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RESEARCH ARTICLE

Toward Reaching a Consensus on the Concept of Power System Resilience: Definitions, Assessment Frameworks, and Metrics

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ABSTRACT The electric power system plays an integral part in the well-being of the modern society. Because of climate change, the ageing power system infrastructure is under threat due to the ever-increasing intensity and frequency of high-impact, low-probability (HILP) events. Although, in most cases, these events are area-specific, the impact of such events, if unaddressed, can lead to cascading failures. Therefore, it is vital for the grid of tomorrow to not only be reliable but also be resilient in view of the broad inter-dependencies. Despite being a widely researched topic, the applicability of the concept of resilience, especially in power systems terms, is not a straightforward task due to the lack of consensus on a consistent definition, or a set of robust metrics. This paper starts with an analysis of different definitions, frameworks, and metrics related to resilience proposed by multiple researchers and research organizations which is then followed by determination of the damage cost and risk associated with an extreme event which is pivotal in resilience enhancement decisions. We then present two case studies: 1) for determining the customer damage cost that underpins the increase in customer cost as a result of major event, 2) for estimating the risk index of the network that helps support resilience-oriented decision making. We also summarize some of the guidelines and standard practices followed by electric utility companies concerning extreme weather events in terms of preparedness and recovery actions, resilience improvement plans, etc. Moreover, to ascertain the improvement in the grid resilience indices, as a result of resilience enhancement application, a case study (Case Study 3) that evaluates three resilience improvement techniques is presented.

INDEX TERMS High-impact, low-probability (HILP) events, power system reliability and resilience, customer damage cost, risk index, electric utility response.

I. INTRODUCTION

An electric power system is the heart of today's modern society as it is inextricably interconnected with a multitude of the critical infrastructure sectors. Stable operation of the electrical power system is essential, particularly during external disruptive events, for the societal well-being because of the interdependencies. Even minor interruptions in the electricity supply may result in a considerable material as well as economical losses. While modern electric power systems are designed to withstand short duration power disruptions, it's the longer duration disturbance that is of primary concern. The concept of power system resilience has gained significant attention in recent years due to the increase in the amount of extreme weather-induced long duration outages. Such extreme weather events that challenge the power system resilience are called high-impact, low-probability (HILP) events for obvious reasons. As climate change becomes more prevalent, the frequency and the severity of such events will be more compelling [1].

The reliability concept is well established and is being widely used to define the system performance during planned and unplanned events. The reliability standards defined by NERC and IEEE, can be partially applied to quantify

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TABLE 1. Reliability vs Resilience.

Reliability	Resilience
Applicable to low impact, high probability events	Applicable to high impact, low probability events
Deals with the ability to provide power during the normal operating conditions (blue sky days) [2]	Deals with the ability to operate fully or under reduced form during abnormal operating conditions (black sky days) [2]
The events that deal with the reliability of a system are spread across the network area	The events that deal with resilience of a system are area and time specific (spatiotemporal).
Outages/interruptions last for minutes to hours	Outages/interruptions last for hours to days
Lower interruption costs	Higher interruption costs
Systems are usually designed to have a certain level of reliability based on the widely accepted standards	Currently, there are no standards for designing system that need to fulfill a certain level of resiliency

resilience. However these standards are not sufficient to get a comprehensive view of a network's resilience as there are inherent differences between the concept of reliability and resilience. Some of the distinctions between these two concepts are highlighted in Table 1.

In the past two decades, extreme weather events have caused major disruptions to power system infrastructure and operations that have led to widespread social and economic losses. The most recent Texas grid failure as a result of the winter storm Uri caused about 4.5 million people to lose power [3]. The northeastern region of the United States was hit by hurricane Irene in 2011 and hurricane Sandy in 2012 that resulted in around 6.69 million and 8.66 million people losing power respectively [4]. The southern parts of the United States experienced loss of power to about 2 million customers due to the landfall of category 4 hurricane Harvey in 2017 [5]. The tsunami which was a consequence of the great earthquake in the eastern part of Japan caused loss of power to roughly 8.5 million customers [6]. The California wildfire of 2018 also known as the ''Camp fire'' caused due to the negligence of aging transmission infrastructure damaged approximately 18,804 structures and around 84 individuals lost their lives [7]. This wildfire was a consequence of prolonged draught situation in the area and human error. Reference [8] presents all the billion-dollar disaster events that affected the United States between 1980 to 2021. Statistics shows that frequency of the weather-related events was about 6.7 events/year in the 2000s (2000-2009) which increased to about 18.7 events/year in the last three years (2019-2021). During the period from 1980 to 2021, severe storms caused the highest number of billion-dollar events ($\sim$ 160 *events*) while tropical cyclones brought about the most damages ($\sim$ \$1, 194.4 *billion*).

Although power system resilience is a widely studied concept, due the lack of general consensus on the standard power system resilience definitions, framework, and metrics, the applicability of the resilience enhancement techniques is not straight forward [9]. Therefore, there is a need to provide a review of the power system resilience concepts and how different researchers and research organizations are adopting these concepts to perform this field related studies. Several review papers have been published in recent years that address power system resilience [10], [11], [12]. A unified approach to study and define power system resilience is presented in [10]. The authors contributed towards developing a resilience evaluation and assessment framework used to identify and apply resilience improvement strategies. A review of grid resilience concepts, frameworks, and methodologies for resilience assessment is presented in [11]. In [12] a critical review of the current practices, challenges, and research gaps in the field of power system resilience is performed. The aim of the aforementioned paper was to develop comprehensive understanding and provide constructive recommendation towards universally accepted resilience definition, framework, and metric development.

Any power system enhancement-related planning decision requires a cost-benefit analysis (CBA). This is the process used to quantify the future benefits as a result of certain decisions minus the costs associated with those decisions [13]. While some research papers do consider the cost aspect associated with the resilience improvement techniques [14], the extent to which the concept of determining this cost and the benefits it provides has not been studied extensively. In an attempt to bridge this gap, this paper provides different techniques used to determine the customer and societal damage cost as a consequence of a resilience event. This cost can be integrated into the applicable resilience metrics for informed resilience-oriented decision making. The major contributions of this paper are:

- A comprehensive analysis of the concept of power system resilience is presented that includes different resilience definitions, frameworks, and metrics. The current status of resilience definition adoption through highlighting definitions used by some of the prominent research institutions is also included.
- Different resilience frameworks that can be used to assess power system resilience are discussed.
- A detailed study of the available power system resilience metrics is presented. The importance of considering customer damage cost for resilience assessment (metrics quantification) and the concepts that are currently being used to determine these values are studied.
- A two part case study (Case Study 1) is performed to demonstrate the use of industry-standard customer damage cost estimator. The first part deals with estimating customer outage costs using the state-wide reliability indices as input to the calculator. Circuit-level event-specific indices calculation is proposed to generate appropriate indices at each restoration iteration. These indices are then used (as an input to the calculator) in the second part of the case study to evaluate the customer damage cost.

- Models that add extra dimensions to the resilience metrics in the form of societal well-being losses and risk-based analysis are investigated. An approach to calculate the risk index for an extreme event as part of resilience assessment process is proposed. Case study (Case Study 2) demonstrating the use of the proposed approach is later discussed.
- A summary of power system resilience improvement strategies adopted by utility companies (as a response to a certain major event) is provided. The final case study (Case Study 3) that implements resilience improvement techniques is presented.

The remainder of this paper is structured as follows. Section II presents power system resilience definitions. Multiple resilience assessment frameworks proposed by various researchers and research organizations are discussed in Section III. Deliberation of different power system resilience metrics is presented in Section IV. Case studies for understanding customer damage cost estimation during an extreme event and risk index calculation are also included in this section. Section V outlines current guidelines and practices for improving resilience along with a case study that evaluates a few resilience improvement techniques. Section VI includes concluding remarks.

II. CONCEPT OF POWER SYSTEM RESILIENCE

In the United States' Presidential Policy Directive-21 (PPD-21) [15] the term resilience is defined from the perspective of critical infrastructure where a resilient critical infrastructure is able to adapt to and withstand the changing conditions and/or recover promptly from a disrupted state during any contingency event. This resilience definition can intentionally be applied to power systems since, apart from being a critical infrastructure itself, a power system enables functionalities for other critical infrastructures. The U.S. Department of Energy (DOE) proposed a model called the North American Energy Resilience Model (NAERM) [16] which incorporates long-term energy planning and real-time situational awareness capabilities to ensure reliable and resilient energy delivery. This framework adopts the resilience definition proposed in the PPD-21. The Sandia National Laboratory (SNL) also used the resilience definition proposed in PPD-21 to quantify and develop enhancement strategies for power system resilience [17].

The Pacific Northwest National Laboratory (PNNL) has adopted a similar definition where resilience is defined as the ability to prepare for and adapt to changing conditions, withstand and recover rapidly from disruptions for a number of disruptive events [18]. Likewise, the authors in [19] from NREL have quoted the definition proposed in PPD-21 in their work that involves improving distribution system resilience using Model Predictive Controlled (MPC) critical load restoration. It should be noted that the above-mentioned national laboratories (in addition to a few others) are members of the Grid Modernization Laboratory Consortium (GMLC) [20] which was established as a strategic partnership between the DOE and the national labs for collaborative work on grid modernization. The resilience definition followed by the labs, which are part of this consortium, is standard in all the studies performed under the Grid Modernization Initiative (GMI) [21] and can be stated as "*the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and rapidly recover from disruption through adaptable and holistic planning and technical solutions*" *[22]*.

A resilience definition applicable to the distribution system resilience was proposed by the Electric Power Research Institute (EPRI) that constitute three components: prevention, recovery, and survivability [23]. The United Kingdom Energy Research Center (UKERC) [24] regards resilience as the capability of a system to tolerate and continue to deliver affordable services during an extreme event. It further emphasizes the recoverability aspect of resilience and highlights the importance of alternative means to provide post-disastrous event services. In a report created for the National Association of Regulatory Utilities Commissioners (NARUC) [25], the importance of the robustness and recoverability characteristics is highlighted for a resilient utility infrastructure operation that help avoid or minimize service interruptions. The International Council of Large Electric Systems (CIGRE) [26] defines power system resilience as the ability to limit the extent, severity, and duration of system degradation after an extreme event.

A generalized definition for resilience which is the ability to absorb, adapt to, and/or recover rapidly from a degraded state was provided by the National Infrastructure Advisory Council (NIAC) [27]. When it comes to critical infrastructures this definition can be extended to be the ability to maintain critical functions and operations, prepare, respond, and manage resources during a crisis event, and to return to normal operating conditions as quickly and efficiently as possible. The North American Reliability Corporation (NERC) considers resilience as the time-dependent component of reliability as defined in the Adequate Level of Reliability (ALR). The ALR performance is determined by the stable operation of the Bulk Electric System (BES) during normal and predefined disturbances [28]. The objective of the ALR assesses the BES over four time horizons: 1) steady-state; 2) transient state; 3) operations state; 4) recovery and system restoration state. These four states corresponds to the four resilient power system characteristics defined by the NIAC in [27]. Hence, the ALR definition filed by NERC is consistent with the NIAC resilience framework and the FERC definition [29] for resilience that addresses the robustness, resourcefulness, rapid recovery, and adaptability of the bulk power system.

