), term VE_E symbolizes the power capacity of ESSs (kWh), r indicates the discount percentage, and LT particularizes ESS lifetime (year). The commensurate annual cost is essentially characterized as the annual expense across the lifetime [114].

$$Cost_{Inv.} = (E_E \times VE_E \times IE_E)\left(\frac{r \times (1+r)^{LT}}{(1+r)^{LT} - 1}\right) \quad (\$/year). \tag{17}$$

The operation cost of ESSs is given by Eq. (18) in \$/year, where, OE_t indicates the operation cost (\$/kWh) at hour t. Eq. (18) represents ESSs operation cost in \$/year, where at hour t, term OE_t manifests the operation cost (\$/kWh).

$$Cost_{Op.} = \sum_{t=1}^{T} (E_t \times VE_t \times OE_t) \quad (\$/year), \tag{18}$$

When ESSs are incorporated with grid, the total load demand E_d for the observation period, decreases during the discharging phase of ESSs. E_d can be determined as follows [115];

$$E_d = \begin{cases} E_{demand} - E_{discharge}, & t \in t_{discharge} \\ E_{demand}, & t \notin t_{discharge}, \end{cases} \tag{19}$$

where $E_{discharge}$ is the discharged energy from ESS, $t_{discharge}$ is the discharging time, and E_{demand} is the energy of loads.

5.3. Year-to-year energy management

Management of hydroelectric power plays a significant role for grid reliability enhancement. Hydro-energy control relies on the reservoir's scale, load variation profiles, and the hydrological conditions during the observation year. The approach aims to conserve water in an average or wet year with little adverse effect on system stability by integrating diurnal, seasonal, and annual storage. A sufficient amount of water will be available for the coming year of energy instability. The hydrological condition's instability in an upcoming year is depicted by a common monthly or seasonal fluctuation in hydrological data acquired employing Eq. (20). Here, W_X is the average seasonal hydrological data of the year with hydrological condition X, and $P(X)$ is the year's probability having hydrological condition X.

$$W = \sum_X P(X) \times W_X. \tag{20}$$

5.4. Demand side management (DSM)

DSM refers to any action taken by a utility that gradually changes the utility's entire system load curve. To have a good DSM scheme, utilities require clear targets for modifying the loading curve's shape. Eq. (21) is used for simulating the process of peak shaving and load shifting. P are the system's pre-specified top requirement, as a consequence of DSM initiatives. Load above the specified peak limit is shifted to off-peak hours. Based on the value of a in Eq. (21), the quantity of energy is substituted to offpeak hours. The vector p is the first time that the initial load is higher than the previously defined peak value ($L(t) > P$). The vector q reflects the last moment on the same day that the initial load is higher than the previously defined peak demand ($L(t) > P$). t_1 and t_2 are the initiating and terminating time for the off-peak power recovery. The gap amid t_2 and t_1, signified as h, is the quantity of time throughout which power will be retrieved. a depends on the amount of restored power needed during off-peak times and ranges between $0 \le a \le 1$. If a has a value of 0.7, 70% of the power decreased throughout on-peak times are retrieved during off-peak times [115].

$$\hat{L}(t) = L(t) - (L(t) - P)\Omega L(t). \tag{21}$$

$$\hat{L}(t) = a \left[\frac{\sum_{T=p}^{q} (L(t) - P)\Omega L(t)}{h} \right] \lambda_{t_1,t_2}(t). \tag{22}$$

Here for $L(t) > P$, $\Omega(L(t)) = 1$ and for $L(t) \le P$, $\Omega(L(t)) = 0$. For $t_1 \le t \le t_2$, $\lambda_{t_1,t_2}(t) = 1$ and for other values of t, $\lambda_{t_1,t_2}(t) = 0$.

5.5. Smart grid and microgrid technologies

Using smart grid and microgrid systems, the impacts of both external and internal faults can be mitigated in the operating zone of an electrical power transmission system. Automation of feeder through smart grid innovations can be used to improve grid reliability. Diagnosing the fault manually can be dangerous, burdensome, and time-wasting, eventually leading to low service reliability. Fault diagnosis and management can be performed more effectively by fewer people in far less time based on the aspects of the enforced feeder automation scheme, which improves the reliability and productivity of the delivery system. Besides, the control scheme introduced also reduces the voltage sags encountered by consumers and the disruption to the delivery network system by minimizing the amount of inrush current generated by the fault re-ignition operations needed to find the fault. For instance, Fig. 18 demonstrates how fault management practices could continue with and without an advanced feeder automation scheme being employed [116]. When managers of control centers handle a simultaneous outage situation, the periods seen would be increased even further under disaster situations.

