Exploring acute weather resilience: meeting resilience and renewable goals

Madeline Macmillan1,2,[[1]](#footnote-1)([madelinemacmillan@mines.edu](mailto:madelinemacmillan@mines.edu), ORCID: 0000-0002-7423-0090), Caitlin Murphy2 ([caitlin.murphy@nrel.gov](mailto:caitlin.murphy@nrel.gov)), and Morgan D. Bazilian3 ([mbazilian@mines.edu](mailto:mbazilian@mines.edu))

1 = Advanced Energy Systems Graduate Program, The Colorado School of Mines, 1500 Illinois Street, Golden, CO 80401, USA

2 = National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO 80401, USA

3 = Payne Institute, The Colorado School of Mines, 1500 Illinois Street, Golden, CO 80401, USA

**Abstract:** The United States is affected by an average of almost seven severe weather events a year, often resulting in billions of dollars in physical and economic damages, a subset of which are related to power outages. There is a need to better understand and implement the strategies that help reduce net-economic and societal consequences associated with power outages by improving the resilience of the electric power system. In addition, there are incentives to reduce power system emissions and meet climate goals, several pathways of which include resilient technologies. Including resilience constraints and metrics in power system planning models may help inform the design of more resilient systems that are also more renewable and sustainable. This paper reviews qualitative definitions of resilience, quantitative approaches to resilience, and recent examples of the inclusion of resilience in power system models with respect to acute climatological threats. We then identify key components and steps to effectively incorporate resilience against such threats into power sector modelling tools and recommend future areas of research to bridge the current modelling gaps.

**Highlights:**

* To date, resilience concerns have been lacking in power systems optimization models.
* Research is needed to better understand how renewables can contribute to resilience.
* Resilience concerns should include uncertainty and translate to economic costs.
* Future modeling efforts should co-optimize renewable and resilience goals.

**Keywords:** Resilience; Natural disasters; Power system models; Optimization models

**Word count:** 6367 (from introduction to conclusions, not including SI)

**Abbreviations:** IEA, International Energy Agency; NOAA, National Oceanic and Atmospheric Administration; SDG, Sustainable Development Goals; VoLL, Value of lost load; CBA, Cost-benefit analysis; SoS, System of systems; HILP, High impact low probability; LOLF, Loss of load frequency; LOLE, Loss of load expectation; MRP, Markov Reward Process; ICE, Interruption Cost Estimator; GDP, Gross Domestic Product; DER, Distributed energy resources.

1. **Introduction**

The latest International Energy Agency (IEA) *Net-Zero by 2050* report develops a roadmap for the global energy sector to achieve net-zero emissions and offers an in-depth analysis of pathways for meeting emissions targets [1]. In addition to accomplishing climate goals, the report highlights that a wider implication of a net-zero energy system is the potential for greater consequences associated with power interruptions, due to increased electrification present in many net-zero pathways. Because the grid is often vulnerable to the effects of severe weather, there is a clear need to mitigate the consequences of climatological threats to electricity infrastructure.

Historical data from the U.S. National Oceanic and Atmospheric Administration (NOAA) indicate an upward trend in the frequency and impact of high-impact weather disasters [2], [3]. These extreme weather events often cause power outages [4], [5] along and adjacent to their tracks. For example, Hurricanes Michael and Florence both occurred in 2018 and resulted in power outages for an estimated 1.7 million people across six southeastern states. That year, customers in affected states experienced an average of 30 hours of power outages [6]. During the California wildfires in 2019, the utilities issued power outages to nearly 500,000 people [7]. A week-long freeze in Texas in February 2021 affected 4.5 million people at its peak [8].

In addition to costly physical damages from severe weather events, annual power outages induce an average of $25 billion in economic damages due to lost economic activity [9]. These economic consequences reflect the country’s reliance on the power system for many industries and critical services, including clean water, communications, education, healthcare services, national security, and production and extraction of essential fuels. The combination of increases in electrification for net-zero pathways, severe weather events, and dependency on the electric grid further indicate that improving the ability of the electric grid to withstand and recover from major weather events could have significant economic and social benefits.

The concept of withstanding disturbances such as hurricanes or wildfires that would otherwise cause power outages has taken many forms in the literature, namely as resilience. Resilience is recognized as an important initiative on the international scale. For example, resilience is included in the Sustainable Development Goals (SDGs) adopted by members of the United Nations: goal 9 emphasizes building resilient infrastructure and goal 11 strives to make cities resilient [10].

The varying and broad definitions of resilience present a challenge when trying to incorporate resilience decision-making into investment and operational models. Specifically, when attempting to represent resilience in power system tools—such as power system optimization models that could be used for short-term operations and long-term investment planning of renewable systems—the necessary metrics and scenario definitions are unclear [11]–[13]. We investigate the current implementation of resilience considerations and determine the benefits of including them in power system planning models. This paper directs improvements for the incorporation of resilience to minimize the consequences of weather-induced power outages into investment and operational decisions made by power system optimization models [14]. Throughout this review, we explore the power system resilience implications of renewables and how they can meet both the United Nations SDGs and the IEA net-zero initiatives for a resilient and sustainable future.

1. **Experimental procedures**

The methods used in this review are based on the strategies in [15]. This review includes a coded search using Boolean operators and keyword combinations generated from two lists: 1) resilience and resiliency, and 2) metric, algorithm, compositive indicators, definition, principles, and index. A similar search was conducted to review studies that explore the resilience of renewables by including search terms renewables, and distributed energy resources.

The results were filtered based on their abstracts to include those studies presenting a unique definition of resilience and/or a relatively broad approach to measuring and quantifying resilience. This step helps exclude studies implementing previous literature findings or methods and limits studies creating specific resilience metrics for niche systems less applicable to other systems and disciplines. While reading the papers that satisfy the requirements, additional studies were identified through the reference lists. The remaining articles introducing a unique definition or quantification of resilience were reviewed and synthesized or where the resilience of renewables is investigated.

1. **Literature Review**

Resilience is a concept that has been explored in several disciplines. Holling [16] defined resilience in 1973 as “a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables”. There are several examples of definitions of general resilience [17]–[46], however, some discipline-specific examples of resilience research include ecological resilience [16], [47], community resilience [47]–[49], disaster resilience [50]–[52], psychological and healthcare resilience [53]–[59], transportation resilience [39], [60], and power system resilience [22], [27], [32], [33], [36], [61]–[67].

**3.1 Qualitative definitions of resilience**

There is significant diversity among qualitative resilience definitions, but some commonalities exist. First, the most consistently used terms from the literature review include “ability”, “system”, “recover”, “withstand”, and “event”. To identify these keywords, a brief analysis was performed to count the number of appearances of each word within the definitions from this literature review. The words with the most number of appearances were those labeled as keywords. Syncategorematic words, or words that do not stand by themselves such as ‘a’, ‘of’, ‘the’, and ‘to’, were not included in this analysis. Second, reference [22] analyzed the definitions of resilience across a multitude of sectors including ecological resilience, psychological resilience, and risk management resilience. Diversity, redundancy, efficiency, and system structure and organization were identified as important qualities for any system to be considered resilient [22].

System resilience can be defined in a way that is threat agnostic or threat specific [39], [46], [48], [53], [68]. A literature review looking at the resilience of transportation infrastructure found resilience to be dependent on several factors including disturbances experienced by the system in question [39]. For example, a transportation system resilient against a natural disaster such as a hurricane must be able to withstand the physical impacts of the weather event including flooding and obstacles blown into the path. A transportation system resilient against cyber-attacks must be able to withstand threats such as malware and phishing [68]. Each hazard presents unique challenges to the transportation system’s resilience. To effectively assess the resilience improvement opportunities of a system, disturbance context is often needed to define strategies and investments.

Resilience has also been related to the concept of stability [26], [47]. For example, ecological resilience and ecological stability are similar yet distinct: both are related to a system operating in equilibrium, but *stability* is the ability of a system to return to its known equilibrium state post-disturbance, while *resilience* allows for multiple equilibrium states. Therefore, the potential for fluctuations between multiple operating states under resilience results in low stability. Inversely, in a complex ecosystem, an abundance of stability is indicative of a lack of resilience, which can lead to system collapse [47]. For a system to be resilient, the structure must allow flexibility to enable the system to move between several states of equilibrium.

In addition to a variety of satisfactory operating states, it is also important to consider the investment opportunities available to improve system resilience. In a series of studies, Panteli and Mancarella explore various investment and operational options for improving resilience [63], [69]. For example, [63] tests how investments in robustness, redundancy, and responsiveness improved power system resilience and found various resilience benefits associated with each attribute tested. This paper emphasized the importance of considering resilience enhancements for power systems with respect to both infrastructural and operational pathways.

Based on the previously defined scope of this study, we argue that a power system is resilient against acute weather events if it can withstand and recover from them by adapting to different operational and/or infrastructural states of equilibrium. A power system will remain resilient if the system continues to meet quality standards and customer demand throughout a disturbance. The degree of resilience is determined by the extent to which quality and demand requirements are met and economic consequences associated with power outages are minimized.