In [30], Haimes introduced resilience as the flexibility of the grid to restore its operation, with little or no human intervention, to a normal and reliable operating state. This definition was adopted in [31] to quantify the resilience improvement measures. Another definition for resilience was proposed by the North American Transmission Forum (NATF) which is the ability of the system and its components to minimize damage and improve recovery from a non-routine disruptions in a reasonable timeframe [32]. From the power system's standpoint, the authors of [33] have defined resilience as the system's ability to resist HILP events and rapidly recover from such events and adapt its operation and structure to mitigate impact of such events in the future.

Since there is no universally accepted definition for power system resilience, its applicability largely depends on the type of problem being tackled. Nevertheless, based on the review of the literature that solely focuses on defining power system resilience, resilience features can be standardized to form the building blocks of power system resilience definition. These building blocks can be stated as: the ability to anticipate and sustain a disruptive event or adapt to and recover efficiently after a disruptive event (anticipate and sustain or adapt and recover). An important point to note is by standardizing power system resilience definition (characteristics), the possibility of standardizing power system resilience metrics for quantifying resilience improvement techniques and driving resilience oriented investments, increases drastically. Nonetheless, developing a "one size fits all" resilience metric is an arduous task due to the inherent characteristics of resilience-oriented studies that largely depends on the predefined set of resilience goals.

III. POWER SYSTEM RESILIENCE ANALYSIS FRAMEWORK

Due to the increased importance of the concept of resilience as part of grid modernization operations and planning efforts, it is vital to develop a robust resilience framework and quantification approaches. A resilience framework would help provide a set of instructions to analyze the system's resilience. The results of the analysis will form the basis for the resilience-oriented system operations and planning decisions. Metrics to quantify resilience improvement are required in order to weigh certain techniques against others for supporting investment strategies. In this section, different power system resilience assessment framework are discussed.

The authors of the report presented in [34] developed a method for assessing baseline resilience and evaluating resilience improvement measures called the Resilience Analysis Process (RAP). The RAP is a risk-based decision making process for stakeholders and decision-makers that contains six steps (seven steps if the resilience improvement evaluation is included) for assessing system performance. The RAP processes begins by defining high-level resilience goals which sets the foundation for the following steps. Defining the system and resilience metrics that involves setting the scope of the analysis is performed in the second step. Information from the stakeholders regarding the type of consequences to be considered in the analysis is considered in this step. Threat characterization is performed in step three. The extent of damage to the system due to a specific threat (threat determined in step three) is estimated in step four. Information related to the disrupted components is then used as an input to the system models for system's state evaluation (in step five). In step six, the results obtained from the system models are quantified and mapped to the resilience metrics defined in step two. The evaluation of resilience improvement techniques is performed in step seven, if the goals defined in step one involves proposing resilience enhancement strategies. Figure 1 represents the steps involved in the RAP.

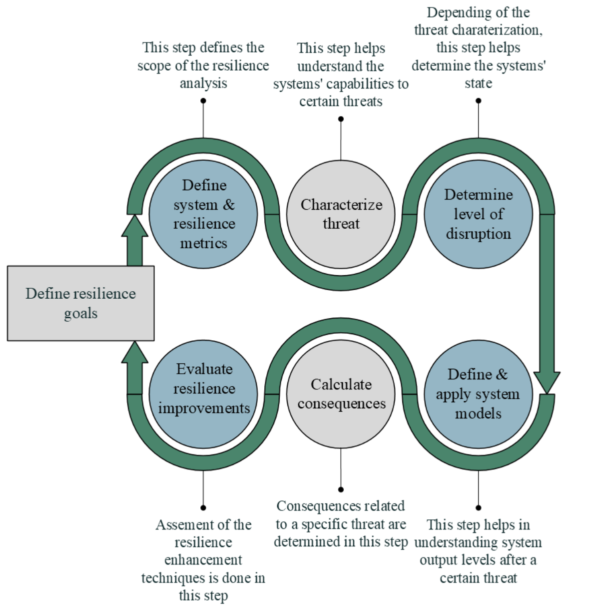


FIGURE 1. The resilience analysis process.

Organizations seeking to improve the resilience of the system can use the RAP to streamline their resilience-oriented studies. First, the baseline level of the system's resilience to a specific threat can be estimated following the aforementioned six steps of the RAP. The resilience goal defined by an organization can be to improve the recovery of the system after an extreme event. Metrics that can quantify such improvement would then be defined to estimate the effects of such events on the system at its current state (the measure of the consequences can be to determine the duration for which customers were out of power). Once the baseline resilience is quantified, improvement techniques can be applied and evaluated to ascertain the advancement in the resilience metric (step seven). To summarize, the metrics defined in the RAP can be used for two purposes: first, to provide the system's baseline resilience performance index, and second, to evaluate the improvement in the system's resilience after an improvement technique is applied by providing a means to compare the improved performance vs the baseline performance.

A framework for power system resilience evaluation was proposed in [35] where the system resilience evaluation was grouped into two categories: 1) Qualitative framework 2) Quantitative framework. Qualitative framework can be used to evaluate the power system resilience and other interdependent systems where capabilities such as emergency preparedness, mitigation strategies, rapid response and recovery, etc. are studied. Resilience evaluation methods include surveys and questionnaires matrix development; a two-dimensional framework used to quantify improvement in energy-related attributes due to measures taken in an interdependent sector [36], etc. Quantitative framework depends on the quantification of the system's performance attributes. Resilience metrics developed using the quantitative framework are event-specific and provide a basis for decision making [34]. The approaches used for resilience evaluation include simulations-based, analytical-based, and statistical-based approaches.

Based on the above literature review, the main step in any resilience-oriented studies is to define a proper set of resilience goals. As mentioned earlier, it is unrealistic to consider all resilience related issues to be addressed in these studies. Therefore, it is crucial to have clearly defined resilience goals followed by the steps and a robust set of metrics not only to achieve these goals but also to justify the applicable resilience enhancement strategies, as the implementation of such strategies involves a considerable amount of initial investments. Moreover, having disaster preparedness guidelines also helps the system operators to be ready for a certain set of consequences by appropriately planning their system's event response.

IV. POWER SYSTEM RESILIENCE METRICS

Reliability and resilience oriented enhancement strategies are largely governed by the extent of the benefits its implementation render to the society. To assess the benefits of reliability improvement techniques, well-defined reliability metrics has been defined for power distribution systems, eg. System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI), Momentary Average Interruption Frequency Index (MAIFI) [37] as well as for the transmission systems, eg. Loss Of Load Probability (LOLP) and Loss Of Load Expectation (LOLE) [38] which forms the basis for reliability improvements. On the other hand, to assess the benefits of resilience improvement techniques, currently there are no standard well-defined set of metrics that can guide resilience investments. Although, in many cases, a more reliable system can be considered as a more resilient system and vice versa, that is not true in every situation [39]. Moreover, application of reliability metrics to justify resilience improvement techniques might fall short of evaluating certain key factors associated with resilience (event impact, outage duration, etc.). Hence, knowing what factors are important for developing resilience metrics is crucial in the metric development process.

In [34] a set of recommendations for developing resilience metrics are presented. These include:

1) Metrics should be defined considering a specific type of the HILP event.
2) Metrics should appropriately quantify the performance of the system under study.

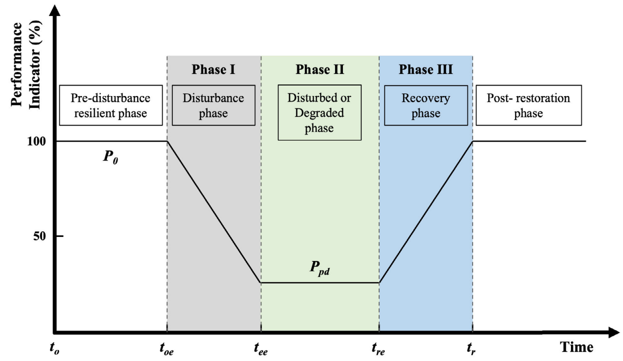


FIGURE 2. Multi-phase resilience trapezoid.

3) Metrics should capture the threat level associated with each extreme event.
4) Metrics used to quantify resilience must account for the uncertainties associated with the HILP
5) Metrics should effectively capture the resilience attributes like the ability to anticipate, prepare, withstand, adapt, and recover

Additional guidelines/recommendations towards developing resilience metrics were proposed in [9] where the authors emphasized that the metrics used should be able to enumerate the system's resilience for a particular category of consequences. From [40], resilience metrics must also address the geographical and time-varying aspect that an extreme event has on the system's resilience. Several other desirable properties of the resilience metrics were presented in [41] which includes ease of application, comprehension, and interpretation. Although, the specified recommendations will help develop resilience metrics, it is not a requirement for resilience metrics to include all the above points as the metrics would depend on the resilience goals. Thus for different applications/improvement strategies, different metrics can be proposed or developed.

The authors in [42] proposed an extended version of the concept of resilience triangle called a multi-phase resilience trapezoid which was used to develop the resilience metrics. Figure 2 shows the proposed multi-phase resilience trapezoid. The different phases of the multi-phase resilience trapezoid that characterize power system states during an extreme event are described below:

1) Phase I indicates the disturbance phase ($t \in [t_{oe}, t_{ee}]$) with two key elements of the resilience metrics linked to this phase. The first element describes how quickly the system's resilience decreases (from $[P_0$ to $P_{pd}]$) during the extreme event whereas the second element gives the magnitude of the drop in resilience $[P_0 - P_{pd}]$.
2) Phase II indicates the disturbed or degraded state (post extreme event) of the power system. During this state the time, for which the system remains in the degraded state, is considered as the resilience measure ($t \in [t_{ee}, t_{re}]$).

3) Phase III is associated with the recovery phase post extreme event ($t \in [t_{re}, t_r]$). The measure of resilience depends on how quickly the system recovers from the degraded state to the pre-fault or acceptable level (state).

On the basis of the multi-phase resilience trapezoid concept, the authors developed a $\Phi\Lambda E\Pi$ (*FLEP*) metric. Φ and Λ metric measures how fast and how low the resilience drops, E represents how long the post-event degradation lasts and the Π metric quantifies the promptness of the network recovery. In addition to the four metrics, an area metric was also proposed that essentially considers the integral of the trapezoid for the event duration. Based on the applicability, the standard multi-phase resilience trapezoid concept cane be extended to consider the operational and infrastructure aspects of system resilience.