A microgrid may be a smart grid that provides more stability and efficiency for the device control and security with advanced computing technologies and smart meters [117]. It has risen as a scalable architecture that can address the broad spectrum of needs for multiple groups to implement DER [118]. Fig. 19 amalgamates various concepts related to microgrids. The integration of microgrid components such as RESs, DERs and ESSs help to improve the overall grid resilience and reliability. Monitoring and controlling the grid through smart technologies are contributing to the upgrade of the conventional grid to smart grid.

6. Grid resilience enhancement strategies

Many approaches can be employed to optimize the grid's resilience to perturbational incidents by leveraging the inherent redundancy in grid and infrastructure. In this understanding, the provider is responsible, with a limited amount of available personnel, for ensuring the grid resilience of essential network loads. Several grid resilience enhancement strategies ranging from both Physical hardiness and Operational capability are required along with renewables, IoT, and AI support to render this job.

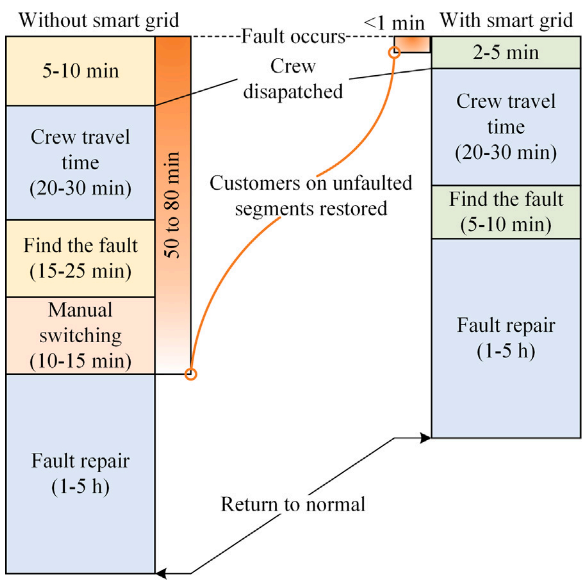

Fig. 18. Impact of smart grid and microgrid in overall fault control exercises. Blue boxes represent that time is the same, red box represents additional time, yellow boxes represent longer time duration, and the green boxes represent shorter required time duration [116].

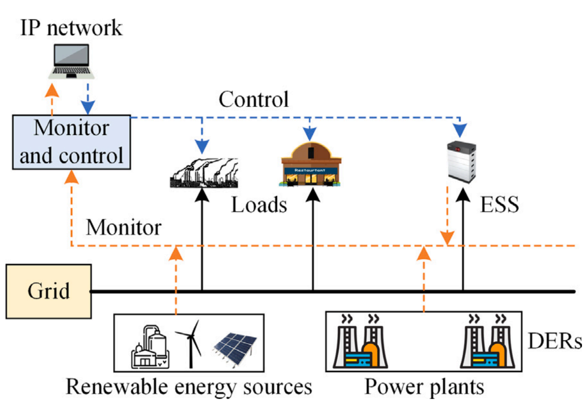

Fig. 19. Integration of renewable energy sources, Distributed Energy Resource (DER), and Energy Storage System (ESS) to electric grid. Blue dotted line denotes the control line, red one denotes control of grid.

6.1. Physical hardiness

Due to constraints in budget, time, etc., a deliberate decision to execute an enhancement strategy is critical. The policy for grid resilience enhancements serves two purposes: to decrease the severity of the immediate effect of an extreme weather event and, after extreme weather events, to reestablish grid functionality as soon as possible. Generally, an improvement in physical grid resistance is employed to minimize the effect and decrease restoration time by improving the grid's operational capability [119].

6.1.1. Vegetation management

Vegetation management involves the planned plantation of trees, and pruning existing trees such that they do not create obstacles to T&D lines. The most common type of fault is single line to ground fault, accounting for 80–90% of power system faults. Such faults are caused by collapse of big trees during storms or strong winds. Vegetation management aims to prevent damage to T&D lines and poles, and short circuits. Thus, vegetation management contributes to improving grid resilience. For overhead line distribution arrangements, Kuntz presented a planning algorithm for the optimal management of vegetation [120]. The Edison Electric Institute presented an exhaustive description of the practical use of vegetation management to improve grid resilience [121].