* 1. **Quantitative approaches to resilience**

In addition to qualitative definitions, various approaches exist for quantifying resilience. A clear quantitative framework is important when considering the implementation of resilience within a power systems optimization model.

Power system resilience metrics can guide system planning and operational decisions by providing decisionmakers with a comparable measurement for evaluating resilience and, in turn, its value. Existing literature includes a broad array of power system resilience metrics, which can be classified by unit of performance or consequence, spatial resolution, temporal scale, and threat.

Despite the abundance of metrics in the literature, there is not an accepted, standardized, and validated metric for measuring resilience [64], [70]. Drawing on an extensive literature review, we highlight key gaps and important attributes among existing resilience metrics to inform power system planning and operational decisions.

There are two primary types of resilience metrics: performance-based and attribute-based. Attribute-based metrics compile system properties contributing to resilience such as vulnerability, responsiveness, and adaptability [54], [66], [71]. These properties (or attributes) are then used to establish a baseline of a system’s current resilience, and they can also help assess resilience improvement strategies. Attribute-based resilience metrics are not commonly implemented with power system modelling efforts and so are not discussed in this paper.

Performance-based metrics are useful in quantitative analyses in power sector modeling tools. These metrics are evaluated by quantifying performance shortfalls and their resulting consequences, which often accompany disruptions on the power systems. Generally, these performance shortfalls are characterized by the demand exceeding the supply, as summarized by Equation 1:

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

where t0 and tf are the start and end of the disruption in electricity services, respectively. The functions Cpre and Cpost are the performance curves with and without a disturbance. The integral over time represents the total loss of functional capacity from the start of the disturbance to after. This functional form is employed in several papers and applications for quantifying the reduction in system performance due to a disturbance [45], [46], [48]. Figure 1 provides a visual representation of how the performance losses in Equation 1 are determined with respect to a power system experiencing a disturbance. With respect to a hypothetical acute weather event, the system function level at t0 represents the performance of the system prior to any disturbance. The time t1 is when the event occurs, and the system performance begins to fall due to the impacts of the disruption. Note that causes of performance shortfalls can be attributed to a variety of things—not all of which are deterministic nor independent—and are an important component of performance-based resilience metrics. Between times t2 and t3, the natural disaster continues and/or there is a delay in recovering system performance. Beyond t3, the system begins to recover and regain system performance as restoration strategies are implemented until it has reached tf. Ultimately, maximizing resilience involves minimizing the area between the purple dashed line and the solid black line, which corresponds to minimizing Equation 1.

*Diagram

Description automatically generated*

Figure 1. A resilient power system during a disruption, adapted from [65]

There are several shortcomings with recent applications and demonstrations of performance-based resilience metrics. For example, the stochastic nature of both severe weather events and their resulting impacts (including power outages) must be incorporated into power system planning. Some approaches for incorporating uncertainty in power system models include Monte Carlo simulations and Markov chains, both offering a unique stochastic framework [66], [72], [73]. Applying components of uncertainty into data needed to define parameters that inform power system planning would also broaden the scope and understanding of the resilience of the system under various scenarios and increase the real-world applicability of the model results.

Interdependencies are also important to consider when implementing performance-based metrics in power system planning models. Within the power sector, an example of an interdependency is between the electric and natural gas systems where the presence of natural gas and electricity are essential to one another to meet end-user demand and transport fuel to generation facilities [74]–[76]. Sectoral interdependencies remain important when considering the impact of extreme weather events and their accompanying hazards. When intense rain hits, roads can become impassable which limits the transportation of essential fuels and maintenance required to sustain the operations of a power system. High winds hitting a power line can disrupt communications which makes it harder for the grid operators to maintain or recover service to customers. Omitting sectoral interdependencies in power system resilience planning can lead to an incomplete understanding of the impacts of power outages and can misinform stakeholders and decisionmakers.

Another challenge with implementing performance-based metrics is converting the values into economic consequences to inform decisions about investments and strategies to mitigate the effects of severe weather-induced power outage events. The economic losses associated with outages is often aggregated into value of lost load (VoLL) metric or indicator [77]–[84]. In the real-world, the VoLL value can vary due to several factors including outage duration, season, time of day, location, and customer type (residential vs. industrial vs. commercial). Equation 1 can be adapted to include the appropriate VoLL associated with a weather-induced power outage, as seen in Equation 2.

|  |  |  |
| --- | --- | --- |
|  |  | (2) |

In a journal article discussing the economic impact of Superstorm Sandy, the value of the VoLL can range from $10-300/kWh [45]. In this study and a similar one, the adopted VoLL for an extreme event was $100/kWh [85]. How this value was assigned, however, was not discussed in further detail [45], [85].

Although the VoLL can be sufficient for short duration outages, its value is (a) often implemented as a static cost-per-load unserved and (b) not well understood for longer-duration outages. In the literature, Ericson et al. [86] have taken steps to address this through a flexible framework to develop an outage duration-dependent VoLL. This framework is able to reflect both fixed outage costs and costs that vary throughout an outage event (classified in the study as fixed, stock, and flow costs) of any duration. Despite this progress, in many instances, the system-wide VoLL is often underestimated by regulators [81]. To continue to expand the utility of the VoLL to applications in severe weather events, more research is needed into how severe weather events might affect the value and duration-dependence of the metric or indicator.

In summary, many existing performance-based power system planning and operation metrics are still restricted by their inability to fully reflect inter- and intra-sector interdependencies, represent uncertainty, and to quantify the economic and social consequences of various resilience events.

**3.3 Resilience in power system optimization models**

A review of the energy modeling literature indicates that energy sector models are typically either well established and broadly applied, or they include resilience considerations; only very limited examples exist for models that fall under both categories.

On the one hand, several models have been demonstrated that aim to improve system resilience while representing the consequences of severe weather on power infrastructure [63], [87]–[95]. However, many of these models lack experience, as they have only been demonstrated on a single test system.

On the other hand, [96] provides a large review of energy and electricity system models that have been more widely applied but include little to no resilience considerations. Outside of the review conducted in Ringkjob et. al., one example of a popular model with resilience considerations is REopt, or the more accessible version known as REopt Lite, from the National Renewable Energy Laboratory. REopt Lite employs a value of resilience metric in post-processing to calculate the potential economic benefits of providing backup power during grid outages based on the recommended system configurations [97]. Though this example of a resilience metric in an existing model is noteworthy, it is not necessarily useful to all users. The REopt Lite model assumes the user knows the value of resilience for their system. Throughout literature, the numeric value of the VoLL ranges significantly between $10-$300/kWh and is highly dependent on numerous factors including the season, time of day, outage duration, geographical location, and customer breakdown [98], [99]. Given these complexities behind a VoLL metric, it is not reasonable to assume the user has calculated the VoLL or that they have all the resources needed to do so. Additionally, the value of resilience is not considered in the actual optimization problem. In other words, the optimization problem determines the necessary distributed energy resource mix with the highest net present value, not accounting for any resilience value; therefore, the system is not optimized to maximize resilience, but instead treats the value of resilience as a separate stream based on any avoided outages the system would be expected to experience without the model-recommended system amendments. Due to the lack of resilience metrics and the inability to effectively populate power systems models with power outage and resilience considerations, there exists an opportunity to enhance existing models to consider resilience against natural disasters within their formulation.

**3.4 Resilience of renewable systems**

Given the IEA net-zero initiatives, it is also important to consider the unique resilience characteristics of renewable systems. Our current understanding of resilience implications of renewables is nascent. There are limited empirical studies to demonstrate the effects renewable generation has on the resilience of the electrical grid [45], [100]–[103]. Much of our understanding is limited to assumptions and theories of how renewables, especially variable renewables, operate with traditional generation and their potential impacts on power system resilience.

Many renewable resources are considered resilient because they are primary forms of energy and lend themselves to distributed systems. Distributed resources are less likely to be impacted by disturbances affecting the centralized grid [104]. Despite their abundant fuel supplies and tendency toward distributed systems, renewable technologies have vulnerabilities, including to acute natural disasters. Although the fuel supply of renewables is not interdependent on foreign relations and/or transportation, it is variable. For example, wind and solar profiles are highly dependent on the wind and sunlight patterns, while hydropower is susceptible to droughts [105]. The efficiencies of several renewable technologies, such as solar panels, are sensitive to extreme temperatures [12]. As a result, when depending on a renewable system for power *during* a natural disaster such as a hurricane or heat wave, solar power and wind power are not necessarily the most resilient options.

Another technology considered resilient that has played a role in net-zero initiatives is energy storage. Batteries can be charged by the grid and/or distributed renewables before the natural disaster strikes, ensuring that the system can continue to maintain power [32]. There are still challenges with this approach because natural disasters are variable, potentially leaving insufficient time to charge a battery. This method also implies that the battery be used primarily for resilience purposes, rendering it expensive and relatively useless at other times. The infrastructure for non-distributed renewable resources also remains vulnerable. High winds can cause damage to renewable technologies directly or by blowing debris. Flooding and intense rain also threaten any electronic equipment. Undamaged renewable systems may be more consistently beneficial in the aftermath of a natural disaster when the cloud cover is gone, the winds have calmed, the flooding has recessed, and other threats have subsided.