The mathematical expression associated with each of the aforementioned metrics is presented below. The Φ metrics is calculated using Equation (1) where the measuring unit could be the MW/hours lost or Number of lines tripped/hour.

$$\Phi = \frac{P_{pd} - P_0}{t_{ee} - t_{oe}} \tag{1}$$

The mathematical expression for the Λ metrics, which measures the total MW or Number of lines tripped during an event, is given by Equation (2)

$$\Lambda = P_0 - P_{pd} \tag{2}$$

The metric E that measures the hours for which the system remains in the degraded state can be expressed by Equation (3)

$$E = t_{re} - t_{ee} \tag{3}$$

The MW (load) or the number of lines restored per hour is quantified by the Π metric whose mathematical expression is given by Equation (4)

$$f_b(x) = \frac{P_0 - P_{pd}}{t_r - t_{re}} \tag{4}$$

Equation (5) provides the *Area* metrics' mathematical expression, which is used to determine the performance of the system during an extreme event

$$Area = \int_{t_{oe}}^{t_r} P(t) \tag{5}$$

A similar approach was used in [43] where a standard resilience trapezoid was considered and the system resilience was quantified as the reciprocal of the system's loss of performance. The loss of performance was determined using the largest deviation from the normal level of performance and the integration of the relative deviation during the degradation phase. The metrics also considers the rapid recovery aspect by considering performance degradation duration. The authors in [33], developed a Severity Risk Index (SRI) as a metric to determine whether the proposed resilience enhancement technique should be implemented. The SRI depends on the

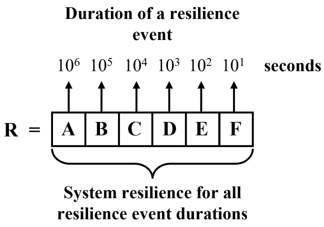


FIGURE 3. Code-based resilience metric.

TABLE 2. Scaling of code-based resilience metrics.

m'	1.00-3.71	3.72-6.42	6.43-9.13	9.14-11.85	11.86-14.56	14.57-17.27	17.28-19.98	19.99-22.70	22.71-25.41
m	1	2	3	4	5	6	7	8	9
	Low resilience			Moderate resilience				High resilience	

probability of an extreme event and the consequences associated with a specific extreme event.

A majority of extreme events has a spatiotemporal aspect associated with it. To address this aspect, the authors of [44] have proposed a time-series analysis approach to assess current and future system resilience. The metrics used for the analysis include time to repair (TTR) which is a function of the severity of the event, and reliability-based metrics like the loss of load frequency (LOLF), expected energy not served (EENS), and loss of load expectation (LOLE). To analyze the improvement in the power system resilience due to the use of microgrids, the authors in [45] proposed four indices that are combined to form a power grid resilience metric 'Θ'. The indices include an index K for expected number of line outages, an index for loss of load probability (LOLP) to measure load loss probability, an index for energy demand not served (EDNS) to enumerate expected demand that was not satisfied, and an index G for measuring the level of difficulty in grid recovery.

A code-based resilience metric was proposed in [41] where the measure of the network's resilience was governed by an empirical equation which is designed to capture the impact of an unfavorable event. The authors proposed six variables A, B, ..., F that correspond to the event's time duration in 10^i secs (where $i = 0, 1, 2 \ldots, 6$) of an extreme event shown in Figure 3 and has a resilience value between 1 to 9 associated with it.

$$m' = c(\alpha + e^f)(1 + f) \tag{6}$$

$$f = \frac{\text{Load unaffected by an extreme event (kW)}}{\text{Total load (kW)}} \tag{7}$$

The unscaled resilience value is calculated using Equation (6), where c is the binary indicator for extreme event occurrence, α is the event duration time, and f is the fraction of unaffected loads given by Equation (7). The calculated unscaled resilience value is appropriately scaled using Table 2 to get a resilience value between 1 to 9.

The authors of [46] proposed a resilience vector that included five resilience indices which were used to quantify the resilience of the network. The first index was associated with the load shedding cost saved ($), whereas the second index considered the cost saved during the restoration process ($\$/hr$). The next two indicators were graph theory-based indices which were the weighted algebraic connectivity and weighted betweenness centrality. The last index was a function of the first two indices and was termed as the adaptability index. In [47], the authors developed a multi-temporal resilience metrics that quantifies the anticipate, withstand, and recovery aspects of power system resilience. In that paper, each aspect of power system resilience has its own set of indices/impacting factors that are used to develop the resilience score. The anticipate metric score relies on the weighted sum of the three domains namely, threat & vulnerability, power delivery & loads, and restoration & recovery. For the withstand aspect, the resilience score R_w depends on the critical loads not served, total available generation, critical load demand, topological robustness, and threat impact (here topological robustness was determined using graph theory concepts). Lastly, the score of recovery metrics depends on the critical load restored, path redundancy, generation redundancy, switching operations, and switching time.

In [31], the authors used three metrics to define the system's operational resilience. The first metric was system flexibility index that measured the demand served after each recovery iteration given by Equation (8).

$$R^{\lambda}_{i,n,d,t} = \frac{\sum\limits_{i \in I} \sum\limits_{n \in N} P^{t|\epsilon}_{d_n,i}}{P^T_d} \tag{8}$$

The second metric was the outage cost recovery which is the amount of customer costs regained after each corrective action - Equation (9)

$$R^{\mu}_{i,n,d,t} = \sum_{i \in I} \sum_{n \in N} C_{d_n} \left(P^{t|\epsilon}_{d_n,i+1} - P^{t|\epsilon}_{d_n,i}\right) \tag{9}$$

The percentage of demand recovered in each recovery step compared to the total demand lost was the last metric named as the outage recovery capacity metric given by Equation (10).

$$R^{\vartheta}_{i,n,d,t} = \sum_{i \in I} \sum_{n \in N} \frac{(P^{t|\epsilon}_{d_n,i} - P^{t_d|\epsilon}_{d_n})}{(P^T_d - P^{t_d|\epsilon}_{d_n})} \times 100 \tag{10}$$

Here, the $R^{\lambda}_{i,n,d,t}$, $R^{\mu}_{i,n,d,t}$, and $R^{\vartheta}_{i,n,d,t}$ are the flexibility, recovery capacity, and outage cost recovery metrics of load demand d ($\forall d \in D$: System demands) at load node n ($\forall n \in N$: System buses) after the adoption of the i^{th} ($\forall i \in I$: Iteration count for recovery process) network reconfiguration plan at time t ($\forall t \in T$: Time step). Also, C_{d_n} is the value of lost load d at node n, $P^{t|\epsilon}_{d_n,i}$ is the active power demand at bus n after the i^{th} recovery action for ϵ extreme event, $P^{t_d|\epsilon}_{d_n}$ is the active power demand at node n when the extreme event ϵ ends, and P^T_d is the total active power demand at node n during normal conditions.

Resilience of the distribution system is measured in terms the critical load restoration capability in [48]. It is governed by the integral of the performance function $F(t)$ given in Equation (11) which is proportional to total power supplied to the critical loads weighted by their priority.

$$R = \int_{t_r}^{t_r+T^0} F(t)dt \tag{11}$$

The resilience metric R is defined for the restoration period $[t_r, t_r + T^0]$ where T^0 is the duration of the outage and t_r is the time at which the first restoration action is taken.

The metrics mentioned in the previously studied literature can be viewed with reference to the multi-phase resilience trapezoid concept presented in [42]. Table 3 compares the aforementioned research work that explicitly or ambiguously uses the concept of the multi-phase trapezoid for quantifying resilience. The metrics used in [42], that evaluate resilience during each phase of the resilience trapezoid, are provided in Equation (1), (2), (3), (4). A similar approach was observed in [43], where the authors proposed a loss function for each resilience phase. The equations presented in Table 3 show the congruence between the metrics proposed in [42] and [43] with a difference being the way in which the metrics value was ascertained. For example, the calculated Phase I "Φ" metric is a negative value indicating the rate at which the resilience decreases, whereas the calculated Phase I "$loss_I$" is the loss observed which is a positive value. Nonetheless, the ultimate indicator is the answer to the question "how fast or how deep the resilience drops?" In [44] the authors used reliability based metrics (loss of load expected, $LOLE$, loss of load frequency, $LOLF$, and expected energy not served, $EENS$) to quantify the state of the system after a resilience event (i.e. during Phase I). Similarly, the authors of [45] included a fragility function f combined with the reliability indices such as loss of load probability, $LOLP$, and expected demand not served, $EDNS$. During Phase I, it makes sense to use a probabilistic approach to determine the impact of extreme weather on the power systems components. Another approach to quantify the drop or expected drop in resilience during Phase I was proposed in [46]. In this work, the authors used the concept of graph theory to estimate the robustness of the system which was combined with the load lost value (value of load lost, $VOLL$, total demand, D, and load shed, LS) due to load shedding.

Authors of [42] and [43] proposed a way to quantify the resilience during the Phase II of the multi-phase trapezoid, where [42] used the duration of Phase II as a metric while [43] calculated the area under the curve bounded by the duration of Phase II to quantify resilience. The aforementioned works consider the recovery phase (Phase III) of power system resilience as one of the most important phase of the resilience trapezoid. References [42] and [43] used a recovery rate function to determine how quickly the system returns to the normal or acceptable operating limits. In [44]

TABLE 3. Multi-phase trapezoid application comparison.

Reference	Phase I	Phase II	Phase III
[42]	$\Phi = \frac{P_{pd}-P_0}{t_{ee}-t_{oe}}, \Lambda = P_0 - P_{pd}$	$E = t_{re} - t_{ee}$	$\Pi = \frac{P_0-P_{pd}}{t_r-t_{re}}$
[43]	$loss_I = \frac{P_0-P_{pd}}{P_{pd}}$	$loss_{II} = \int_{toe}^{tr}[\frac{P_0-P(t)}{P(t)}]dt$	$loss_{III} = \frac{1}{t_r-toe}\int_{toe}^{tr}[\frac{P_0-P(t)}{P(t)}]dt$
[44]	$\text{LOLE} = \frac{1}{N}\sum_{i=1}^{N}\text{LLD}_i$, $\text{LOLF} = \frac{1}{N}\sum_{i=1}^{N}\text{LLO}_i$, $\text{EENS} = \frac{1}{N}\sum_{i=1}^{N}(\text{LLO}\times\text{LLD})_i$	-	$\text{TTR} = f_w(w(s)) \times \text{TTR}_{norm}$
[45]	$f = P_d(k\|V), K = \int_0^\infty k \cdot f(k)dk$ $\text{LOLP} = \sum_{e_i \in S_e} P_{e_i}$, $\text{EDNS} = \sum_{e_i \in S_e} P_{e_i} \cdot C_{e_i}$	-	$G = \sum_{i=1}^{5} w_i \cdot \eta_i, where \sum_{i=1}^{5} w_i = 1$
[46]	$\Delta C_{LS}^R = \text{VOLL} \cdot (D - LS)$ Weighted algebraic connectivity, Weighted betweenness centrality, Adaptability index	-	$\Delta C_T^R = w^T \cdot (\text{NT} \cdot 1 - T)$
[47]	-	-	Equation(8), Equation(9), Equation (10)

the time to repair (*TTR*) is used to quantify the resilience during this phase. This *TTR* was expressed as a function of wind speed ($f_w(w(s))$) and normal time required for a power system component to repair (TTR_{norm}). A grid recovery index was proposed in [45] which essentially provides information regarding the severity associated with the recovery efforts. Here, the authors assigned weights (w_i) and values (η_i) to each (i^{th}) factor affecting the recovery of the system. The metric proposed to quantify Phase III of the resilience trapezoid in [46] deals with evaluating the restoration cost savings (ΔC_T^R). The higher the restoration cost saving, the quicker is the system recovery (shorter Phase III). Different researchers use different metrics to quantify resilience based on their research question. Nonetheless, these metrics can be categorized based on the respective resilience phases to which it is being applied to. For example: the Phase I metric might include reliability based metric, or a probability based metric whereas the Phase III metric might consist of a cost-based or a time-based metric. Considering an approach that uses resilience phases to standardize a set of metrics for each of these phases can help regulate how resilience is quantified.