6.1.2. Selective undergrounding

The T&D lines beneath the poles and cables are used to lessen the vulnerability due to extreme weather incidents. Nevertheless, it is crucial to carry out a comprehensive analysis to find out if the hardening technique in each grid is suitable, as the cost of transforming the overhead lines into underground lines is considerably higher [122]. It is more realistic to follow the selective undergrounding strategy than full undergrounding. The latest studies have shown that limited underground power lines have benefited from decreased losses and costs instead of converting all overhead lines to underground ones [123,124]. An evaluation of the cable structure and aging can be used in select underground planning, provided through a research by Kopsidas [46].

6.1.3. Physical upgradation

Through modernizing the old system structure with newer technologies, the grid resilience can be strengthened. For example, the poles can be upgraded using with more sturdy materials to withstand stronger wind speeds and provide more protection, like the guy wire and arm guy [10]. Ma researched grid upgrading and vegetation management by updating distribution poles and found that both approach combinations are more effective than individual implementation [74]. Ref. [125,126] identified an algorithm for improving the physical strength model for the power poles based on which, the fragility of the power poles can be assessed. The modification or upgrade needed by the pole was proposed. As defined in recent studies, earthquake-resistant construction can increase physical hardiness, decreasing the risk of failure of grid components failure [127,128]. Navarro-Espinosa proposed a model for evaluating the steps needed to increase grid resilience to earthquakes [129].

6.1.4. Water barrier and elevated substation

The substation is endangered to harsh weather circumstances triggering floods. Some of the most convenient methods of shielding the substation are lifting it above the flood level and building water barriers along the substation's perimeter [130,131]. Ideally, if floods regularly occur in the substation, a permanent water block might be needed. Interim water blocks may be built when the water level is expected to rise early [132].

6.1.5. Substation resettlement and lines diversion

The resettlement of substation, T&D lines, albeit the high costs of implementation, can increase the grid resilience. When a substation serves many critical consumers, where extreme weather may occur, relocation and re-routing is a priority, based on historical evidence [133]. A case study conducted by Entergy Corp. in 2011, on Hurricane Sandy and Irene power outage, strengthened that relocating components of the grid from the coastal territory was significantly more economical than adopting other hardening strategies [134]. For the convenience of relocation of sub-stations or rerouting of tracks, long-term analytic thinking is therefore necessary.

6.2. Operating capability

The grid operating capability is related to the dynamic infrastructure of the grid, ensuring that the grid is as stable as possible in a vulnerable situation in order to maintain continuous supply. A rapid grid recovery is the basic principle of grid operating capability. Efficient resource deployment and the recovery sequence are crucial to a successful recovery [135].

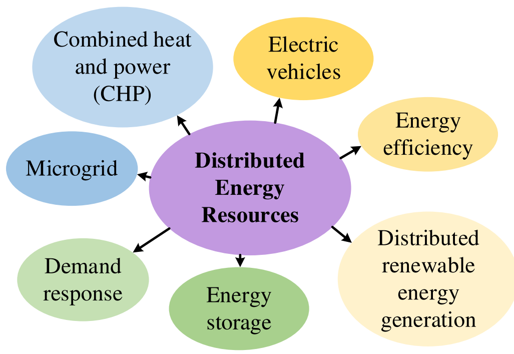

Fig. 20. Role of DER for grid resilience enhancement strategies. In this context, DER is most beneficial for microgrid, demand response, energy storage, and distributed renewable energy generation.

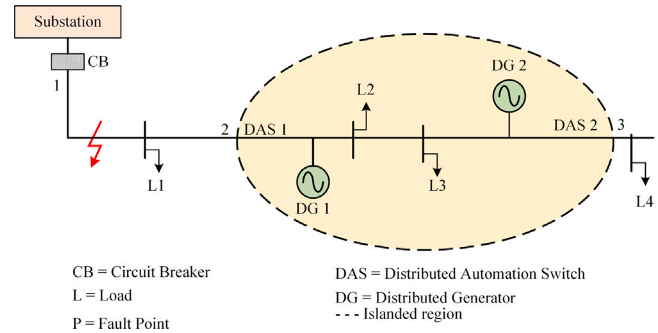

Fig. 21. Illustration of microgrid islanding. After occurrence of fault at point P, the isolation of zone 2 and 3 form an islanded microgrid bounded by DA switches 1 and 2, where distributed generators DG1 and DG2 support loads L2 and L3.