Evaluations of the resilience of a system during a natural disaster, including that of a renewable system, have included cost-benefit analyses (CBA). A study on the resilience value provided by solar and battery observed that including the value of resilience due to power outages encourages and justifies increased adoption of photovoltaic and battery technologies [106]. In a similar study, the analysis came to the same conclusion: including the avoided outage costs in the CBA made renewable systems more cost effective [101]. Another instance of valuing the resiliency of renewables did so during an acute natural disaster, Superstorm Sandy [45]. This approach used insurance premium discounts to inform stakeholders of incentives for renewable energy. Considering the short list of studies exploring the resilience of renewable systems, renewable energy has been consistently found to improve the net present value of a system when the avoided outage costs are considered. Improving and expanding on resilience assessment methods of renewable systems can lend itself to meeting resilience goals and net-zero initiatives.

Throughout the literature, there is significant variability between definitions and quantifications of resilience. Research to assign a monetary value to the resilience of renewable power systems has also been met with challenges. With respect to power system resilience against severe weather events, there are several stakeholders and many reports declaring a need for more work in this field. Given the importance of this work, inconsistencies and limitations in quantifying and representing resilience in power system optimization planning models highlight an unfulfilled area of research.

1. **Adapting and enhancing existing models**

Due to the identified knowledge gap of the inability to effectively inform power systems models with power outage and resilience considerations, especially within renewable systems, there exists an opportunity to enhance existing models to consider resilience against natural disasters within their formulation. When considering a power systems optimization planning model that accounts for resilience against extreme weather events, the wheel does not need to be reinvented. Instead, these proposed adaptations and enhancements have the potential to be applied into existing, commonly used power systems optimization models with base formulations that have already undergone rigorous testing and analysis.

**4.1 Improving data collection and availability**

Improved data and data collection are essential to a thorough resilience analysis. Power sector resilience metrics will only be as useful in informing power system planning and operational decisions as they can be applied and appropriately populated. While better data collection could help improve the understanding of the economic relationships between power system resilience and other sectors, the cost of acquiring said data might be prohibitive or unjustifiable.

Any efforts to enhance power system resilience metrics and the associated data collection should target applications that would serve to directly inform the quantification of power system resilience benefits, planning, and operational decisions with respect to acute weather events. It would be beneficial to generate and incorporate more data thorough power system component fragility curves, of both renewables and non-renewables, against multiple risks. This will help represent the probabilities of infrastructure failure with respect to various climatological threats in the decision-making process within the optimization model. It would also be of interest to better understand the relationship between natural disasters, changes in the electric load, and changes in capacity. For example, during a severe winter storm and/or freeze, electric heating consumption is likely to increase, the availability of solar and wind will be dependent on the cloud cover and wind patterns, respectively, and conventional generation may be affected if it is difficult to transport the fuels [102]. As a result, the model parameters within a power systems operations model during an acute natural disaster should reflect these differences from the “business as usual” parameters. Within a power system planning model, an example of longer term variable data could be the variation in the rated capacity of transmission lines throughout the year as the ambient temperature changes.

A benefit of improved data collection is increased application, validation, and testing of existing resilience metric frameworks. Many resilience studies propose their own resilience metric as opposed to adopting a one of the many existing (and broad) metrics from a previous study [107]–[110]. Through increasing existing resilience metric applications, instead of routinely developing new ones, the metrics will be subject to greater testing and provide an enhanced understanding of the validity of resilience metrics across disciplines.

If data collection proves too difficult, time consuming, expensive, or otherwise infeasible, there are alternative ways to populate a model’s input. One method in the literature uses energy system model outputs to inform power system model inputs [111]. Similarly, using outputs from other external models that simulate power system performance-based metrics can be used as inputs into power system planning models. This combines the advantages and capabilities of the individual models. For power system resilience planning, this approach could be adapted to accomplish similar goals. For example, a model that simulates fragility curves of a power system component against varying climatological threats relevant to hurricanes could be used to populate survival probabilities [66]. Another approach to producing more and higher quality data is through digitalization. From an operations standpoint, machine learning techniques can be employed to detect irregular patterns that may lead to a power outage. This awareness can help the system adapt to the evolving conditions.

Economic Input-Output models can also be used to inform power system models. In [40], a mathematical approach for understanding the interdependencies between a system of systems (SoS) is introduced. System failures that affect other sectors are determined by performance thresholds. By making educated assumptions about the maximum tolerable lost service, a robust space of the various states that can be assumed by the SoS is generated. This space, potentially exhibiting several dimensions, can output performance shortfalls experienced in other sectors based on interruptions in a separate, but connected, sector, such as a power outage. The addition of these cascading economic consequences in the objective function of an optimization model can help inform resilient power system planning decisions. Although regulated utilities may be unable to make investments based on “cascading economic consequences”, these proposed efforts could put bounds on the level and types of investments that would be needed to help avoid such consequences. Informing power system optimization models with the output of external models is not novel [66], [111], but specifically doing so for improved resilience planning against hurricanes is a relatively nascent space.

**4.2 Implementing stochastic frameworks**

To improve the capacity to consider power system resilience against acute weather events, models in [96] need to incorporate uncertainty frameworks. Some common examples to model the impacts of extreme weather on power systems include analytical frameworks such as the Markov approach and simulation techniques such as the Monte Carlo method, both of which can incorporate metrics such as time to restore values, time to repair values, and fragility curves [15], [42], [103]. Employing an uncertainty framework into power system optimization would allow for the stochastic and time-varying nature of natural disasters to be represented and improve resilient decision making.

To consider uncertainty, the relationships between the variability of climatological threats (such as high wind speeds and severe flooding from a hurricane or extreme temperatures from a heat wave or freeze) and component failure are combined to understand the likelihood of power outages. This combination can be implemented through fragility curves which assign failure probabilities associated with the climatological risks of acute weather events to respective power system components. Incorporating a range of climate projections into power system modelling efforts helps to consider uncertainty associated with climate change when planning infrastructure, including the power system [112]. Failures, and resulting performance shortfalls, due to extreme weather can then be incorporated into an optimization framework for the power system.

The studies conducted in [63] and [113] provide examples of stochastic frameworks applications for the resilience of a power system during extreme weather. These approaches have potential to be added into a more widely used model. In [63], the authors model the influence of high impact, low probability (HILP) weather on the resilience and reliability of a power system. Using Monte Carlo simulations, varying weather conditions and restoration times are used to understand the impacts on outage frequency and duration. The operating status of power system components are determined by a combination of component fragility curves with respect to a weather parameter and a random number generator. This technique was tested under a variety of scenarios: (1) a robust network with stronger technology and materials, resulting in fragility curves shifted to the right, (2) a redundant network with duplicated lines in the system, and (3) a response network with restoration time to damaged components during extreme weather conditions equal to that of normal weather conditions. When compared to the results of a normal system, this study found that robust networks and redundant networks offer the most consistent and most significant improvement in outage frequency (loss of load frequency, LOLF) and duration (loss of load expectation, LOLE) under extreme weather conditions. This study also looked at the impact of a delay in response time to repair the damaged component (whether it be attributed to lack of awareness, communication, or access by the repair crew). It was found that with or without a delay in response, redundant and robust systems still resulted in the best resilience performances.

A variation of this technique can be incorporated into an existing power system model. In a more experienced model, the components of Monte Carlo simulations could be applied to each time step for each relevant power system component, assuming the power system component fragility curve data are available. Applying this framework to a power system experiencing severe weather events would potentially involve representing multiple weather parameters, especially rain intensity and wind speed [114].

In another study, analytical approaches were used to model the resilience of power systems during extreme events [113]. The paper develops a function of system states with a transition matrix with a Markov Reward Process (MRP). An MRP is a Markov model with reward structures integrated into the various model states. In this study, the power system experiences a direct loss when it transitions to a state with lower performance due to a disruptive event. An additional, indirect loss is incurred by the system when it remains in the low performance state. To calculate the conditional probabilities of the system in each performance state, probabilistic combinational models can be employed using a tool such as SAPHIRE [115]. In this same study, an algorithm is developed to calculate the resilience of a system based on the recovery, resistance, and absorption characteristics of the system. This methodology was applied to a power system consisting of a nuclear power plant and a diesel generator. The authors were able to calculate resilience parameters and resilience probabilities of the system with confidence intervals.

Both methods provide a stochastic framework that can be applied to an existing model; however, the simulation approach requires fewer additions and is more straightforward. As further explored in the previous subsection, data to form and populate the fragility curves, time to repair, and time to restore are sparse.

**4.3 Valuing economic consequences and co-optimization**

To incorporate severe weather events into power systems planning optimization models, it is important to think about the unique characteristics associated with these events. Acute weather events put the physical attributes of the power system as well as the economic activity of the affected areas at risk. Given a variety of acute weather events, there are several threats and anticipated impacts to consider. Adapted from [102], Table 1 summarizes the impacts and consequences of acute weather events. The acute weather events considered include droughts, flooding, extreme temperatures (heat waves and freezes), severe storms, wildfires, and winter storms.