Additional work on developing resilience metrics was conducted by the Grid Modernization Laboratory Consortium (GMLC) Metrics team [49] who proposed a resilience metric comprising of two main categories. The first category is the multi-criteria decision analysis (MCDA) which provides a baseline understanding of the network's resilience in the form of a resilience index (RI) and facilitates improvement options consideration. The second category is a performance-based metric that quantitatively describes the effect of a certain extreme event on the network. Key indicators for the performance-based metric include cumulative customer-hours of outage, time to recovery, loss of utility revenue, etc. In [39], the authors present two metrics where the first metric focuses on the recovery aspect during the first 12 hours of a storm, while the second metric quantified the robustness and ability to withstand the event.

Although performance and attribute-based quantification of power system resilience is important, it is not sufficient to capture holistic significance of resilience enhancement strategies. One of the key factors according to the resilience enhancement circle [40] is the benefit/cost analysis for selecting the appropriate enhancement strategy. Typically, there are two approaches for appraising resilience, namely the bottom-up approach and the economy-wide approach [50]. The bottom-up approach uses customer preferences, responses, or behavior in determining the value of resilience whereas the economy-wide approach estimates resilience value by considering the effects of a power outage on regional economies using appropriate indicators. The chart presented in Figure 4 shows the subcategories and different models used in each of these subcategories for valuing resilience.

One of the concepts (which is based on the bottom-up approach) used to perform economical evaluations of power systems is the concept of Value of Lost Load (VoLL). Monetizing the value that represents the importance of electricity continuity helps in informed decisions-making. VoLL is the

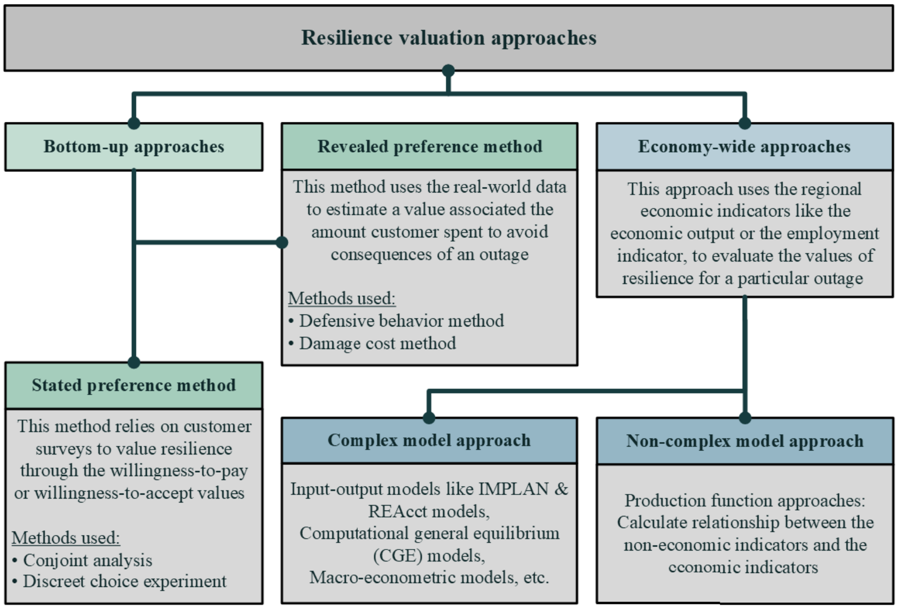


FIGURE 4. Resilience valuation approaches.

''perceived'' value that a consumer places on the convenience of having uninterrupted supply of electricity [51]. The VoLL is generally estimated using the stated preference approach where customer response to certain outage situations are recorded via. customer surveys and converted into a monetary metric. However, using the VoLL calculated for a short-term outage cannot be used to justify the resilience-oriented investments as it does not capture the compounding effects of a long-term outage on the customer damage cost estimation [52]. Moreover, in a majority of studies that incorporate VoLL for resilience decision assessment, VoLL has been assumed to be a static or a constant value [53] which is not an accurate representation of customer outage cost as it over-simplifies the damage cost.

In [54] a new way of calculating the customer damage cost is presented which considers the effect of a long-term power interruption called the customer damage function. The customer damage function provides the damage cost as a function of outage duration. The factors/characteristics that contribute toward estimating the customer damage cost are the outage characteristics, customer characteristics, and some other factors [55]. Outage characteristics include the elements that account for the outage duration, frequency, time of day, day of week, season of the year, etc. The customers characteristics that influence the customer damage cost are the type of customer (commercial, residential, etc,), number of customers, in each of these types, affected and the criticality index of the affected customers.

The U.S. Department of Energy (DOE) along with the Lawrence Berkeley National Laboratory (LBNL) and Nexant [56] have developed a tool using the customer damage function called the interruption cost estimate (ICE) calculator. ICE is a two-part regression model that estimates the customer interruption cost function. The inputs to the ICE calculator are the reliability indices like SAIDI, SAIFI, and CAIDI, and the outaged customer mix. To demonstrate the use of the ICE calculator for determining the customer outage cost, a case study is presented below.

A. CASE STUDY 1: CUSTOMER DAMAGE COST ESTIMATION

The case study is performed to determine the customer damage cost associated with an extreme weather event using the ICE calculator. Two scenarios are considered for the case study. The differentiating factor between the two scenarios is the way the indices for the ICE calculator are calculated. In the first scenario, the state-wide indices were used as an input to the ICE calculator for customer damage cost estimation. In the second scenario, a circuit/feeder level analysis was performed for estimating these indices. Therefore, in addition to estimating the customer damage cost, this case study would help in determining the best approach to model the indices which would serve as an input to the customer damage cost estimator. An important point to note is that the second case-study provides customer damage cost estimation for a single extreme weather event. However, a similar approach can be used for multiple extreme weather events experienced at the same feeders over a certain time-frame to get an average value for these indices.

For the analysis, three actual feeder networks that are vulnerable to the extreme weather events located on the east coast of the United States were used. To respect the non-disclosure agreement, the exact names and locations of those feeder networks are not published in this paper. The information used is typically the number of customers and customer types located at those feeder networks. Table 4 shows the

TABLE 4. Feeder level customer information.

Customer type	Feeder #1	Feeder #2	Feeder #3
Residential	1617	1546	242
Small C&I	247	390	258
Medium and Large C&I	13	15	53
Total customers	1877	1951	553

TABLE 5. Customer outage information.

Customer type	Feeder #1	Feeder #2	Feeder #3
Residential	594	1450	241
Small C&I	32	361	220
Medium and Large C&I	0	11	53
Total customers	626	1822	514

TABLE 6. Customer outage cost (using state-wide indices).

Feeder No.	Residential (in $)	Small C&I (in $)	Medium & Large C&I (in $)	All Customers (in $)
Feeder #1	11,316.30	121,295.30	0	132,611.60
Feeder #2	27,623.80	1,368,363.0	374,831.30	1,770,818.20
Feeder #3	4,591.30	977,943.60	1,806,005.40	2,788,540.30

number and types of customers located on these feeders. An extreme weather event is simulated that caused multiple outages at those feeder networks causing customers to lose power. The number of customers affected in each class are provided in Table 5.

1) CUSTOMER DAMAGE COST-ESTIMATION USING THE STATE-WIDE RELIABILITY INDICES

Scenario 1 considers the state-wide reliability indices obtained from [57] for the state where the feeders are located. The SAIDI, SAIFI, and CAIDI values, which are 437.40 minutes/year, 1.718 times/year and 254.6 minutes/interruption respectively (including major event days), for the year of 2020 were selected for generating the outage costs. Table 6 shows the outage costs associated with each type of customer obtained from the ICE calculator.

It can be observed, from Table 5, that Feeder #2 and Feeder #3 are the worst hit feeders when it comes to the number of customers (93% of the total customer) without power. However, from the perspective of the customer outage cost, Feeder #3 is the worst performing feeder with an outage cost of approximately $2.8 million followed by Feeder #2 with $1.8 million. The main reason for the high outage cost for Feeder #3 is the customer mix. On this feeder, the total percentage of small, medium, and large C&I customers is equal to 56.2% which pushes the outage cost to a higher value compared to that for Feeder #2 which has about 20.8% of small, medium, and large C&I customer. Therefore, in addition to knowing the customer outage cost for applying resilience improvement techniques at the feeder level, it is equally important to understand the feeder's customer mix as the outage cost is highly dependent on it.

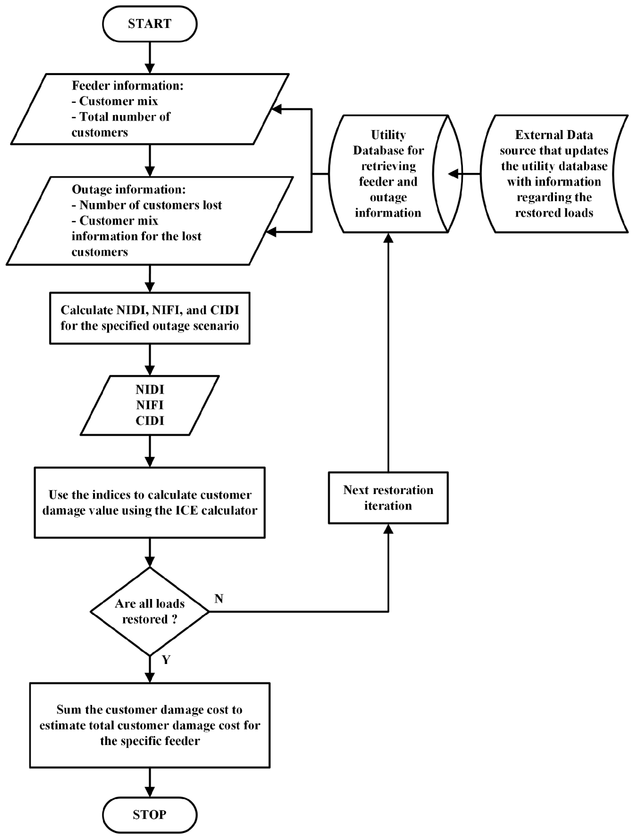


FIGURE 5. Circuit-level damage cost estimation indices flowchart.