6.2.1. *Emergency generator and mobile substation*

A typical approach to reestablish power supplies for endangered areas is to provide mobile or portable power generators or substations [136,137]. During emergencies provoked by severe weather disasters, an emergency diesel generator or battery can maintain electrical supplies, especially for remote but indispensable consumers. The grid functionality may be partially restored for compromised substations or crumbled distribution lines until complete reconstruction is achieved. Besides, an emergency energy supply will support a blackstart state [138].

6.2.2. *Microgrids and distributed energy resources*

In extreme weather events, the development of sophisticated grids and microgrids bring tremendous advantages to the grid, and their use increases grid resilience. The microgrid is less vulnerable to weather extremities by generating, storing, and regulating electricity locally. Smart grids and microgrids are able to react to the impact of severe natural events faster and more efficiently. Defensively isolated microgrids can even enable the maximum restoration of the grid [81]. The strategy allows for maximization of grid capacity. Also, DERs and microgrid systems can alleviate the impacts of the failures of power T&D lines. Different roles of DERs are shown in Fig. 20. According to the smart electric power alliance [139], a five-stage approach can be used by utilities, local and state administrations to transform existing microgrids for enhanced grid resilience. The approach includes identification of critical customers and sites, defining high risk zones, evaluation of load profiles, microgrid sizing, and testing deployment scenarios.

6.2.3. *Defensive islanding*

Defensive islanding is directed at isolating fragile entities and stopping outages from cascading. The scheme involves a weather-adaptive integrated preventive control system. Using data recorded by Phasor Measurement Units (PMUs), the topology of network and loading conditions is calculated [140]. Fig. 21 illustrates a microgrid islanding where the substation is powering four loads. When power outage occurs at the interconnection of $L1$, an island is formed at the circled area. Two distributed generators $DG1$ and $DG2$ energize the islanded region until the fault is cleared. The system is built to separate the fragile buses on the island; the more significant the island, the better is its resilience against the branches' loss. The islanding solution with limited interference to the flow of power is believed to maximize load release. These islands act as autonomous structures.

6.2.4. *Spare parts and repair crew management*

Replacement parts are crucial to minimizing restoration time in the course of severe natural disasters [141]. Several factors, such as grid size, have to be taken into consideration when engineering replacement parts. The utility grid comprises many elements. These are repaired on priority basis, and the priority can be understood by determining the extent of the fault, impacts, investment costs, and complexity of the operation and installation of the component [142], besides the location of these repairs, quick access to damaged areas, and number of repair teams. Faulty replacement parts and restricted access to the affected area can result in longer recovery times and even more damage [143,144].

6.2.5. *Grid monitoring system*

The information available in real-time is essential for swift and efficient preparation and implementation of restoration measures in severe weather conditions. Nonetheless, the channel used to exchange information may be out of order because of the extreme weather crisis. Alternate solutions for information communication are, therefore, required. For example, Unmanned Aerial Vehicles (UAVs) assist the Airborne Damage Assessment Module (ADAM) Module to reduce acknowledgment times and expenses [145]. ADAM supports the breakdown management system, the geographic information system, and the system for asset management.

A data visualization strategy is being formed by the Electric Power Research Institute (EPRI) for utility operations and engineering. The data can be retrieved from operators in real-time via computer, tablet, or phone via the utility pole and lines by merely targeting the camera on the inspected equipment. The disaster area can be investigated, and based on the data given by this equipment, it is feasible to appraise the shortest viable path for deploying the repair and reinforcement team. Another advantage of this strategy is that the drone can be reached better in the damaged region than other vehicles, mostly when roads are blocked. Situational awareness can also be improved by monitoring grid conditions that improve grid resilience [146,147]. The network operator and other relevant parties' effective responses will maintain the grid's functionalities, towing to their knowledge of the latest conditions. A damage assessment may also be performed to track the grid condition for an extreme weather event [76,148].

6.2.6. *Design standards upgrading*

Management and regulations are reinforced after rattling incidents so that adequate rules and management are available to enhance grid resilience, defining the time needed for the recovery and costs [121,149]. A pre-event arrangement between utility providers and other industries is a mutual assistance agreement. The policy stipulates that the utility provider is a priority for assistance from other industries during severe weather events. The frequency of severe natural disasters demands the alteration and enhancement of the current engineering and design specifications for operation and maintenance. To cope with severe weather, the study of the current power infrastructure and the frequency of the upcoming disasters will elicit ideas for improving the design. Therefore, if the grid is extended, the proposed grid configuration may be implemented. A significant investment is prerequisite to enhance grid resilience. Again, a non-resilient grid will incur huge costs in case of disasters. Either ways, investments are required. An optimum cost–benefit analysis can help to make an optimum selection. Considering long-term goals, it is definitely wiser to invest in resilience enhancement strategies by upgrading the design standards, rather than taking active steps after the damage is done.