Table 1: Summary of the potential risks and consequences associated with acute weather events that could be incorporated into power sector planning tools' optimization framework

|  |  |
| --- | --- |
| **Risk** | **Potential Impacts** |
| Extreme temperatures | * Reduced efficiency * Reduced generation capacity * Reduced transmission capacity * Increased demand |
| Water scarcity | * Reduced generation capacity * Changes in operations   + Especially with coal, natural gas, and nuclear facilities |
| Flooding | * Physical damage * Changes in operations |
| High winds | * Physical damage   + Power line damage and/or failure   + Debris hitting generation, transmission, and/or distribution equipment * High-speed shutoff for wind |
| Variable weather conditions | * Variable resource potential for wind and solar * Reduction in generation capacity |
| Wildfires | * Physical damage   + Power line damage and/or failure * Reduced transmission capacity |

There are examples in the literature calculating the losses attributed to natural disasters [116], [117]. Some of these existing studies are their own models that strictly compute service losses (unmet kWh). Therefore, an important step to incorporating the losses into the optimization is through mapping them to the associated parameters and functions within the model formulation. By establishing these links, a more thorough account of the lost electrical service can be considered by the optimization model. Additionally, some of these losses could be hardcoded into a model instead. Assuming a binary variable indicating whether the system is currently experiencing a weather event, a scaling factor could be initialized to account for the reduction in generation capacity of renewables. Whether it is hardcoded or more in depth integration, this effort will take time to execute. It would be of interest to prioritize the most substantial economic losses first.

Another important component of accounting for the economic consequence is the VoLL. As discussed, the VoLL is a commonly used dynamic metric based on several factors, yet has been arbitrarily assigned in past analyses [45], [98], [99]. A VoLL can be used to translate electric service losses into a dollar value that can be incorporated into the optimization as a cost variable. The more specific a VoLL is to a particular community and/or system, the more accurate the economic consequences of a power outage can be calculated. A common method for determining the VoLL is through customer surveys [77]. In addition to the phrasing of the questions, the results of these surveys vary by location and customer type. As opposed to conducting surveys that fit each criterion, the existing VoLL survey results could be used to inform the VoLL for other scenarios. By aggregating the data collected thus far, along with accompanying characteristics of the surveys and those being surveyed, machine learning techniques could develop a model to predict the VoLL of a given scenario. A similar study was conducted for the calculation of reliability indices [118]. This study contributed to the development of the Interruption Cost Estimator (ICE) calculator which has been used in other journal articles and by reliability planners [100], [119]. This calculator employs a “cost per unserved kW” metric to inform its output. These values are based on the state and the customer composition. If more parameters linked to the system could be included, the values used by the ICE calculator that mimic the VoLL could be more accurate. One way to do this could be through improving the spatial resolution considered and increasing it from U.S. states to U.S. counties. An outage in a county with a higher gross domestic product (GDP) and/or higher distributed energy resources deployment (DER), might experience different economic losses than a power outage in a county with a lower GDP and/or lower DERs deployment [120]. It would also be important to implement approaches that uphold environmental justice principles to maintain equal and fair access to electricity services.

An advantage to valuing economic consequences associated with a power outage is including resilience goals alongside the net-zero goals of a power system in the model formulation. While renewable goals have been at the forefront of power systems planning for some time, resilience goals are still gaining footholds in the decision making process. The significance of net-zero goals and their resultant increase in renewable deployment, has raised into question the implications these goals might have on grid reliability and resilience. Such as reference [103] did for a smaller distribution model, integrating net-zero and resilience constraints into the formulation of a widely used and robustly tested power system optimization model would produce empirical results to inform us how the two interact and how we can co-optimize our power systems planning.

1. **Conclusions**

There has been a growing interest in power system resilience due to a combination of net-zero initiatives on the horizon, the critical importance of the power sector to society, and the increasing frequency and severity of power service disruptions from natural disasters. This article reviews the expanding literature on power system resilience definitions and metrics. By assessing the various components and characteristics important to resilient and renewable systems, techniques for adapting existing power system optimization models are discussed.

Although there have been efforts to incorporate robust resilience considerations in power systems models, there remain limited applications in large models and scenarios. As a result, there are several future areas of interest. There is a need for greater development of performance-based resilience metrics that capture sectoral interdependencies, and applicable economic consequences as well as model formulations that include probability distributions. Understanding these relationships and their value in power system resilience metrics and power system planning optimization models will increase the utility of the outputs. The incorporation of a stochastic framework will simulate robust output and help inform power system planners faced with increased resilience threats, especially uncertain, severe natural disasters. For these models to capture the intricacies of resilience, improved data are needed. To maximize the impact of this work to enhance model capabilities, there should be a concerted emphasis on easily accessible and publicly available data and modelling developments. Additionally, by considering the new resilience goals alongside the pre-existing goals, especially renewable deployment and emissions goals, the grid can be co-optimized for resilience and net-zero considerations, resulting in a more sustainable power system.

Beyond the identified modeling gaps in this paper, there are other avenues for future work. Transmission and distribution system operators could work with material scientists to develop more robust materials for system components such as substations and power lines that can withstand acute weather events while maintaining the necessary level of service. Additionally, more demand response programs could be explored to help offset the potential increase in electric load during acute natural disasters. To establish a manageable workload, it might also be of interest to integrate the losses of one acute weather event at a time. These efforts would contribute directly to the potential improved resilience of a power system and could ultimately be represented in future formulations of power system optimization models. If consequences such as weak physical infrastructure and peak loads can be mitigated, there will be more options for optimization models to consider.

By increasing resilient power systems planning, there can be significant potential to decrease the economic consequences experienced by electricity customers, utilities, and dependent sectors during power outages due to natural disasters. The power system will not only become more resilient, but also well suited to meet net-zero goals.

**Figure Captions**

Figure 1. A resilient power system during a disruption, adapted from [65]

**Acknowledgements:** The authors would like to thank Dr. Bie from Xi-an Jiaotong University for sharing the rights to a figure from their publication “*Battling the Extreme: A Study on the Power System Resilience”.*

**Funding:** This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U. S. Department of Energy (DOE) under Contract No. DE-AC36- 08GO28308. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

1. **References**

[1] “Net Zero by 2050 – Analysis,” *IEA*. https://www.iea.org/reports/net-zero-by-2050 (accessed May 25, 2021).

[2] A. B. Smith and NOAA National Centers For Environmental Information, “U.S. Billion-dollar Weather and Climate Disasters, 1980 - present (NCEI Accession 0209268).” NOAA National Centers for Environmental Information, 2020. doi: 10.25921/STKW-7W73.

[3] “Hurricanes Like Laura Are More Likely Because Of Climate Change,” *NPR.org*. https://www.npr.org/sections/hurricane-laura-live-updates/2020/08/27/906633395/hurricanes-like-laura-are-more-likely-because-of-climate-change (accessed Aug. 28, 2020).

[4] “Hurricane Matthew caused millions of customers to go without power - Today in Energy - U.S. Energy Information Administration (EIA).” https://www.eia.gov/todayinenergy/detail.php?id=28372 (accessed Jul. 07, 2020).

[5] “Hurricane Michael caused 1.7 million electricity outages in the Southeast United States - Today in Energy - U.S. Energy Information Administration (EIA).” https://www.eia.gov/todayinenergy/detail.php?id=37332 (accessed May 01, 2020).

[6] “U.S. customers experienced an average of nearly six hours of power interruptions in 2018 - Today in Energy - U.S. Energy Information Administration (EIA).” https://www.eia.gov/todayinenergy/detail.php?id=43915 (accessed Jun. 22, 2020).

[7] E. Newburger, “‘There are lives at stake’: PG&E criticized over blackouts to prevent California wildfires,” *CNBC*, Oct. 23, 2019. https://www.cnbc.com/2019/10/23/pge-rebuked-over-imposing-blackouts-in-california-to-reduce-fire-risk.html (accessed May 25, 2021).

[8] J. B. February 19 and 2021 97, “The Texas Blackout Is the Story of a Disaster Foretold,” *Texas Monthly*, Feb. 19, 2021. https://www.texasmonthly.com/news-politics/texas-blackout-preventable/ (accessed May 25, 2021).

[9] E. Kabir, S. D. Guikema, and S. M. Quiring, “Predicting Thunderstorm-Induced Power Outages to Support Utility Restoration,” *IEEE Trans. Power Syst.*, vol. 34, no. 6, pp. 4370–4381, Nov. 2019, doi: 10.1109/TPWRS.2019.2914214.

[10] “Transforming our world: the 2030 Agenda for Sustainable Development .:. Sustainable Development Knowledge Platform.” https://sustainabledevelopment.un.org/post2015/transformingourworld (accessed May 21, 2020).

[11] L. Martišauskas, J. Augutis, and R. Krikštolaitis, “Methodology for energy security assessment considering energy system resilience to disruptions,” *Energy Strategy Rev.*, vol. 22, pp. 106–118, Nov. 2018, doi: 10.1016/j.esr.2018.08.007.

[12] I. F. Abdin, Y.-P. Fang, and E. Zio, “A modeling and optimization framework for power systems design with operational flexibility and resilience against extreme heat waves and drought events,” *Renew. Sustain. Energy Rev.*, vol. 112, pp. 706–719, Sep. 2019, doi: 10.1016/j.rser.2019.06.006.