2) CUSTOMER DAMAGE COST-ESTIMATION USING THE CIRCUIT-LEVEL INDICES

Using the state-wide reliability metrics might not be the most accurate indicators to use for calculating the outage cost at the feeder level. These values can generate results that in some cases undervalue (or sometimes overvalue) the customer damage cost for a specific event. Hence, in this scenario, the customer outage cost is generated by calculating the input indices at each outage restoration step. The complete process of determining the customer damage cost using the circuit-level indices is presented in Figure (5). The feeder information that includes the total number of customers and the customer mix on the respective feeders is retrieved from the network database. Outage information was obtained after simulating an outage scenario on the respective feeder networks. This information was used to calculate the appropriate indices using Equation (12), (13), (14). These indices were then used as an input to the ICE calculator to approximate customer damage value. The customer damage values are estimated for every restoration iteration and the final damage cost is determined by summing each of these damage costs for the respective feeder networks.

TABLE 7. Customer outage cost estimation results (using feeder-level indices).

Feeder #1 (experienced 5 outages)									
No. of customers affected	Outage duration	Customer-hours	Residential customers lost	Small C&I customers lost	Medium & Large C&I customers lost	Network interruption duration index (in mins)	Network interruption frequency index	Customer interruption duration index (in mins)	Total cost (in $)
626	4	2504	594	32	0	80.04	0.33	240	26,558.40
420	3	1260	399	21	0	40.28	0.22	180	8,607.70
300	5	1500	290	10	0	47.95	0.16	300	5,382.90
125	2.5	312.5	116	9	0	9.99	0.07	150	909.40
70	1.5	105	65	5	0	3.36	0.04	90	199.90
Feeder #2 (experienced 6 outages)									
No. of customers affected	Duration of outage	Customer-hours	No. of Residential customers lost	No. of Small C&I customers lost	No. of Medium & Large C&I customer lost	Network interruption duration index (in minutes)	Network interruption frequency index	Customer interruption duration index (in minutes)	Total cost (in $)
1822	7	12754	1450	361	11	392.23	0.93	420	1,972,665.40
1200	4.5	5400	900	294	6	166.07	0.62	270	559,001.00
845	3	2535	661	180	4	77.96	0.43	180	156,552.70
570	5	2850	473	95	2	87.65	0.29	300	99,100.50
320	3.5	1120	285	35	0	34.44	0.16	210	11,827.80
150	2.5	375	148	0	2	11.53	0.08	150	1,875.10
Feeder #3 (experienced 3 outages)									
No. of customers affected	Duration of outage	Customer-hours	No. of Residential customers lost	No. of Small C&I customers lost	No. of Medium & Large C&I customer lost	Network interruption duration index (in minutes)	Network interruption frequency index	Customer interruption duration index (in minutes)	Total cost (in $)
514	8	4112	241	220	53	446.15	0.93	480	2,975,676.90
230	3	145	65	20	6	74.86	0.42	180	156,187.20
110	2.5	60	38	12	4	29.84	0.20	150	38,352.70

Table 7 shows the outage cost calculated for the duration of power loss experienced due to the extreme event. Here the average values for the reliability indices are not being considered (since damage cost due to only one extreme event is being calculated); rather these values are estimated for each restoration iteration. Therefore, the terminologies used for these indices are different although their applicability remains the same. Network Interruption Duration Index (NIDI), Network Interruption Frequency Index (NIFI), and the Customer Interruption Duration Index (CIDI) are the indices used as an input to the ICE calculator whose formulation is given by Equation (12),(13),(14), respectively.

$$NIDI = \frac{(C_l - C_r)_t \times h_{l,t} \times 60}{C_m} \tag{12}$$

$$NIFI = \frac{(C_l - C_r)_t}{C_m} \tag{13}$$

$$CIDI = \frac{NIDI_t}{NIFI_t} \tag{14}$$

Here, $C_{l,t}$ are the total number of customers lost during the event at t^{th} time interval, $C_{r,t}$ are the total number of customers restored at t^{th} time interval, $h_{l,t}$ is the number of hours the customers were out of power (time until the next restoration cycle), and C_m is the total number of customers on the specific feeder network.

It was assumed that Feeder #1, Feeder #2, and Feeder #3 experienced 5 outages, 6 outages, and 3 outages respectively. The total restoration times for the respective feeders were 16 hrs (Feeder #1), 25.5 hrs (Feeder #2), and 13.5 hrs (Feeder #3). The load restoration is presented in Table 7. Comparing the total outage cost obtained after performing the customer damage cost calculation using the feeder-level (Scenario 2) indices with that using the state-wide indices (Scenario 1), it can be seen that for Feeder #1, the total estimated outage cost is lower in Scenario 2 than that with Scenario 1 ($ 132,611.60 in Scenario 1 vs $41,658.30 in Scenario 2). This has two possible reasons, one of which is the outage duration. The second reason is the number of customers who are without power. In Scenario 1, since the indices considered all events across the complete state, the values of the indices gets normalized and are not really area-specific. But most of the resilience events are area-specific events and hence these state-wide values might not represent the real-world event specific outage costs. Nonetheless, as far as calculation of the overall outage cost (across multiple events and larger event windows) is concerned, the state-wide indices will yield better results.

On the contrary, the total outage cost estimated for Feeder #2 and #3 in Scenario 2 are higher than that estimated in Scenario 1. The reason is that, in Scenario 2 the indices are calculated dynamically as the loads are being restored, whereas in Scenario 1, these values are static values based on the historical event data. The total customer outage costs for Feeder #2 and #3 are around $2.8 million and $3.2 million, respectively. Again, the importance of considering the customer mix in addition to the number of customers lost is highlighted by the total customer outage cost values. Thus, these values obtained can be integrated with power system resilience assessment framework and can be used as metrics to drive resilience related decisions.

Disruptions in the power sector can inadvertently affect a multitude of dependent sectors like transportation, communication, gas, etc. The consequences of such disruptions cause widespread well-being losses. Computation of such losses in resiliency studies add supplementary dimensions to the resilience metrics that provide multi-dimensional functionalities while assessing resilience. A multi-agent-based stochastic dynamical model was proposed in [58] which captures the change in the different dimensions of the community resilience during a disastrous event. The dimensions or general functionalities considered by the authors are:

- Well-being functionality: This functionality depends on community's mental and physical health during a disastrous event.
- Community capital functionality: The metric that governs this functionality is the level of cooperation observed within the community during a disastrous event.
- Power system functionality: The effect of available power during the disastrous event either via. the utility or the customer owned distributed energy resources on the community resilience is captured by this functionality.
- Community functionality: This functionality essentially considers the average of all previously mentioned functionalities viz. well-being, community capital, and power system functionality.

Risk-based community resilience assessment presented in [59] adds another dimension to the resilience metrics. The authors developed a formula, shown in Equation (15), for estimating the risk associated with a certain hazard.

$$Risk = \frac{Vulnerability \times Hazard}{Capacity\ to\ cope} \tag{15}$$

Thus, for a given set of hazards, knowing the vulnerability and the network's ability to cope, the associated risk index can be calculated. Use of risk-based circuit level assessment is proposed in the Case Study 2. The level of risk associated with each of the feeder networks, under study, was quantified. Integrating this measure into the resilience metrics can provide an additional incentive for resilience investments.

B. CASE STUDY 2: FEEDER-LEVEL RISK INDEX CALCULATION

The methodology to determine the Risk Index (RI) stated in Equation (15) is demonstrated in this case study and the results obtained highlights its usability as one of the factors to be considered during resilience assessment. RI comprises of three entities: Hazard, Vulnerability, and the Capacity to Cope [59]. Equation (16) provides a premise for RI calculation (for f^{th} feeder) which consists of Hazard, Hd, Vulnerability Factor, VyF, and Capacity to Cope, CtC.

$$RI_j = \frac{Vy_f \times Hd_f}{CtC_j} \tag{16}$$

A hazard can be considered to be the threat that a community faces which is categorized into a man-made hazard (terrorist/cyber attack, etc.) and natural hazard (hurricane, floods, etc.). Although, it is easy to comprehend what threats a community might face, it is often challenging to quantify them. These challenges are further exacerbated by the spatio-temporal properties of the resilience events. Hence, in this work, a hazard is represented as the probability of a certain event happening given a specific location. To estimate these location-specific hazard probabilities, historical extreme weather data was used. The extreme weather hazard considered for this analysis was a storm event. As a consequence, all storm-related extreme weather event occurrences (tropical storm, hurricane, etc.) data for the past 30 years was used to evaluate the possibility of such events. Since all the three feeder networks are closely located, the probability of a certain event happening given a specific location was considered the same for all these feeders. Equation (17) provides a mathematical basis to estimate the value of Hd.

$$Hd_f = \sum_{n=1}^{N} P(N_n|G)_f + P(H_E|G)_f + \left[P(T_A|G)_f \times L_{M,f}\right] \tag{17}$$

Here, $P(N_n|G)_f$ is the probability of the natural event n^{th} ($\forall n \in N$: Set of same category extreme weather events) happening given G is the location of the f^{th} feeder ($\forall f \in F$: Set of feeders). $P(H_E|G)_f$ is the probability of human error given G is the location of the f^{th} feeder. Due to the lack of data on the human induced outage occurrences at the specified feeder locations, $P(H_E|G)_f$ is assumed to be around 10% across all three feeders. $P(T_A|G)_f$ is the probability of the terrorist/cyber attack happening given G is the location of the f^{th} feeder. $P(T_A|G)_f$ depends on the total number of customers, and the customer mix (for example: number of critical customers) located at feeder f. So, to consider that aspect in the calculation, Customer Mix factor, $L_{M,f}$, was introduced which is given by Equations (18),(19).

$$L_{M,f} = \frac{W_{A,f}}{\sum_{f=1}^{F} W_{A,f}} \tag{18}$$

$$W_{A,f} = \frac{\sum_{l=1}^{L} w_{l,f}.C_{l,f}}{\sum_{l=1}^{L} w_{l,f}} \tag{19}$$

The L_{M_f} is calculated as the fraction of the weighted average $W_{A,f}$ of the customer mix on the respective feeders. $C_{l,f}$ is the number of customers in the l^{th} customer category ($\forall l \in L$: Set of customer mix) at the f^{th} feeder whereas $w_{l,f}$ is the weight assigned to the l^{th} customer category at the f^{th} feeder.

TABLE 8. Parametrization of *Hd* for circuit-level risk index calculation.

Feeder info.	$P(N_N\|G)$	$P(H_E\|G)$	Total number of customers			W_A	L_M	Hd
			Residential	Small C&I	Medium/Large C&I			
Feeder #1	0.471	0.10	1617	247	13	243.60	0.3704	0.593
Feeder #2	0.471	0.10	1546	390	15	280.60	0.4267	0.596
Feeder #3	0.471	0.10	242	258	53	133.40	0.2029	0.583

TABLE 9. *CtC* parameters.