6.3. Role of renewables and energy storage systems

Renewable Energy Sources (RESs) are sporadic in nature, which is why they require storage. Energy Storage Systems (ESSs) are the array of systems and approaches which are used to store different forms of energy [150]. ESSs are a reservoir for energy to counteract the consequences of DERs' fluctuating performance [151]. Superior economic efficiency and increased operational productivity are provided by renewable grids and storage facilities [152]. The storage devices' energy capacity should be high, and an appropriate Energy Management System (EMS) should be used. ESSs can decrease the intermittencies due to grid integration of RESs, thereby increasing both the grid resilience and reliability [153]. The resilience in meshed and radial grids can be improved with the addition of solar photovoltaic systems with energy storage [42], in addition to cost savings and emergency power backups.

Many rural areas and islands are beyond the cost-effective reach of the utility grid. Microgrids powered by local RESs, and equipped with sufficient storage facilities are reliable energy sources for such communities. In addition, the urban landscape is changing from central electric to decentralized micro-grid and small, self-sustaining RE generation systems. This move is primarily focused on environmental and economic factors. The use of RE helps the transition to a decentralized and therefore, more reliable, electricity grid. Despite large initial costs, the use of ESS leads to multiple benefits in addition to backup power, such as load leveling, frequency and voltage regulation, power quality improvement, time shifting, blackstart the leveling of load and power [153]. Pumped hydro storage is a great method to serve as a peaking power plant, to meet peak loads and avoid power shortage. ESSs, particularly batteries, are extensively used to provide backup power during emergencies, and provide blackstart services, thereby contributing to improving grid resilience.

6.4. IoT and AI technologies

Modern technologies such as Internet of Things (IoT) and Artificial Intelligence (AI) are applied in a myriad of systems. The power grid also benefits from these technologies by improving resilience. In addition, blockchain based technologies also aid grid resilience.

6.4.1. IoT based technologies

The IoT has been designed to link objects via tags to the Internet with their information stored in databases [154]. To validate the grid emergency response program's combined efficiency, Lizon implemented a range of sub-systems: communication, power electronics, and machine learning [155]. The IoT contains three essential features:

1. Comprehensive sense: using sensors, RFID, 2D code to gather object data anywhere, anytime,
2. Reliable transmission: dependable concurrent distribution of object data by meshing a diversity of telecom meshwork and the Internet, and
3. Intelligent processing: applying advanced computing to manipulate and analyze large amounts of data to implement smart object controls, such as cloud computing and fugitive identification.

Even more DERs and versatile demands provide the potential for a more robust and transactive power grid. It contributes to the need for an integrated design approach to handle this transition. IoT architecture aims to incorporate market activities, taking into account the cybersecurity of the grid [156]. IoT can boost the upgrade of the power grid into a smart grid, and thereby improve grid resilience by making it more well-informed, robust, and prepared.

6.4.2. AI based technologies

Different machine learning (ML) algorithms such as artificial neural networks (ANN), multilayer perceptron, support vector machines (SVM), wavelet neural network, ANFIS, decision tree, deep learning, etc., analyze the construction of algorithms, from which data can be learned and predicted. In practice, system planners can be provided with multiple grid hardening options. The most suitable alternative is a daunting challenge since many factors include simulation and, besides, the behavior and aftermath of the case cannot be captured entirely by mathematical approaches. Because of the amount of data on previous hurricanes and because of the system's complexity, ML can be a viable option to address this problem. AI enables the system to learn and predict historical data without being explicitly programmed. A wide variety of research efforts in the power and energy fields use machine training approaches, like safety assessment, load forecasting, detection of the distribution failure, and power failure forecast [148,157].

6.4.3. Blockchain based technologies

Blockchain is a database system or digital ledger that logs value transactions by using an intrinsically modified cryptographic signature [158]. It makes the decentralized modern grid and incorporates IoT and grid edge devices linked to the internet. Blockchain is known by means of the inherently modified cryptographic signature, the distributable database, or digital ledger recording value transactions [158]. The integration of Blockchain-based intelligent contracts with machine-learning algorithms provides opportunities like increased speed, size, safety, and the autonomy of complex IoT environments. To have an effective and resilient means of facilitating transactions within an energy community and allowing wholesale business acceptance, Vangulick proposed applying blockchain technology to energy societies [159]. Smart contracts enable peer-to-peer energy exchange by allowing energy purchasers and procurement to trade energy. The arrangement of power producers and suppliers at different prices is distinct, rather than multi-layered [160]. The electricity grid is currently devoid of the protection and durability necessary to avoid cyber-attacks on grid edge devices, DERs, and related electricity infrastructure [161]. To evaluate all of such grid resilience improvements, proper justification of grids is needed to understand better a grid, comparison between two or more grids, and, above all, strategy adjustment.