[13] Y.-P. Fang and E. Zio, “An adaptive robust framework for the optimization of the resilience of interdependent infrastructures under natural hazards,” *Eur. J. Oper. Res.*, vol. 276, no. 3, pp. 1119–1136, Aug. 2019, doi: 10.1016/j.ejor.2019.01.052.

[14] “Economic Benefits of Increasing Electric Grid Resilience to Weather Outages,” *Energy.gov*. https://www.energy.gov/downloads/economic-benefits-increasing-electric-grid-resilience-weather-outages (accessed Jun. 09, 2020).

[15] X. Yue, S. Pye, J. DeCarolis, F. G. N. Li, F. Rogan, and B. Ó. Gallachóir, “A review of approaches to uncertainty assessment in energy system optimization models,” *Energy Strategy Rev.*, vol. 21, pp. 204–217, Aug. 2018, doi: 10.1016/j.esr.2018.06.003.

[16] C. S. Holling, “Resilience and Stability of Ecological Systems,” *Annu. Rev. Ecol. Syst.*, vol. 4, no. 1, pp. 1–23, 1973, doi: 10.1146/annurev.es.04.110173.000245.

[17] L. M. Polonenko, M. A. Hamouda, and M. M. Mohamed, “Essential components of institutional and social indicators in assessing the sustainability and resilience of urban water systems: Challenges and opportunities,” *Sci. Total Environ.*, vol. 708, p. 135159, Mar. 2020, doi: 10.1016/j.scitotenv.2019.135159.

[18] C. Folke, “Resilience: The emergence of a perspective for social–ecological systems analyses,” *Glob. Environ. Change*, vol. 16, no. 3, pp. 253–267, Aug. 2006, doi: 10.1016/j.gloenvcha.2006.04.002.

[19] S. Dekker and E. Hollnagel, “Resilience Engineering: New directions for measuring and maintaining safety in complex systems,” May 2020.

[20] J. Ryu, T. M. Leschine, J. Nam, W. K. Chang, and K. Dyson, “A resilience-based approach for comparing expert preferences across two large-scale coastal management programs,” *J. Environ. Manage.*, vol. 92, no. 1, pp. 92–101, Jan. 2011, doi: 10.1016/j.jenvman.2010.08.020.

[21] Y. Hu, “The Modeling, Analysis and Control of Resilient Manufacturing Enterprises,” *Theses Diss.--Electr. Comput. Eng.*, Jan. 2013, [Online]. Available: https://uknowledge.uky.edu/ece\_etds/15

[22] L. Molyneaux, C. Brown, L. Wagner, and J. Foster, “Measuring resilience in energy systems: Insights from a range of disciplines,” *Renew. Sustain. Energy Rev.*, vol. 59, pp. 1068–1079, Jun. 2016, doi: 10.1016/j.rser.2016.01.063.

[23] “Presidential Policy Directive -- Critical Infrastructure Security and Resilience,” *whitehouse.gov*, Feb. 12, 2013. https://obamawhitehouse.archives.gov/the-press-office/2013/02/12/presidential-policy-directive-critical-infrastructure-security-and-resil (accessed May 21, 2020).

[24] V. Proag, “The Concept of Vulnerability and Resilience,” *Procedia Econ. Finance*, vol. 18, pp. 369–376, Jan. 2014, doi: 10.1016/S2212-5671(14)00952-6.

[25] “AR5 Synthesis Report: Climate Change 2014 — IPCC.” https://www.ipcc.ch/report/ar5/syr/ (accessed May 22, 2020).

[26] D. D. Woods, “Four concepts for resilience and the implications for the future of resilience engineering,” *Reliab. Eng. Syst. Saf.*, vol. 141, pp. 5–9, Sep. 2015, doi: 10.1016/j.ress.2015.03.018.

[27] “Conceptual Framework for Developing Resilience Metrics for the Electricity, Oil, and Gas Sectors in the United States (September 2015),” *Energy.gov*. https://www.energy.gov/oe/downloads/conceptual-framework-developing-resilience-metrics-electricity-oil-and-gas-sectors (accessed Sep. 03, 2020).

[28] S. Meerow, J. P. Newell, and M. Stults, “Defining urban resilience: A review,” *Landsc. Urban Plan.*, vol. 147, pp. 38–49, Mar. 2016, doi: 10.1016/j.landurbplan.2015.11.011.

[29] M. Ouyang, “A mathematical framework to optimize resilience of interdependent critical infrastructure systems under spatially localized attacks,” *Eur. J. Oper. Res.*, vol. 262, no. 3, pp. 1072–1084, Nov. 2017, doi: 10.1016/j.ejor.2017.04.022.

[30] S. Moslehi and T. A. Reddy, “Sustainability of integrated energy systems: A performance-based resilience assessment methodology,” *Appl. Energy*, vol. 228, pp. 487–498, Oct. 2018, doi: 10.1016/j.apenergy.2018.06.075.

[31] “Resilience Roadmap.” https://www.nrel.gov/resilience-planning-roadmap/ (accessed Aug. 11, 2020).

[32] J. Zhou, S. Tsianikas, D. P. Birnie, and D. W. Coit, “Economic and resilience benefit analysis of incorporating battery storage to photovoltaic array generation,” *Renew. Energy*, vol. 135, pp. 652–662, May 2019, doi: 10.1016/j.renene.2018.12.013.

[33] “Grid Modernization: Metrics Analysis (GMLC1.1) Resilience | Grid Modernization Lab Consortium.” https://gmlc.doe.gov/resources/grid-modernization-metrics-analysis-gmlc1.1-resilience (accessed Jun. 24, 2020).

[34] “Solving the Climate Crisis: The Congressional Action Plan for a Clean Energy Economy and a Healthy and Just America,” *Select Committee on Climate Crisis*, Jun. 29, 2020. https://climatecrisis.house.gov/report (accessed Aug. 13, 2020).

[35] Y. Y. Haimes, “On the Definition of Resilience in Systems,” *Risk Anal.*, vol. 29, no. 4, pp. 498–501, 2009, doi: 10.1111/j.1539-6924.2009.01216.x.

[36] “A resilience assessment framework for infrastructure and economic systems: Quantitative and qualitative resilience analysis of petrochemical supply chains to a hurricane - Vugrin - 2011 - Process Safety Progress - Wiley Online Library.” https://aiche.onlinelibrary.wiley.com/doi/full/10.1002/prs.10437?casa\_token=ASlLnO33pCUAAAAA%3AF2jNq4mHC1erL97BybxLNOwqTKuXUb6761mBOmAMw9zS6OlIfaDEYUq0VrdBSXYxvL5OTd42Fqjm (accessed May 28, 2020).

[37] R. Neches, “Engineered Resilient Systems (ERS) S&T Priority Description and Roadmap,” OFFICE OF THE DEPUTY ASSISTANT SECRETARY OF DEFENSE FOR SYSTEMS ENGINEERING WASHINGTON DC, Nov. 2011. Accessed: Aug. 13, 2020. [Online]. Available: https://apps.dtic.mil/sti/citations/ADA554841

[38] S. R. Goerger, A. M. Madni, and O. J. Eslinger, “Engineered Resilient Systems: A DoD Perspective,” *Procedia Comput. Sci.*, vol. 28, pp. 865–872, Jan. 2014, doi: 10.1016/j.procs.2014.03.103.

[39] D. Freckleton, K. Heaslip, W. Louisell, and J. Collura, “Evaluation of Resiliency of Transportation Networks after Disasters:,” *Transp. Res. Rec.*, Jan. 2012, doi: 10.3141/2284-13.

[40] A. Alessandri and R. Filippini, “Evaluation of Resilience of Interconnected Systems Based on Stability Analysis,” in *Critical Information Infrastructures Security*, Berlin, Heidelberg, 2013, pp. 180–190. doi: 10.1007/978-3-642-41485-5\_16.

[41] F. Gracceva and P. Zeniewski, “A systemic approach to assessing energy security in a low-carbon EU energy system,” *Appl. Energy*, vol. 123, pp. 335–348, Jun. 2014, doi: 10.1016/j.apenergy.2013.12.018.

[42] S. Espinoza, M. Panteli, P. Mancarella, and H. Rudnick, “Multi-phase assessment and adaptation of power systems resilience to natural hazards,” *Electr. Power Syst. Res.*, vol. 136, pp. 352–361, Jul. 2016, doi: 10.1016/j.epsr.2016.03.019.

[43] R. Arghandeh, A. von Meier, L. Mehrmanesh, and L. Mili, “On the definition of cyber-physical resilience in power systems,” *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1060–1069, May 2016, doi: 10.1016/j.rser.2015.12.193.

[44] J. Glynn, A. Chiodi, and B. Ó Gallachóir, “Energy security assessment methods: Quantifying the security co-benefits of decarbonising the Irish Energy System,” *Energy Strategy Rev.*, vol. 15, pp. 72–88, Mar. 2017, doi: 10.1016/j.esr.2016.11.005.