Feeder #1				
m	Measure	U_m	w_m	CtC
1	Early warning system	1	0.25	0.65
2	Network reconfiguration	1	0.1	
3	Microgrid formation	0	0.1	
4	Mobile resource	1	0.2	
5	Emergency shelter	0	0.2	
6	Network's robustness	1	0.1	
Feeder #2				
m	Measure	U_m	w_m	CtC
1	Early warning system	1	0.25	0.6
2	Network reconfiguration	1	0.1	
3	Microgrid formation	0	0.1	
4	Mobile resource	0	0.2	
5	Emergency shelter	1	0.2	
6	Network's robustness	1	0.1	
Feeder #3				
m	Measure	U_m	w_m	CtC
1	Early warning system	1	0.25	0.65
2	Network reconfiguration	1	0.1	
3	Microgrid formation	1	0.1	
4	Mobile resource	0	0.2	
5	Emergency shelter	0	0.2	
6	Network's robustness	1	0.1	

It is important to note that, the purpose of this case study is to demonstrate how the feeder-level risk index can be calculated. Therefore, all the probability values were estimated using publicly available data. In general, all the major utility companies will have a robust outage database which can be used to approximate these values more accurately.

The susceptibility of a community to the damage caused due to a hazard can be treated as the community's vulnerability toward that hazard. Vulnerability (*Vy*) of a community can be ascertained by quantifying the total number of customers affected due to the hazard. Equation (20) can be used to determine feeder's vulnerability.

$$Vy_f = \frac{\sum_{l=1}^{L} w_{l,f}.C_{l_{lost},f}}{\sum_{l=1}^{L} w_{l,f}.C_{l,f}} \tag{20}$$

The number of customers lost in the l^{th} customer (load) category located at the f^{th} feeder is denoted by $C_{l_{lost},f}$ whereas the total number of customer in each of the customer category is given by $C_{l,f}$.

CtC is an important factor to consider while calculating the risk associated with any resilience event. This determines the ability of the community to respond or recover from the disrupted state. Community's *CtC* can be expressed as a weighted sum of the available measures to reduce the impact of the resilience event which is given by Equation (21).

$$CtC_f = \sum_{m=1}^{M} w_{m,f}.U_{m,f} \tag{21}$$

where,

$$U_{m,f} = \begin{cases} 1, & \text{if } m^{th} \text{ measure is available at } f^{th} \text{ feeder} \\ 0, & \text{otherwise} \end{cases}$$

The quantity $w_{m,f}$ ($\forall m \in M$: Set of resilience improvement measure available) is the weight assigned to each of the *CtC* measure. Ideally, this value is estimated by conducting customer surveys to identify customer preferences regarding each of the available measures. However, for this case study, this value was determined using an educated estimate which is partially based on [60]. This report highlights the findings from six public hearings on the utility company's restoration performance relative to Hurricane Irene. Based on testimonies from these hearings, the Board of Public Utilities identified certain areas of improvement for the utility companies. This included outage or restoration time duration communication, restoration prioritization, etc. which provided a high-level understanding of public priorities during such event that led to the weight estimation (provided in Table 9).

The feeder networks used in the customer damage cost estimation case study were used for the circuit-level *RI* calculation. *RI* for each of these feeders was estimated for a tropical event (that includes tropical storm events, tropical depression events, etc.). To calculate the probability of these hazards happening, the past 30 years of data associated with the occurrence of such events was used. A 10% probability of human error was considered whereas the base probability of terrorist/cyber attack was considered to be around 6%. Table 8 provides the values for hazard associated with each of the feeders respectively.

The vulnerability, *Vy*, for Feeders #1, #2, and #3 were calculated to be 0.283, 0.926, and 0.914, respectively. Table 9 provides the information about the *CtC* measures available at each of the three feeders. The *CtC* observed were 0.65,

TABLE 10. ***RI*** **results.**

Feeder #1			
Hd	**Vy**	**CtC**	**RI**
0.593	0.283	0.65	0.258
Feeder #2			
Hd	**Vy**	**CtC**	**RI**
0.596	0.926	0.6	0.920
Feeder #3			
Hd	**Vy**	**CtC**	**RI**
0.583	0.914	0.65	0.969

0.5, and 0.65 for the three feeders respectively. This quantity along with the probability of a specific *Hd* and *Vy* were used to calculate the *RI*.

Table 10 provides the *RI* associated with each of the feeders. It can be seen that Feeder #2 has the maximum *RI* at 1.16 followed by Feeder #3 at 0.969 and Feeder #1 at 0.258. Higher *RI* for Feeder #2 is due to the fact that this feeder has relatively higher number of customers and lacks certain measures to sustain/recover from the hazard. Feeder #3 can also be considered to be at a higher risk because of the customer mix at this feeder (more number of small, medium, and large C&I customers located at this feeder). In this case study, *Vy* was calculated considering the customer lost for just one event. However, this methodology can be extended to encompass a multitude of events to evaluate the *Vy* of a typical feeder. *RI* provides a good insight into which feeders to apply resilience enhancement measures (targeted resilience improvement), thus adding an extra dimension to the resilience metrics that would govern resilience oriented decisions.

V. POWER SYSTEM RESILIENCE ENHANCEMENT TECHNIQUES

In this section, some of the traditional and some more recent techniques incorporated by some utility companies for resilience improvement are summarized. Resilience enhancement strategies can be applied in regards to the two aspects of resilience as suggested in [61], which are the infrastructure resilience improvement aspect, and the operational resilience improvement aspect. As the name suggests, infrastructure resilience improvement [62], [63], [64], [65] deals with boosting the robustness of the system components, whereas the operational resilience improvement [66], [67], [68] deals with maintaining secure supply to the loads during an imminent disaster.

Despite the fact that the operational and infrastructure resilience improvement techniques are distinctive in the sense of its implementation, for every operational resilience improvement technique, there is an infrastructure resilience improvement prospect (planning phase) associated with it. Hence it is crucial to understand, from the utility company standpoint, its preference in applying resilience improvement

TABLE 11. **No. of customers lost and the customer damage cost (after resilience enhancement).**

Feeder No.	Residential	Small C&I	Medium & Large C&I	All Customers	Customer Damage Cost
Feeder #1	382	28	0	410	$ 15,868.00
Feeder #2	906	312	7	1225	$ 1,321,318.40
Feeder #3	103	48	35	186	$ 314,004.90

measures, as both infrastructure and operational resilience improvement measures involves a planning phase to some extent.

In the wake of recent extreme weather events, some of the regulatory authorities stepped up to provide a set of guidelines or areas to address for the utility companies under its jurisdiction. The New Jersey Board of Public Utilities, in the past, has addressed some of the issues mentioned below that were experienced previously during extreme weather events [69]. These issues include the improvement in communication with customers and emergency management officials, setting restoration priorities, improved vegetation management, supplemental crew acquisition, frequent equipment inspection and repair, and employee training. The review of Florida's electric utility hurricane preparedness and restoration actions (2018) report published by the Florida public service commission provided some of the key guidelines to improve the adequacy and reliability of the state's transmission and distribution assets [70]. The commission adopted extensive storm hardening initiatives that included targeted undergrounding of certain laterals, provisions to inspect and harden non-utility poles, vegetation management of the trees that are outside the utility's right-of-way, etc.

The recent winter storm Uri has highlighted the vulnerabilities caused due to the interdependencies between the energy sectors. The report [71] provides key recommendations for improving generation cold weather reliability, improved natural gas infrastructure, cold weather joint preparedness with the grid, advance grid emergency preparedness, and some additional recommendations that include revising load shedding plans, improved communication with the interdependent sector, etc. In order to avoid the risk of experiencing an event like the California wildfire of 2018 (Camp Fire 2018), a wildfire mitigation plan has been developed by the utility company [72]. It reflects the measures that involve undergrounding 10,000 circuit miles of distribution line that lie in the high fire threat districts (HFTDs), expanding enhanced powerline safety settings, using SCADA enabled automatic sectionalizing devices, single phase reclosers, and advanced sensors, enhanced vegetation management [73], and developing advance situational awareness schemes and equipment inspection protocols.

While it is vital to analyze the baseline resilience of the power system network, it is equally important to ascertain the network's resilience after the application of resilience improvement technique. Although it is not part of the scope of the paper to evaluate resilience enhancement techniques, Case Study 3 provides a high-level overview of how the application of resilience improvement measure can improve the metrics discussed in Case Study 1 (customer damage cost) and Case Study 2 (risk index).

A. CASE STUDY 3: EVALUATING THE RESILIENCE ENHANCEMENT TECHNIQUES

In this case study, three resilience improvement techniques are applied to the aforementioned feeder networks. The resilience improvement techniques under discussion are: 1) targeted undergrounding; 2) targeted pole reinforcement (hardening); and 3) Enhanced Vegetation Management (EVM). These techniques were appropriately applied to the respective feeder based on the customer damage cost and the risk index calculated in Case Study 1 and Case Study 2. For Feeder #1, since the customer damage cost and risk index are relatively low, only targeted pole reinforcement was performed for 15 poles that were directly (or are likely to cause outages in the future) to be responsible for the outage. Feeder #2 had the highest risk index and comparatively higher customer damage cost. Hence 240 poles were reinforced and a three-phase distribution line section of around 9.26 miles was selected to undergo vegetation management (EVM). Out of all the three feeders, Feeder #3 had the most customer damage cost and relatively high risk index due to the customer mix at this feeder. Therefore, all the three enhancement techniques were applied to this feeder where 132 poles were reinforced, 13.5 miles of three-phase distribution line section underwent vegetation management (EVM), and 4 miles of ‘‘high risk distribution’’ lines were undergrounded.

Costs associated with the application of these techniques were used to calculate the actual benefits of applying these techniques. Undergrounding distribution lines is by far the most expensive of the three techniques applied and hence it is only applied to the worst hit feeder. The cost of undergrounding distribution lines depends on multiple factors like the line length, terrain type, voltage level, etc. Based on the report presented in [74], the average cost of undergrounding is around $ 280,000 per mile (for low density rural areas) for that specific state located on the east coast. Considering an average inflation rate of 2.56%, the value of underground is approximately equal to $ 470,000 per mile (as of April 2023 based on January 2003 data). Pole reinforcement costs around $1200-$1300 per pole as per [75]. The cost for EVM was determined using a report and a rebuttal testimony provided in [76] and [77], respectively. Similar to undergrounding distribution lines, the cost of vegetation management depends of several factors including the type of terrain, length of the distribution section, etc. The cost of EVM for the section where the feeders are located was ascertained to be around $40,100 per mile.

A methodology similar to the Case Study 1 (Customer damage cost-estimation using the circuit-level indices) was used to estimate the customer damage cost after the application of the resilience enhancement techniques. Table 11 shows the number of customers lost and customer damage cost associated with the respective feeders after the application of the resilience improvement techniques. A considerable amount of reduction in the customer damage cost was observed across all the feeders. However, it is important to consider the investment cost as well to evaluate the benefits of the improvements.Therefore, the benefits to cost ratio for Feeder #1 was around 1.323, for Feeder #2 was around 2.165, and for Feeder #3 was around 1.102. It is important to note that this case study provides a high-level information about the evaluation resilience improvement techniques. A more in-depth benefit-cost analysis for resiliency studies can be found in [76].