Table 11 combines the enhancement strategies which can render improved grid resilience and reliability. The table also includes the technological readiness level (TRL) of each strategy, alongside the cost comparison and maintenance requirement.

7. Challenges and future research needs

Given the initial challenge to identify and define resilience and reliability issues in energy systems, it is a difficult task to figure out specific solutions to these problems. The problem is more pronounced in electricity grids due to the complex and intricate nature of the grid. The analysis of standardized quantification and metrics, cyber–physical threats modeling, inter-dependency management, disaster simulation and recovery exercises mentioned in this section require extensive research and industrial support to proceed for integration with the extant policies and for the real-world implementations. Possible challenges and corresponding future scopes for grid resilience and reliability research are mentioned below. The challenges and research gaps in the field of grid resilience and reliability are summarized in Table 12. The technological readiness level (TRL) of each challenge is also provided.

Table 11
Various grid enhancement technologies and their roles to improve resilience and reliability. Italic fonts denote Physical enhancement strategies; the others are operational capability.

Grid enhancement strategies	Resilience	Reliability	TRL	Cost comparison	Maintenance requirement	References
Vegetation management	High	Low	9	Low	Low	[162,163]
Selective undergrounding	High	High	9	High	High	[123,124]
Physical upgradation	Medium	High	8	High	High	[127,129]
Water barrier and elevated infrastructure	High	Medium	9	High	Low	[131,132]
Grid resettlement	Medium	Medium	9	High	High	[133,134]
Smart grid	High	High	8	High	Medium	[164,165]
Microgrid	High	Medium	8	Medium	High	[166–168]
Mobile generator	Medium	High	8	Medium	High	[136,138]
Distributed energy resources	High	Medium	6	Medium	High	[169–171]
Defensive islanding	High	High	7	Low	High	[172,173]
Repair elements management	Medium	High	8	Medium	Medium	[142,144,174]
Grid monitoring system	High	High	7	Medium	Low	[146–148]
Design standards upgrading	High	High	8	High	Medium	[149,175,176]
IoT and AI technologies	High	High	7	Medium	Low	[155,156]
Renewables	High	High	9	Medium	Medium	[177,178]

Table 12
Challenges and research gaps in the study of grid resilience and reliability along with the Technological Readiness Level (TRL) of each challenge.

Challenges	TRL	Approaches	Research gaps
Reliability metrics	7	Objective-based concept fulfilling crucial stresses restoration, time reducing load failure [167,179]	Universal reliability metrics integration in real time smart grid.
Resilience metrics	6	Multi-domain resilience metrics separated by the case timeline [84]	Grid infrastructure density and nature.
Renewable threat	4	Wind turbine syndrome, Liability Risk [180]	Flicker effect
Cyber security threat	8	Reconnaissance, scanning, exploiting and maintaining access [181]	Denial of Service (DoS) attacks
Threat modeling with multiple infrastructures	6	Wind tempestsí impact on power poles; fragility curve [50]	Over-simplifications in fragility curve
Resilience with ESS and DERs	6	Control techniques; battery inverter device [182]	Fleets of electric vehicles; portable power storage facilities
Utilizing data from smart devices	9	μPMU technology [183]	Faster constructive control schemes
Co-simulation of inter dependent systems	8	GECO, FNCS, HELICS, and EPOCHS transmission systems [184]	Interdependent system under specific high impact disasters.
Disaster evaluation and recovery exercises	9	UAV technology [185]	Disaster categorization

7.1. Standardized quantification

An effective unison requires to be established on the principle of resilience to standardize resilience quantification and promote the strategy. For several works, the system-level concept of ‘system capacity to predict, resist, react, adjust, and recover from a disturbance’ is quoted as resilience [180]. The objective-based concept of resilience may be ’the capacity of design to sustain performances required for mission achievement across a broad spectrum of situations, environments, and challenges, despite hostile acts or adverse conditions [179]. The goal may be to fulfill crucial stresses, reduce load failure, restoration time, or damage to equipment. Across other fields, there are other theories of resilience. Nevertheless, as there is no unison, researchers frequently use the concept that refers to their suggested problem description. The network is often needed for a control procedure such as non-preference load shedding, where its importance is scientifically based on this case but cannot pretend to be robust where its importance is based on the system level.