[45] K. Anderson *et al.*, “Quantifying and Monetizing Renewable Energy Resiliency,” *Sustainability*, vol. 10, no. 4, p. 933, Mar. 2018, doi: 10.3390/su10040933.

[46] G. Quitana, M. Molinos-Senante, and A. Chamorro, “Resilience of critical infrastructure to natural hazards: A review focused on drinking water systems,” *Int. J. Disaster Risk Reduct.*, vol. 48, p. 101575, Sep. 2020, doi: 10.1016/j.ijdrr.2020.101575.

[47] C. P. Roberts, D. Twidwell, D. G. Angeler, and C. R. Allen, “How do ecological resilience metrics relate to community stability and collapse?,” *Ecol. Indic.*, vol. 107, p. 105552, Dec. 2019, doi: 10.1016/j.ecolind.2019.105552.

[48] Y. Qiang, Q. Huang, and J. Xu, “Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster,” *Sustain. Cities Soc.*, vol. 57, p. 102115, Jun. 2020, doi: 10.1016/j.scs.2020.102115.

[49] C. C. Abenayake, Y. Mikami, Y. Matsuda, and A. Jayasinghe, “Ecosystem services-based composite indicator for assessing community resilience to floods,” *Environ. Dev.*, vol. 27, pp. 34–46, Sep. 2018, doi: 10.1016/j.envdev.2018.08.002.

[50] K. A. Foster, “A Case Study Approachto Understanding Regional Resilience,” *undefined*, 2006. /paper/A-Case-Study-Approachto-Understanding-Regional-Foster/28fa17bc5d7e8677766233e7a3fee844e6fe2789 (accessed Aug. 11, 2020).

[51] A. Asadzadeh, T. Kötter, and E. Zebardast, “An augmented approach for measurement of disaster resilience using connective factor analysis and analytic network process (F’ANP) model,” *Int. J. Disaster Risk Reduct.*, vol. 14, pp. 504–518, Dec. 2015, doi: 10.1016/j.ijdrr.2015.10.002.

[52] O. Ladipo, G. Reichard, A. McCoy, A. Pearce, P. Knox, and M. Flint, “Attributes and metrics for comparative quantification of disaster resilience across diverse performance mandates and standards of building,” *J. Build. Eng.*, vol. 21, pp. 446–454, Jan. 2019, doi: 10.1016/j.jobe.2018.11.007.

[53] J. Johnson, M. Panagioti, J. Bass, L. Ramsey, and R. Harrison, “Resilience to emotional distress in response to failure, error or mistakes: A systematic review,” *Clin. Psychol. Rev.*, vol. 52, pp. 19–42, Mar. 2017, doi: 10.1016/j.cpr.2016.11.007.

[54] K. M. Connor and J. R. T. Davidson, “Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC),” *Depress. Anxiety*, vol. 18, no. 2, pp. 76–82, 2003, doi: 10.1002/da.10113.

[55] A. S. Masten and J. L. Powell, “A resilience framework for research, policy, and practice,” in *Resilience and vulnerability: Adaptation in the context of childhood adversities*, New York, NY, US: Cambridge University Press, 2003, pp. 1–25. doi: 10.1017/CBO9780511615788.003.

[56] J. Gerhart, S. O’Mahony, I. Abrams, J. Grosse, M. Greene, and M. Levy, “A pilot test of a mindfulness-based communication training to enhance resilience in palliative care professionals,” *J. Context. Behav. Sci.*, vol. 5, no. 2, pp. 89–96, Apr. 2016, doi: 10.1016/j.jcbs.2016.04.003.

[57] S. Yoon *et al.*, “Defining resilience in maltreated children from the practitioners’ perspectives: A qualitative study,” *Child Abuse Negl.*, vol. 106, p. 104516, Aug. 2020, doi: 10.1016/j.chiabu.2020.104516.

[58] L. J. Thomas and S. H. Revell, “Resilience in nursing students: An integrative review,” *Nurse Educ. Today*, vol. 36, pp. 457–462, Jan. 2016, doi: 10.1016/j.nedt.2015.10.016.

[59] E. Hollnagel, *Safety-II in Practice: Developing the Resilience Potentials*. Taylor & Francis, 2017.

[60] J. Renne, B. Wolshon, P. Murray-Tuite, and A. Pande, “Emergence of resilience as a framework for state Departments of Transportation (DOTs) in the United States,” *Transp. Res. Part Transp. Environ.*, vol. 82, p. 102178, May 2020, doi: 10.1016/j.trd.2019.11.007.

[61] M. C. W. Kintner-Meyer, J. S. Homer, P. J. Balducci, and M. R. Weimar, “Valuation of Electric Power System Services and Technologies,” Pacific Northwest National Lab. (PNNL), Richland, WA (United States), PNNL-25633, Aug. 2017. doi: 10.2172/1393762.

[62] M. Mahzarnia, M. Moghaddam, P. Teimourzadeh Baboli, and P. Siano, “A Review of the Measures to Enhance Power Systems Resilience,” *IEEE Syst. J.*, vol. PP, pp. 1–12, Jan. 2020, doi: 10.1109/JSYST.2020.2965993.

[63] M. Panteli and P. Mancarella, “Modeling and Evaluating the Resilience of Critical Electrical Power Infrastructure to Extreme Weather Events,” *IEEE Syst. J.*, vol. 11, no. 3, pp. 1733–1742, Sep. 2017, doi: 10.1109/JSYST.2015.2389272.

[64] Department of Energy, “Valuation of Energy Security for the United States, Report to Congress,” United States. Department of Energy, Article, Jan. 2017. Accessed: Dec. 15, 2020. [Online]. Available: https://www.hsdl.org/?abstract&did=

[65] 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, doi: 10.1109/JPROC.2017.2679040.

[66] M. Panteli, C. Pickering, S. Wilkinson, R. Dawson, and P. Mancarella, “Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures,” *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3747–3757, Sep. 2017, doi: 10.1109/TPWRS.2016.2641463.

[67] D. N. Trakas and N. D. Hatziargyriou, “Optimal Distribution System Operation for Enhancing Resilience Against Wildfires,” *IEEE Trans. Power Syst.*, vol. 33, no. 2, pp. 2260–2271, Mar. 2018, doi: 10.1109/TPWRS.2017.2733224.

[68] M. Buinevich and A. Vladyko, “Forecasting Issues of Wireless Communication Networks’ Cyber Resilience for An Intelligent Transportation System: An Overview of Cyber Attacks,” *Information*, vol. 10, no. 1, Art. no. 1, Jan. 2019, doi: 10.3390/info10010027.

[69] M. Panteli and P. Mancarella, “Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies,” *Electr. Power Syst. Res.*, vol. 127, pp. 259–270, Oct. 2015, doi: 10.1016/j.epsr.2015.06.012.

[70] “A comparative overview of resilience measurement frameworks: analysing indicators and approaches,” *ODI*. https://www.odi.org/publications/9632-comparative-overview-resilience-measurement-frameworks-analysing-indicators-and-approaches (accessed Dec. 15, 2020).

[71] E. Vugrin, A. Castillo, and C. Silva-Monroy, *Resilience Metrics for the Electric Power System: A Performance-Based Approach (Technical Report No*. Issues SAND2017-1493, 2017. [Online]. Available: http://prod.sandia.gov/techlib/access-control.cgi/2017/171493.pdf

[72] C. Wang, P. Ju, S. Lei, Z. Wang, F. Wu, and Y. Hou, “Markov Decision Process-Based Resilience Enhancement for Distribution Systems: An Approximate Dynamic Programming Approach,” *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2498–2510, May 2020, doi: 10.1109/TSG.2019.2956740.

[73] X. Bai, L. Liang, and X. Zhu, “Improved Markov-chain-based ultra-short-term PV forecasting method for enhancing power system resilience,” *J. Eng.*, vol. n/a, no. n/a, doi: https://doi.org/10.1049/tje2.12015.

[74] Federal Energy Regulatory Commission, “Report on the FERC-NERC-Regional Entity Joint Review of Restoration and Recovery Plans, Recommended Study: Blackstart Resources Availability,” North American Electric Reliability Corporation, Atlanta, 2018.

[75] E. National Academies of Sciences, *Enhancing the Resilience of the Nation’s Electricity System*. 2017. doi: 10.17226/24836.

[76] North American Electric Reliability Corporation, “Polar Vortex Review,” North American Electric Reliability Corporation, Atlanta, 2014.

[77] L. Lawton, M. Sullivan, K. Van Liere, A. Katz, and J. Eto, “A framework and review of customer outage costs: Integration and analysis of electric utility outage cost surveys,” Lawrence Berkeley National Lab. (LBNL), Berkeley, CA (United States), LBNL-54365, Nov. 2003. doi: 10.2172/821654.

[78] W. Rickerson, J. Gillis, and M. Bulkeley, “The Value of Resilience for Distributed Energy Resources: An Overview of Current Analytical Practices,” *Microgrid Knowledge*, 2019. https://microgridknowledge.com/white-paper/value-resilience-distributed-energy-resources/ (accessed Jun. 22, 2020).

[79] M. Sullivan, J. Schellenberg, and M. Blundell, “Updated Value of Service Reliability Estimates for Electric Utility Customers in the United States,” 2015.