TABLE 12. ***RI* results (after resilience improvement).**

Hd	Vy	CtC	RI
Feeder #1			
0.593	0.191	0.75	0.151
Feeder #2			
0.596	0.671	0.7	0.570
Feeder #3			
0.583	0.343	0.65	0.307

It is essential to update the feeder’s *RI*, once these resilience improvement techniques are applied. Table 12 demonstrates the improvement in the *RI* for all the feeders. The hazard value *Hd* remains constant as this value is area-specific. The vulnerability *Vy* of the feeders decreased, from 0.283 to 0.191 for Feeder #1, from 0.926 to 0.671 for Feeder #2, and from 0.914 to 0.343 for Feeder #3, due to the applied improvements as the number of customer lost as a consequence of the hazard decreased. Also, because of the infrastructure enhancements, the capacity to cope, *CtC* demonstrated an increase, thus reducing the overall risk index across all the three feeders.

VI. CONCLUSION

This paper bridges the gap between the various resilience metrics and techniques that are used to determine the customer and societal damage cost as a consequence of a resilience event. It presents an extensive study of the concept of power system resilience that includes the proposed power system resilience definitions, analysis frameworks, and quantification metrics. The resilience definitions and frameworks used by some of the prominent research organizations were highlighted which demonstrated encouraging indications regarding standardizing the resilience definition. As more and more research organizations adopt a certain resilience definition for conducting studies, it is just a matter of time before an accord is reached on a standard power system resilience definition that encompasses all aspects.

Quantifying resilience is one of the vital aspects of resilience assessment. Hence, some of the key factors to be considered during the development of resilience metrics were documented. Although building a standard resilience metric is exceedingly difficult, additional efforts are needed towards developing a set of guidelines that would guide researchers through a process of resilience assessment. There are some general guidelines that help in the metrics development process; however, these guidelines cannot address the variety of the resilience improvement objectives. Moreover, metrics development will become much easier once a consensus on the power system resilience definition is reached.

An important characteristics of resilience evaluation process is the customer damage cost estimation that can be integrated into the resilience metrics for informed decision-making. Case Study 1, which consists of two subsections, demonstrates how to use the ICE calculator to evaluate the customer damage cost using 1) state-wide reliability indices and 2) circuit-level (event- specific) indices that were proposed in the work. The results of the case study show that the proposed circuit-level (event-specific) indices approach provides a more accurate customer cost estimation values as this approach calculates damage cost at every restoration iteration.

Risk-based approaches that add an additional dimension to the resilience assessment framework were presented to highlight the complexity of the resilience concept. An approach to determine the Risk Index (RI) associated with a feeder was proposed. Case Study 2 demonstrates how the proposed approach can be applied to three actual feeders to determine the level of risk each of these feeders are exposed to, given a specific extreme event. Feeder #3 has the highest RI at 0.969 followed by Feeder #2 at 0.920 and Feeder #1 at 0.258. These results suggest that Feeder #3 and Feeder #2 are at a high risk of experiencing severe damage due to a specific extreme weather event.

Finally, a brief summary of the resilience enhancement techniques that are commonly adopted by the utility companies was presented. Case study 3 was presented to exemplify how the resilience indices (customer damage cost and risk index) vary when a resilience improvement technique is applied. Three different enhancement techniques viz., 1) targeted undergrounding 2) targeted pole hardening, and 3) enhanced vegetation management, were discussed. Using the RI calculated in Case Study 2, appropriate resilience techniques were applied to the critical sections of respective feeders. Results indicate substantial reduction in the customer damage cost and the associated risk (to the extreme event in question). Moreover, high-level benefit-cost ratio calculation (BCR) results (Feeder #1 BCR: 1,323; Feeder #2 BCR: 2.165; Feeder #3 BCR: 1.102) illustrate cost-effectiveness of the applied improvement techniques.

The future of resilience improvement techniques will essentially be determined by its contribution towards modernizing the grid of tomorrow as well as improving the social well-being of the community. Improvement of resilience by using automatic switches for defensive islanding, or use of microgrids for promptly restoring power are some of the techniques that have been studied which can pave the way towards a more resilient electric infrastructure. Another improvement technique that extends the concept of a single microgrid to a more reliable cluster of microgrids is the use of networked microgrids. Microgrids located closely can be networked with each other to support critical loads of the on-emergency microgrid. Thus, by appropriately managing the local resilience resource, the overall reliability and resiliency of the complete network can be improved.

REFERENCES

[1] *Economic Benefits of Increasing Electric Grid Resilience to Weather Outages*, Executive Office President, Council Econ. Advisers, Washington, DC, USA, 2013.

[2] M. Kintner-Meyer, "Towards metrics for resilience characterization and challenges in valuing distribution system resilience improvements," Pacific Northwest Nat. Lab., Richland, WA, USA, Tech. Rep., 2021.

[3] K. Watson, R. Cross, and M. Jones, "The winter storm of 2021. Hobby school of public affairs," Dept. Inf., Hobby School Public Affairs, Univ. Houston, Houston, TX, USA, Tech. Rep., 2021.

[4] P. Hoffman and W. Bryan, "Comparing the impacts of northeast hurricanes on energy infrastructure," U.S. Dept. Energy, Office Electr. Delivery Energy Rel., Washington, DC, USA, Tech. Rep., 2013.

[5] *Hurricane Harvey Event Analysis Report*, North Amer. Electric Rel. Corp., Atlanta, Georgia, Mar. 2018.

[6] H. Aki, "Demand-side resiliency and electricity continuity: Experiences and lessons learned in Japan," *Proc. IEEE*, vol. 105, no. 7, pp. 1443–1455, Jul. 2017.

[7] B. C. D. Attorney, "The camp fire public report: A summary of the camp fire investigation," Butte County District Attorney, Oroville, CA, USA, Tech. Rep., 2020.

[8] NCEI. (2022). *Us Billion-Dollar Weather and Climate Disasters*. [Online]. Available: https://www.ncei.noaa.gov/access/billions/

[9] E. D. Vugrin, A. R. Castillo, and C. A. Silva-Monroy, "Resilience metrics for the electric power system: A performance-based approach," Sandia Nat. Lab., (SNL-NM), Albuquerque, NM, USA, Tech. Rep. SAND2017-1493, 2017.

[10] A. Gholami, T. Shekari, M. H. Amirioun, F. Aminifar, M. H. Amini, and A. Sargolzaei, "Toward a consensus on the definition and taxonomy of power system resilience," *IEEE Access*, vol. 6, pp. 32035–32053, 2018.

[11] F. H. Jufri, V. Widiputra, and J. Jung, "State-of-the-art review on power grid resilience to extreme weather events: Definitions, frameworks, quantitative assessment methodologies, and enhancement strategies," *Appl. Energy*, vol. 239, pp. 1049–1065, Apr. 2019.

[12] N. Bhusal, M. Abdelmalak, M. Kamruzzaman, and M. Benidris, "Power system resilience: Current practices, challenges, and future directions," *IEEE Access*, vol. 8, pp. 18064–18086, 2020.

[13] E. J. Mishan and E. Quah, *Cost-Benefit Analysis*. London, U.K.: Routledge, 2020.

[14] M. Mahzarnia, M. P. Moghaddam, P. T. Baboli, and P. Siano, "A review of the measures to enhance power systems resilience," *IEEE Syst. J.*, vol. 14, no. 3, pp. 4059–4070, Sep. 2020.

[15] B. Obama, "Presidential policy directive 21: Critical infrastructure security and resilience," Cybersecur. Infrastruct. Secur. Agency (CISA), Washington, DC, USA, Tech. Rep., 2013.

[16] *North American Energy Resilience Model*, Office Electr., Dept. Energy, Washington, DC, USA, 2019.

[17] R. F. Jeffers, M. M. Hightower, N. S. Brodsky, M. J. Baca, A. Wachtel, S. Walsh, M. S. Aamir, J. Gibson, W. E. Fogleman, and W. J. Peplinski, "A grid modernization approach for community resilience: Application to New Orleans, LA," Sandia Nat. Lab., (SNL-NM), Albuquerque, NM, USA, Tech. Rep. SAND-2017-11959, 2017.

[18] D. M. Anderson, S. Ganguli, A. L. Cooke, and M. L. Moore, "Grid modernization: Metrics analysis (GMLC1. 1)—Affordability," Pacific Northwest Nat. Lab., (PNNL), Richland, WA, USA, Tech. Rep. PNNL-28562, 2019.

[19] A. T. Eseye, X. Zhang, B. Knueven, and W. Jones, "Enhancing distribution grid resilience through model predictive controller enabled prioritized load restoration strategy," in *Proc. 52nd North Amer. Power Symp. (NAPS)*, Apr. 2021, pp. 1–6.

[20] M. S. Lave, "Grid modernization laboratory consortium testing network (GMLC 1.2. 3)," Sandia Nat. Lab., (SNL-NM), Albuquerque, NM, USA, Tech. Rep. SAND2018-3008C, 2018.