7.2. Resilience metrics

Resilience indicators should be established to support future improvements in resilience approaches and assess the success plan. Among several purposes, it is nevertheless challenging to apply a single systemic resilience measure spanning all dimensions of the cyber–physical distribution network. The number of adverse events involving the delivery network is the most reliable interpretation of this. Various events require various response strategies. For instance, the strategy of conductor hardening is good against atmospheric disturbances, but cannot suffice as a resilience enhancement strategy during cyber-attacks. Therefore, the hazards a given system may encounter must be identified and appropriate strategies must be adopted. The concept of multi-domain resilience metrics separated by the case timeline is thus significantly close to the proposed structure. It assesses the system’s resilience metrics, capabilities, and results before, during, and after hazards to consider the system’s preparedness, robustness, and potential for recovery.

7.3. Renewable threats

In the event of a national catastrophe, renewable energy technologies are immediately exposed to nature, rendering it the most vulnerable points on the national grid. This threatens grid reliability. Moreover, renewable energy technologies are responsible for many human health hazards, which is also a blow to the reliability of the electric grid.

7.4. Cyber security threat

Malicious hackers typically target four phases to control a grid: reconnaissance, scanning, exploiting and maintaining access. The hacker gathers and extracts information about its target during the first phase, reconnaissance. In the second phase, the flaws of the device are checked, in an attempt to classify the ports which are opened and to explore the operation and vulnerabilities in-port. During the exploitation phase, attempts are made to reconcile to gain total control over the target. Until having administrative access to the grid, the attacker manages to retain the access. Implementing a steady and undetectable application will lead to this step; hence, it can quickly return to the target device later on and meddle with the operation of the grid.

7.5. Threat modeling with multiple infrastructures

The prevailing understanding of much of the distribution grid’s failure or threat analysis lacks its multiple dimension to infrastructure. A sequential DER resilience and energy storm research is performed to model wind tempests’ impact on power poles [50,186]. This approach uses fragility graphs that map the risk of component failure to the extent of the hazard. This approach can also be used for other nodes that are likely to fail. Just one fragility curve is employed in several plays. A single curve of fragility can direct a few over-simplifications which can change the hazard model since factors such as the content used, polar age, and the vicinity to the leaflet cannot be taken into consideration. Chen used statistical methods to extract nodes, and the likelihood of failure, from history. For the calculation of effect and failure rates, the analyst employs practical events and statistical models [187].

7.6. Resilience with ESS and DERs

ESSs and DERs, such as electric vehicles (EV), are mostly highlighted as part of greening the grid, and reliability improvement. They are hardly discovered to enhance grid resilience. But they can provide superior performance in case of natural disasters, not only to provide backup power, but also in blackstart services. Emergency power can be supplied through the use of EVs. Therefore, to explore the full potential of ESSs and DERs in enhancing grid resilience and reliability, they must undergo mass usage, research, and documentation. Accordingly, energy management systems (EMSs) should be leveraged in order to serve the grid during disasters threatening grid resilience.

7.7. Utilizing data from smart devices

Particular problems with sensor placements at μPMU include concerns with the delivery network, including the unbalanced complexity of electrical variables due to single-phase loads and the radial topology characteristics. An optimized positioning algorithm for the μPMU positioning can be used for maximum stability observability. The positions will be listed, which track vital loads, distribution assets, and lifeline feeders. The event prediction algorithm μPMU can predict impending failure and provide adequate control to the control system to island and handle crucial parts of the PDS. The use of smart devices is at an embryonic stage in many electrical grids. Even smart grids of today still lack the use of automated techniques to recover the grid post disasters. Until manual intervention takes place, the grid still cannot recover after a shutdown. Automation has to be exercised at all levels of the grid to ensure quick recovery, thereby improving grid resilience.

7.8. Co-simulation of interdependent systems

The co-simulation methods can be used to explore some of the problems of modeling an interdependent cyber–physical network. Co-simulation is an analytical method used in conjunction with simultaneous message transmission and time synchronization for two or more simulators. Some co-simulation software are prepared as middleware, which manage the simulator interactions. There are some methods and frameworks for co-simulation that capture interactions with power and communication systems, but only for GECO and EPOCHS transmission systems [188,189]. Other tools have been developed, such as FNCS and HELICS, which simulate PDSs and communications networks and analyze the impacts on transmission network and distribution grid efficiency of communications network function [184,190]. For various resilience uses, co-simulator capabilities can be leveraged. For example, in Gridlab-D, the current HELICS iteration will model the distribution system, and Network Simulator 3 for the communication network.