[80] T. Schröder and W. Kuckshinrichs, “Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review,” *Front. Energy Res.*, vol. 3, 2015, doi: 10.3389/fenrg.2015.00055.

[81] E. Leahy and R. S. J. Tol, “An estimate of the value of lost load for Ireland,” *Energy Policy*, vol. 39, no. 3, pp. 1514–1520, Mar. 2011, doi: 10.1016/j.enpol.2010.12.025.

[82] A. Shivakumar *et al.*, “Valuing blackouts and lost leisure: Estimating electricity interruption costs for households across the European Union,” *Energy Res. Soc. Sci.*, vol. 34, pp. 39–48, Dec. 2017, doi: 10.1016/j.erss.2017.05.010.

[83] A. J. Praktiknjo, “Stated preferences based estimation of power interruption costs in private households: An example from Germany,” *Energy*, vol. 76, pp. 82–90, Nov. 2014, doi: 10.1016/j.energy.2014.03.089.

[84] S. Küfeoğlu and M. Lehtonen, “Interruption costs of service sector electricity customers, a hybrid approach,” *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 588–595, Jan. 2015, doi: 10.1016/j.ijepes.2014.07.046.

[85] R. Eskandarpour, A. Khodaei, A. Paaso, and N. M. Abdullah, “Artificial Intelligence Assisted Power Grid Hardening in Response to Extreme Weather Events,” *ArXiv181002866 Cs Eess*, Oct. 2018, Accessed: Jun. 17, 2021. [Online]. Available: http://arxiv.org/abs/1810.02866

[86] S. (ORCID:0000000241999215) Ericson and L. Lisell, “A flexible framework for modeling customer damage functions for power outages,” *Energy Syst.*, vol. 11, no. 1, Art. no. NREL/JA-6A50-71904, Nov. 2018, doi: 10.1007/s12667-018-0314-8.

[87] G. Fu *et al.*, “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, doi: 10.1109/JSYST.2017.2700791.

[88] J. Arteaga and H. Zareipour, “A Price-Maker/Price-Taker Model for the Operation of Battery Storage Systems in Electricity Markets,” *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6912–6920, Nov. 2019, doi: 10.1109/TSG.2019.2913818.

[89] R. Billinton and K. E. Bollinger, “Transmission System Reliability Evaluation Using Markov Processes,” *IEEE Trans. Power Appar. Syst.*, vol. PAS-87, no. 2, pp. 538–547, Feb. 1968, doi: 10.1109/TPAS.1968.292051.

[90] P. Wang and R. Billinton, “Reliability Cost/Worth Assessment of Distribution Systems Incorporating Time Varying Weather Conditions and Restoration Resources,” *IEEE Power Eng. Rev.*, vol. 21, no. 11, pp. 63–63, Nov. 2001, doi: 10.1109/MPER.2001.4311187.

[91] S. E. Chang and M. Shinozuka, “Measuring Improvements in the Disaster Resilience of Communities,” *Earthq. Spectra*, vol. 20, no. 3, pp. 739–755, Aug. 2004, doi: 10.1193/1.1775796.

[92] M. Ouyang, L. Dueñas-Osorio, and X. Min, “A three-stage resilience analysis framework for urban infrastructure systems,” *Struct. Saf.*, vol. 36–37, pp. 23–31, May 2012, doi: 10.1016/j.strusafe.2011.12.004.

[93] F. Cadini, G. L. Agliardi, and E. Zio, “A modeling and simulation framework for the reliability/availability assessment of a power transmission grid subject to cascading failures under extreme weather conditions,” *Appl. Energy*, vol. 185, pp. 267–279, Jan. 2017, doi: 10.1016/j.apenergy.2016.10.086.

[94] G. Li *et al.*, “Risk Analysis for Distribution Systems in the Northeast U.S. Under Wind Storms,” *IEEE Trans. Power Syst.*, vol. 29, no. 2, pp. 889–898, Mar. 2014, doi: 10.1109/TPWRS.2013.2286171.

[95] R. Rocchetta, E. Zio, and E. Patelli, “A power-flow emulator approach for resilience assessment of repairable power grids subject to weather-induced failures and data deficiency,” *Appl. Energy*, vol. 210, pp. 339–350, Jan. 2018, doi: 10.1016/j.apenergy.2017.10.126.

[96] H.-K. Ringkjøb, P. M. Haugan, and I. M. Solbrekke, “A review of modelling tools for energy and electricity systems with large shares of variable renewables,” *Renew. Sustain. Energy Rev.*, vol. 96, pp. 440–459, Nov. 2018, doi: 10.1016/j.rser.2018.08.002.

[97] E. Elgqvist, “REopt Lite Web Tool: Capabilities and Features,” p. 30.

[98] T. Schröder and W. Kuckshinrichs, “Value of Lost Load: An Efficient Economic Indicator for Power Supply Security? A Literature Review,” *Front. Energy Res.*, vol. 3, 2015, doi: 10.3389/fenrg.2015.00055.

[99] M. Stadler *et al.*, “Value streams in microgrids: A literature review,” *Appl. Energy*, vol. 162, pp. 980–989, Jan. 2016, doi: 10.1016/j.apenergy.2015.10.081.

[100] A. J. Harker Steele, J. W. Burnett, and J. C. Bergstrom, “The impact of variable renewable energy resources on power system reliability,” *Energy Policy*, vol. 151, p. 111947, Apr. 2021, doi: 10.1016/j.enpol.2020.111947.

[101] N. D. Laws, K. Anderson, N. A. DiOrio, X. Li, and J. McLaren, “Impacts of valuing resilience on cost-optimal PV and storage systems for commercial buildings,” *Renew. Energy*, vol. 127, pp. 896–909, Nov. 2018, doi: 10.1016/j.renene.2018.05.011.

[102] M. (ORCID:0000000233190846) Dumas, B. (ORCID:0000000161265369) Kc, and C. I. Cunliff, “Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods,” Oak Ridge National Lab. (ORNL), Oak Ridge, TN (United States), ORNL/TM-2019/1252, Aug. 2019. doi: 10.2172/1558514.

[103] Q. Zhang, Z. Wang, S. Ma, and A. Arif, “Stochastic pre-event preparation for enhancing resilience of distribution systems,” *Renew. Sustain. Energy Rev.*, vol. 152, p. 111636, Dec. 2021, doi: 10.1016/j.rser.2021.111636.

[104] “Is Renewable Energy the Definition of Resilience?,” *REN21*, Jun. 03, 2020. https://www.ren21.net/renewable-energy-resilient/ (accessed Jul. 28, 2021).

[105] “Ask an Expert: How is the Western U.S. Drought Impacting the Power Grid?,” *College of Natural Resources News*, Jun. 11, 2021. https://cnr.ncsu.edu/news/2021/06/ask-an-expert-how-is-the-western-u-s-drought-impacting-the-power-grid/ (accessed Jul. 29, 2021).

[106] J. A. McLaren, S. Mullendore, N. D. Laws, and K. H. Anderson, “Valuing the Resilience Provided by Solar and Battery Energy Storage Systems,” National Renewable Energy Lab. (NREL), Golden, CO (United States), NREL/BR-6A20-70679, Feb. 2018. Accessed: Jul. 28, 2021. [Online]. Available: https://www.osti.gov/biblio/1420058-valuing-resilience-provided-solar-battery-energy-storage-systems

[107] B. Cai, M. Xie, Y. Liu, Y. Liu, and Q. Feng, “Availability-based engineering resilience metric and its corresponding evaluation methodology,” *Reliab. Eng. Syst. Saf.*, vol. 172, pp. 216–224, Apr. 2018, doi: 10.1016/j.ress.2017.12.021.

[108] S. L. Cutter, C. G. Burton, and C. T. Emrich, “Disaster Resilience Indicators for Benchmarking Baseline Conditions,” *J. Homel. Secur. Emerg. Manag.*, vol. 7, no. 1, Jan. 2010, doi: 10.2202/1547-7355.1732.

[109] Y.-P. Fang, N. Pedroni, and E. Zio, “Resilience-Based Component Importance Measures for Critical Infrastructure Network Systems,” *IEEE Trans. Reliab.*, vol. 65, no. 2, pp. 502–512, Jun. 2016, doi: 10.1109/TR.2016.2521761.

[110] D. Henry and J. Emmanuel Ramirez-Marquez, “Generic metrics and quantitative approaches for system resilience as a function of time,” *Reliab. Eng. Syst. Saf.*, vol. 99, pp. 114–122, Mar. 2012, doi: 10.1016/j.ress.2011.09.002.

[111] A. R. de Queiroz *et al.*, “Repurposing an energy system optimization model for seasonal power generation planning,” *Energy*, vol. 181, pp. 1321–1330, Aug. 2019, doi: 10.1016/j.energy.2019.05.126.

[112] S. Hallegatte, “Strategies to adapt to an uncertain climate change,” *Glob. Environ. Change*, vol. 19, no. 2, pp. 240–247, May 2009, doi: 10.1016/j.gloenvcha.2008.12.003.