[21] A. Ellis, "DOE grid modernization initiative and Sandia R&D," Sandia Nat. Lab., (SNL-NM), Albuquerque, NM, USA, Tech. Rep. SAND2019-0595C, 2019.
[22] J. Torres and N. D. Laws, "Energy resilience through grid modernization and renewables integration," Nat. Renew. Energy Lab., (NREL), Golden, CO, USA, Tech. Rep., 2018.
[23] *Enhancing Distribution Resiliency: Opportunities for Applying Innovative Technologies*, Electr. Power Res. Inst. (EPRI) Washington, DC, USA, 2013.
[24] M. Chaudry, P. Ekins, K. Ramachandran, A. Shakoor, J. Skea, G. Strbac, X. Wang, and J. Whitaker, "Building a resilient UK energy system," UK Energy Res. Center, London, U.K., Tech. Rep. UKERC/RR/HQ/2011/001, 2011.
[25] P. Stockton, "Resilience for black sky days," Rep. Prepared Nat. Assoc. Regulatory Utility Commissioners U.S. Dept. Energy, Washington, DC, USA, Tech. Rep., Feb. 2014.
[26] E. Ciapessoni, D. Cirio, A. Pitto, M. Panteli, M. Van Harte, and C. Mak, "On behalf of CIGRE WG C4. 47 (2019): Defining power system resilience," CIGRE-Electra, Paris, France, Tech. Rep. RP_306_1, 2019.
[27] National Infrastructure Advisory Council (US), *Critical Infrastructure Resilience: Final Report and Recommendations*, Nat. Infrastruct. Advisory Council, Washington, DC, USA, 2009.
[28] *Definition of 'Adequate Level of Reliability'*, NERC, Atlanta, Georgia, 2007.
[29] K. Zitelman, "Advancing electric system resilience with distributed energy resources: A review of state policies about SEIN," Nat. Assoc. Regulatory Utility Commissioners (NARUC), Washington, DC, USA, Tech. Rep. AHQ-8-82076-01, 2020.
[30] Y. Y. Haimes, "On the definition of resilience in systems," *Risk Anal.*, vol. 29, no. 4, pp. 498–501, Apr. 2009.
[31] P. Dehghanian, S. Aslan, and P. Dehghanian, "Quantifying power system resiliency improvement using network reconfiguration," in *Proc. IEEE 60th Int. Midwest Symp. Circuits Syst. (MWSCAS)*, Aug. 2017, pp. 1364–1367.
[32] *Transmission Resilience Overview*, North Amer. Transmiss. Forum, Charlotte, NC, USA, 2021.
[33] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, "Boosting the power grid resilience to extreme weather events using defensive islanding," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2913–2922, Nov. 2016.
[34] J.-P. Watson, R. Guttromson, C. Silva-Monroy, R. Jeffers, K. Jones, J. Ellison, C. Rath, J. Gearhart, D. Jones, and T. Corbet, "Conceptual framework for developing resilience metrics for the electricity oil and gas sectors in the United States," Sandia Nat. Lab., Albuquerque, NM, USA, Tech. Rep. SAND-2014-18019, 2014.
[35] Z. Bie, Y. Lin, G. Li, and F. Li, "Battling the extreme: A study on the power system resilience," *Proc. IEEE*, vol. 105, no. 7, pp. 1253–1266, Jul. 2017.
[36] P. E. Roege, Z. A. Collier, J. Mancillas, J. A. McDonagh, and I. Linkov, "Metrics for energy resilience," *Energy Policy*, vol. 72, pp. 249–256, Sep. 2014.
[37] *IEEE Guide for Electric Power Distribution Reliability Indices*, IEEE Standards 1366-2012, IS Association, 1998.
[38] M. R. Milligan, "Methods to model and calculate capacity contributions of variable generation for resource adequacy planning (IVGTF1-2)," North Amer. Electric Rel. Corp., Atlanta, Georgia, Tech. Rep. NREL/PR-5500-50355, 2011.
[39] B. Chiu and A. Bose, "Resilience framework methods and metrics for the electricity sector," in *Proc. IEEE PES*, Oct. 2020, pp. 7–10.
[40] M. Panteli and P. Mancarella, "The grid: Stronger, bigger, smarter? Presenting a conceptual framework of power system resilience," *IEEE Power Energy Mag.*, vol. 13, no. 3, pp. 58–66, May 2015.
[41] S. Chanda, A. K. Srivastava, M. U. Mohanpurkar, and R. Hovsapian, "Quantifying power distribution system resiliency using code-based metric," *IEEE Trans. Ind. Appl.*, vol. 54, no. 4, pp. 3676–3686, Jul. 2018.
[42] M. Panteli, D. N. Trakas, P. Mancarella, and N. D. Hatziargyriou, "Power systems resilience assessment: Hardening and smart operational enhancement strategies," *Proc. IEEE*, vol. 105, no. 7, pp. 1202–1213, Jul. 2017.
[43] Z. Li, M. Shahidehpour, F. Aminifar, A. Alabdulwahab, and Y. Al-Turki, "Networked microgrids for enhancing the power system resilience," *Proc. IEEE*, vol. 105, no. 7, pp. 1289–1310, Jul. 2017.
[44] G. Fu, S. Wilkinson, R. J. Dawson, H. J. Fowler, C. Kilsby, M. Panteli, and P. Mancarella, "Integrated approach to assess the resilience of future electricity infrastructure networks to climate hazards," *IEEE Syst. J.*, vol. 12, no. 4, pp. 3169–3180, Dec. 2018.
[45] X. Liu, M. Shahidehpour, Z. Li, X. Liu, Y. Cao, and Z. Bie, "Microgrids for enhancing the power grid resilience in extreme conditions," *IEEE Trans. Smart Grid*, vol. 8, no. 2, pp. 589–597, Mar. 2017.
[46] S. Abbasi, M. Barati, and G. J. Lim, "A parallel sectionalized restoration scheme for resilient smart grid systems," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1660–1670, Mar. 2019.
[47] G. Kandaperumal, S. Pandey, and A. Srivastava, "AWR: Anticipate, withstand, and recover resilience metric for operational and planning decision support in electric distribution system," *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 179–190, Jan. 2022.
[48] H. Gao, Y. Chen, Y. Xu, and C.-C. Liu, "Resilience-oriented critical load restoration using microgrids in distribution systems," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2837–2848, Nov. 2016.
[49] F. Petit, V. Vargas, J. Kavicky, M. Kintner-Meyer, and J. Eto, "Grid modernization: Metrics analysis (GMLC1. 1)—Resilience," Pacific Northwest Nat. Lab., Richland, WA, USA, Tech. Rep. PNNL-28567, 2020. [Online]. Available: https://gmlc.doe.gov/sites/default/files/resources/GMLC1.1_Vol3_Resilience.pdf
[50] W. Rickerson, J. Gillis, and M. Bulkeley, "The value of resilience for distributed energy resources: An overview of current analytical practices," Converge Strategies (CSL), Prepared for Nat. Assoc. Regulatory Utility Commissioners (NARUC), Washington DC, USA, Tech. Rep., 2019. [Online]. Available: https://pubs.naruc.org/pub/531AD059-9CC0-BAF6-127B-99BCB5F02198
[51] A. Longo, S. Giaccaria, T. Bouman, and T. Efthimiadis, "Societal appreciation of energy security: Volume 1: Value of lost load—Households (EE, NL and PT)," Publications Office Eur. Union, Luxembourg, Tech. Rep., 2019.
[52] National Academies of Sciences, *Engineering, and Medicine and Others*, Enhancing Resilience Nation's Electr. Syst., Nat. Academies Press, Washington, DC, USA, 2017.
[53] K. Anderson, X. Li, S. Dalvi, S. Ericson, C. Barrows, C. Murphy, and E. Hotchkiss, "Integrating the value of electricity resilience in energy planning and operations decisions," *IEEE Syst. J.*, vol. 15, no. 1, pp. 204–214, Mar. 2021.
[54] G. Wacker and R. Billinton, "Customer cost of electric service interruptions," *Proc. IEEE*, vol. 77, no. 6, pp. 919–930, Jun. 1989.
[55] A. Ratha, E. Iggland, and G. Andersson, "Value of lost load: How much is supply security worth?" in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2013, pp. 1–5.
[56] M. Sullivan, J. Schellenberg, and M. Blundell, "Updated value of service reliability estimates for electric utility customers in the United States," Lawrence Berkeley Nat. Lab., (LBNL), Berkeley, CA, USA, Tech. Rep. LBNL-2132E, 2015.
[57] US Energy Information Administration. (2020). *Reliability Metrics Using IEEE of US Distribution System by State, 2020 and 2019*. [Online]. Available: https://www.eia.gov/electricity/annual/html/epa_11_02.html
[58] J. Valinejad, L. Mili, C. N. Van Der Wal, M. Von Spakovsky, and Y. Xu, "Multi-dimensional output-oriented power system resilience based on degraded functionality," in *Proc. IEEE Power Energy Soc. Gen. Meeting (PESGM)*, Jul. 2021, pp. 1–11.
[59] D. Ribeiro, E. Mackres, B. Baatz, R. Cluett, M. Jarrett, M. Kelly, and S. Vaidyanathan, "Enhancing community resilience through energy efficiency," Amer. Council Energy-Efficient Economy, Washington, DC, USA, Tech. Rep. U1508, 2015.
[60] *Hurricane Irene Electric Response Report*, Board of Public Utilities, Trenton, NJ, USA, 2011.
[61] M. Panteli, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatziargyriou, "Metrics and quantification of operational and infrastructure resilience in power systems," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4732–4742, Nov. 2017.
[62] M. Panteli and P. Mancarella, "Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies," *Electric Power Syst. Res.*, vol. 127, pp. 259–270, Oct. 2015.
[63] E. B. Watson and A. H. Etemadi, "Modeling electrical grid resilience under hurricane wind conditions with increased solar and wind power generation," *IEEE Trans. Power Syst.*, vol. 35, no. 2, pp. 929–937, Mar. 2020.
[64] EPRI, "Distribution grid resiliency: Undergrounding," Electr. Power Res. Institute, Palo Alto, CA, USA, Tech. Rep., 3002006782, 2015.
[65] EPRI, "Distribution grid resiliency: Vegetation management," Electr. Power Res. Institute, Palo Alto, CA, USA, Tech. Rep., 3002006781, 2015.
[66] C. Chen, J. Wang, F. Qiu, and D. Zhao, "Resilient distribution system by microgrids formation after natural disasters," *IEEE Trans. Smart Grid*, vol. 7, no. 2, pp. 958–966, Mar. 2016.

[67] Y. Xu, C.-C. Liu, K. P. Schneider, F. K. Tuffner, and D. T. Ton, "Microgrids for service restoration to critical load in a resilient distribution system," *IEEE Trans. Smart Grid*, vol. 9, no. 1, pp. 426–437, Jan. 2018.

[68] S. Poudel and A. Dubey, "Critical load restoration using distributed energy resources for resilient power distribution system," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 52–63, Jan. 2019.

[69] New Jersey Board of Public Utilities. (2011). *Hurricane Irene Electric Response Report*. [Online]. Available: https://nj.gov/bpu/pdf/announcements/2011/irene.pdf

[70] Florida Public Service Commission and Others, *Review of Florida's Electric Utility Hurricane Preparedness and Restoration Actions*, State Florida: Public Service Commission, Tallahassee, FL, USA, 2018.

[71] *The February 2021 Cold Weather Outages in Texas and the South Central United States*, Federal Energy Regulatory Commission Media, NERC, Regional Entities, Atlanta, Georgia, 2021.

[72] PG&E, *2022 Wildfire Mitigation Plan Update*, Pacific Gas and Electric Company, San Francisco, CA, USA, 2022.

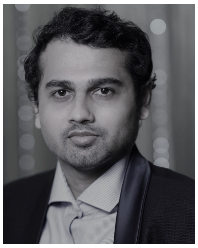
[73] PG&E, *Enhanced Vegetation Management*, Pacific Gas and Electric Company, San Francisco, CA, USA, 2021.

[74] K. McCarthy, "Undergrounding electric lines," Office Legislative Res.: Connecticut Gen. Assem., Hartford, CT, USA, Tech. Rep. 2011-R-0338, 2011.

[75] *Pole Reinforcement Trial*, PowerCo, New Plymouth, New Zealand, 2021.

[76] Central Maine Power Company (CMPC). (2019). *2019-2020 Resiliency Plan*. [Online]. Available: https://npr-brightspot.s3.amazonaws.com/legacy/sites/mpbn/files/201912/april__2019_resiliance_plan___2019-00194.pdf

[77] Central Maine Power Company. (2019). *Central Maine Power Company 2018 Distribution Rate Case Filing: Operations and Resiliency Rebuttal Testimony*. [Online]. Available: https://npr-brightspot.s3.amazonaws.com/legacy/sites/mpbn/files/201912/operations_and_resiliency_rebuttal_testimony_-_public__w7222103-2x7ac2e_.pdf



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