7.9. Disaster evaluation and recovery exercises

More meticulous evaluation of post-disaster destruction to the PDS helps maximize utility restoration steps to restore power after an incident by recognizing degraded lines and equipment, and affording awareness of ground conditions for utility staff to boost restoration efforts faster. A significant advancement in assessing the PDS's resilience is the application of UAVs or drones to evaluate post-disaster status. UAV technology is employed to recognize dangerous environments as first as human interference requires dangers and costs in these situations, and thus proven to effectively identify the degradation of the post-event transmission network. This area of research already appears quite prematurely. The cost of operating UAVs has dramatically decreased with the introduction of rotary-wing drones and multi-copters. Drone image detection technologies can help locate and mitigate possible faults. A drone-based evaluation is provided in and can be used for more research [185].

7.10. Collaboration of academicians, industries, and communities

Although academicians work on grid resilience and reliability issues by conducting theoretical research, industrial experts perform practical experimentation with the organizational facilities and can collaborate with the academicians and provide them with data and resources for facilitating research. Community people are the workforce and administrative policy-makers contributing to both academic and industrial sectors. A tripartite relation between these three entities can provide researchers an opportunity to practically implement their theory, and can help to shape relevant policies and regulations.

8. Outcomes of the study

This is a comprehensive review on power grid resilience and reliability in the course of natural disasters. This paper compiles necessary information about grid resilience and reliability in one place, which will work as a useful research guideline for the researchers in the domain. To summarize, the outcomes of this review paper are:

- Since the electricity grid is the largest and most versatile energy system, the resilience and reliability of the electricity grid are of pivotal importance.
- To attain a national grid resilient to natural disaster, the notion of resilience cycle should be well-defined, and active and passive resilience should be exercised together.
- The existent centralized grid structure undergoes numerous quandaries ranging from economical to environmental, whereas decentralized microgrids can offer an assuring tomorrow.
- Reliability cannot warrant the grid's protection against natural disasters, which is why the assessment, quantification, and enhancement of grid resilience should be prioritized.
- To intensify grid resilience, physical hardiness prepares the grid against natural disasters, and operational capability performs during and after a disaster. Smart grids, distributed energy resources, microgrids, and energy storage can significantly enhance both grid resilience and reliability.
- To get a better conception of the U.S. grid reliability, LOLP and failure rate are appraised, which are effective for low impact disasters. For resilience assessment of the U.S. grid, required for high impact disasters, a novel terminology "resilience risk factor" has been proposed. The U.S. map has been drafted to betoken vulnerability both in grid reliability and resilience perspective.
- Another novel terminology called the "grid infrastructure density" has been proposed in this paper, which is measured on the basis of the industrial GDP per unit area, and acts as an indicator of the development and resilience of the grid. This helps to verify the resilience score, since there is no established method to verify the data.
- Both resilience and reliability metrics are adopted to quantify the grid, but the resilience metrics are not state-of-the-art yet.
- From resilience definition to threat modeling - many parts of grid resilience are not fully explored. These works will be a part of future explorations, which will investigate predictive algorithms and schemes to ensure resilience and reliability.

9. Conclusion

The study of grid resilience and reliability against natural disasters is of utmost importance for understanding the cause, effect, and solutions of the intermittencies in energy systems, particularly in the electricity grid. This paper presents an all-encompassing review of grid resilience and reliability based on the emerging electric infrastructure. The United States has been categorized into four tiers based on the resilience and reliability of its electricity grid. Two maps have been constructed to demonstrate the classification of the states based on grid resilience and reliability. The paper proposes two novel terms — grid infrastructure density and resilience risk factor, which will aid the understanding of how much resilient a grid might be. While grid infrastructure density depends on the population and density of the gross domestic product at a certain place, resilience risk factor takes into account how susceptible a place is to disasters, and its resilience score, and finally denotes the risk associated in a particular grid. The future works shall explore the limitations of the resilience and reliability metrics, making disaster-specific and system -specific resilience and reliability assessments, and quantification of the metrics based on the standard IEEE bus systems. The application of the metrics in case of other energy systems will also be focused in future works.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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