[113] Z. Zeng, Y.-P. Fang, Q. Zhai, and S. Du, “A Markov reward process-based framework for resilience analysis of multistate energy systems under the threat of extreme events,” *Reliab. Eng. Syst. Saf.*, vol. 209, p. 107443, May 2021, doi: 10.1016/j.ress.2021.107443.

[114] “NC DEQ: NC Climate Risk Assessment and Resilience Plan.” https://deq.nc.gov/energy-climate/climate-change/nc-climate-change-interagency-council/climate-change-clean-energy-17 (accessed Jan. 19, 2021).

[115] “SAPHIRE | Home.” https://saphire.inl.gov/#/ (accessed Apr. 02, 2021).

[116] T. Yabe, Y. Zhang, and S. V. Ukkusuri, “Quantifying the economic impact of disasters on businesses using human mobility data: a Bayesian causal inference approach,” *EPJ Data Sci.*, vol. 9, no. 1, Art. no. 1, Dec. 2020, doi: 10.1140/epjds/s13688-020-00255-6.

[117] W. J. W. Botzen, O. Deschenes, and M. Sanders, “The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies,” *Rev. Environ. Econ. Policy*, vol. 13, no. 2, pp. 167–188, Jul. 2019, doi: 10.1093/reep/rez004.

[118] M. Sullivan, M. Mercurio, and J. Schellenberg, “Estimated Value of Service Reliability for Electric Utility Customers in the United States,” 2009.

[119] “Power Outages in NOLA: The Problem, Implications, Solutions, and Moving Forward,” *Alliance for Affordable Energy*. http://www.all4energy.org/2/post/2019/06/power-outages-in-nola-the-problem-implications-solutions-and-moving-forward.html (accessed Sep. 07, 2021).

[120] “U.S. Bureau of Economic Analysis (BEA).” https://www.bea.gov/ (accessed Oct. 01, 2021).

[121] Q. Tong, M. Yang, and A. Zinetullina, “A Dynamic Bayesian Network-based approach to Resilience Assessment of Engineered Systems,” *J. Loss Prev. Process Ind.*, vol. 65, p. 104152, May 2020, doi: 10.1016/j.jlp.2020.104152.

**Supplemental Information:**

SI-Table 1. Definitions of resilience

|  |  |  |
| --- | --- | --- |
| **Discipline** | **Year** | **Definition** |
| General/other resilience | 1973 | “a measure of the persistence of systems and of their ability to absorb change and disturbance and still maintain the same relationships between populations or state variables” [16] |
| 2006 | “the capacity of the system to absorb disturbance and re-organize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks” [17], [18] |
| 2008 | the ability “to adjust its functioning prior to, during, or following changes and disturbances, so that it can continue to perform as required after a disruption or a major mishap, and in the presence of continuous stresses” [19] |
| 2011 | “the capacity to absorb shocks while maintaining system functions” and “the capacity for renewal, re-organization and development, should the system collapse” [20] |
| 2012 | “the ability to absorb shocks and still retain function” [22] |
| 2013 | “the ability to withstand [a] disruption and operate smoothly in a volatile environment” [21] |
| 2013 | “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions, resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents” [23] |
| 2014 | “the direct strength of structures or institutions when placed under pressure” and the “ability of systems to absorb and recover from the impact of disruptive events without fundamental changes in function or structure” [24] |
| 2014 | “the capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganizing in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning, and transformation” [25] |
| 2015 | “the rebound from trauma and return to equilibrium, synonym for robustness, opposite of brittleness, network architectures that can sustain the ability to adapt to future surprises as conditions evolve” [26] |
| 2015 | “the ability to prepare for and adapt to changing conditions and withstand and recover rapidly from disruptions… [including] deliberate attacks, accidents, or naturally occurring threats or incidents” [27] |
| 2016 | “the ability of an urban system-and all its constituent socio-ecological and socio-technical networks across temporal and spatial scales-to maintain or rapidly return to desired functions in the face of a disturbance, to adapt to change, and to quickly transform systems that limit current or future adaptive capacity” [28] |
| 2016 | “withstand and recover quickly from extreme external events such as natural disasters, maintain system operations during an extreme external disruption, return the system to normal operation following a disruption” [61] |
| 2017 | “the capability of a system to withstand internal/external stresses and recover from them” [29] |
| 2018 | “the ability of the system to meet as much of its intended functionalities as possible when interrupted by either external or internal disruptions” [30] |
| 2019 | “the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions through adaptable and holistic planning and technical solutions” [31] |
| 2019 | “the ability of a system to withstand or quickly return to normal condition after the occurrence of an event that disrupts its state” [32] |
| 2020 | “the ability of an individual or a system to adapt to and recover from external shocks or stresses” [48] |
|  | 2020 | “the ability to prepare for an adapt to changing conditions and withstand and recover rapidly from disruptions, including the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents” [33] |
|  | 2020 | “the capability to anticipate, prepare for, respond to, and recover from significant multi-hazard threats with minimum damage to social well-being, health, and the environment” [34] |
|  | 2020 | “the ability of a system to predict a rare disastrous event, withstand or absorb it, to adapt to its consequences, and quickly recover its performance to an acceptable level after facing such an event” [62] |
| Critical infrastructure and system resilience | 2009 | “the ability of systems to withstand a major disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks” [35] |
| 2011 | “given the occurrence of a particular disruptive event, the resilience of a system to that event is the ability to reduce efficiently both the magnitude and duration of the deviation from targeted system performance levels” [36] |
| 2011 | “trusted and effective out of the box in a wide range of contexts, easily adapted to many others through reconfiguration or replacement, with graceful and detectable degradation of function” [37], [38] |
| 2012 | “the ability for a transportation network to absorb disruptive events gracefully and return itself to a level of service equal to or greater than the predisruption level of service within a reasonable time frame” [39] |
| 2013 | “the ability to resist to internal drift and cascading failures, and recover back to the initial operation state” [40] |
| 2014 | An energy system that “can source alternative modes of production or consumption in response to sudden and transient shocks…the ability of the system to tolerate and absorb change” [41] |
| 2015 | “the ability of a power system to withstand extraordinary and high impact-low probability events such as due to extreme weather, rapidly recover from such disruptive events, and absorb lessons for adapting its operation and structure to prevent or mitigate the impact of similar events in the future” [69] |
| 2016 | “the ability of a power system to withstand the initial shock, rapidly recover from the disruptive event, and apply adaptation measures for mitigating the impact of similar events in the future” [42] |
| 2016 | a “system’s ability to maintain continuous electricity flow to customers given a certain load prioritization scheme, [respond] to cyber-physical disturbances in real-time or semi real-time, avoiding interruptions of critical services, [alter] its structure, loads and resources in an agile way” [43] |
| 2017 | “the absence of, protection from, or adaptability to threats that are caused by or have impact on the [system]” [44] |
| 2018 | the “ability [of the system] to withstand extraordinary and high-impact, low-probability events that may have never been experienced before, rapidly recover from such disruptive events, and adapt its operation and structure to prevent or mitigate the impact of similar events in the future” [67] |
| 2018 | “preventing power disruption and restoring electricity supply as quickly as possible when an outage does occur, while mitigating the consequences of the outage” [45] |
| 2020 | “[the ability] to ensure…systems are able to withstand extreme weather events resulting from climate change, terrorism, cyber-attacks and again infrastructure” [60] |
| 2020 | the infrastructure’s behavior and level of service during a disruptive event and subsequent recovery process measured in terms of robustness, redundancy, adaptability, reliability, rapidity, and resourcefulness [46] |
| 2020 | “a power system [that] can recover itself using minimum human interventions as quickly as possible” [62] |
| 2020 | “the probability of a systems functionality state sustaining a high state or restoring to a high state from a low state during and after the occurrence of disruptions in the operation of a system within a specific time” [121] |
| Disaster resilience | 2006 | “the ability of a region to anticipate, prepare for, respond to and recover from a disturbance” [50] |
| 2015 | “the ability of a system, community or society to resist, mitigate, respond and recover from the effects of a hazard/shock in an efficient way and timely manner” [51] |
| 2019 | “functionality prior to, before, and after a natural hazard event, as well as the time it takes to recover functionality” [52] |
| Community resilience | 2018 | “the ability of a socio-ecological system to survive the disturbances, reorganize into a desirable functional system, and anticipate trajectories and strengthen adaptive capacity to floods” [49] |
| 2020 | “the ability to absorb/resist/withstand disturbance and the ability to respond/recover/restore the acceptable level of functioning and structure” [48] |
| Psychological and healthcare resilience | 2003 | “the personal qualities that enable one to thrive in the face of adversity” [54] |
| 2003 | “patterns of positive adaptation in the context of significant risk or adversity” [55] |
| 2016 | “mindfully disengaging from aversive traumatic events to replenish depleted resources such as arrest and social support, and limit exposure to further trauma” [56] |
| 2018 | “the ability to sustain everyday operations under anticipated and unanticipated conditions” [59] |
| 2020 | “surviving, thriving, [persevering] reconciling and integrating traumatic experiences into healthy identity development, and advocating for self [following adversity]” [57] |

1. Corresponding author [↑](#footnote-ref-1)