Measuring and Valuing Resilience: A Literature Review for the Power Sector

Laura Leddy, Donald Jenket, Dana-Marie Thomas, Sean Ericson, Jordan Cox, Nicholas Grue, and Eliza Hotchkiss

National Renewable Energy Laboratory

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List of Acronyms

CCF	common cause failure
CDF	customer damage function
CELID	Customers Experiencing Long Interruption Durations
DOE	U.S. Department of Energy
FEMA	Federal Emergency Management Agency
IEEE	Institute of Electrical and Electronics Engineers
LOLE	loss of load expectation
LOPA	layer-of-protection analysis
MW	megawatts
MWh	megawatt hours
NREL	National Renewable Energy Laboratory
NYSERDA	New York State Energy Research and Development Authority
PRA	probabilistic risk assessment
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
VoLL	value of lost load

Executive Summary

Improving the ability of power systems to remain operational during disruptive natural or human-caused events is vital to maintaining the safety of the communities these systems serve. The ability of power systems to maintain operations during disruptions is the benefit of increased energy resilience. To achieve greater electric power sector resilience, we must understand what energy resilience means in the context of our electricity grids and infrastructure systems. The National Renewable Energy Laboratory (NREL) has defined resilience as "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" (Hotchkiss and Dane 2019), which builds upon the definition of resilience in Presidential Policy Directive-21 (White House 2013). NREL emphasizes planning and technical solutions in part to think more holistically about resilience strategies that include training and operations as well as system design and built infrastructure investments.

The New York State Energy Research and Development Authority (NYSERDA) has partnered with NREL to help address key research needs for New York State in advancing power sector resilience. NYSERDA requested a literature review specifically focused on measuring and valuing energy resilience to identify existing work and research gaps that could inform NYSERDA's energy resilience efforts. While the costs of resilience investments are relatively well known, it is also important to adequately convey the benefits of those investments. This often means assigning metrics and estimating the dollar value of potential resilience enhancements.

Key findings from the literature include:

- Resilience and reliability are interrelated concepts, with resilience as the higher-level concept that includes and extends reliability. Reliability typically deals with routine, shorter-term events, while resilience extends the focus to low-probability, high-consequence disruptions.
- Resilience metrics are in their nascent stage, and there is currently no one-size-fits-all resilience measurement. At a high level, resilience metrics can be categorized as either attribute-based or performance-based. Attribute-based metrics describe the characteristics that make a system more resilient (e.g., robustness, resourcefulness, redundancy), and performance-based metrics typically seek to quantify the impacts of potential resilience investments on system performance (e.g., how much energy demand went unserved, for how long). Consequence-focused metrics are a subset of performance-based metrics that focus on the outcomes or consequences of a disruptive event.
- A variety of methodologies can be used to assess resilience enhancement strategies, including N plus M redundancy (where N represents the minimum number of independent components needed to operate and M the number of redundant components kept available to replace the failure of a component N), network-based methods, layer of protection analysis, and probabilistic risk assessment (PRA).
- There are several methods for monetizing resilience by estimating the dollar value of potential resilience enhancements. Economic valuation methods include the value of lost load (VoLL), customer damage functions (CDFs) (which build on the VoLL methodology), and cost-benefit analyses. Social metrics (such as loss of life, hospitalizations, and loss of economic stability) are a complementary category to economic, consequence-focused metrics in trying to capture the full effect of disruptive events on communities.

This document summarizes the current baseline of literature related to energy resilience metrics and valuation techniques. As this is a dynamic topic of research, however, this review necessarily provides a snapshot of current research as of mid 2023. This paper focuses on energy resilience; the rest of the document uses the term "resilience" as interdependent systems are a key consideration for resilience strategies.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Scope and Purpose

The objective of this paper is to review the existing literature on defining, measuring, valuing, and pricing resilience. Reviewing the literature establishes a foundation for better understanding the current landscape of research related to measuring and quantifying the benefits of resilience investments, and also identifying existing gaps in research. Conducting a landscape survey of available resilience valuation methodologies also provides a stronger basis for analyzing measures to strengthen the resilience of communities. With an expanding ability to measure and value resilience comes the potential for new products, processes, services, and tools that can strengthen the ability of energy systems, the built environment, and communities to prepare for and withstand both climate-induced disturbances and other types of disruptive events.

As a U.S. Department of Energy (DOE) national laboratory, the National Renewable Energy Laboratory (NREL) has a strong history of conducting comprehensive resilience assessments and related research. For the last 15 years, NREL has worked with communities to identify the causes of power outages, outline ways to promptly restore electricity if an outage does occur, and determine how best to prepare for and rebuild from disruptive events (Anderson et al. 2019).[1] Using NREL's resilience assessment methodology as a reference, the New York State Energy Research and Development Authority (NYSERDA) requested internal and external stakeholders to collaborate with NREL staff (Anderson et al. 2019). The goal of these discussions was to assess and expand NYSERDA's current definition of resilience, as well as identify research gaps to help embed resilience in state-wide programs.

This literature review is focused on power sector resilience, although resilience in this sector necessarily impacts society more broadly. Researchers began by reviewing resources across the categories of: (1) historical resilience threats for New York State, (2) methods for analyzing resilience risks, metrics, and potential mitigation techniques, (3) resilience valuation and monetization, and (4) social and cultural resilience. The focus was then narrowed to resilience measurement and valuation, asking how the resources from each of the four original categories related to resilience metrics and monetization or valuation. In total, researchers reviewed approximately 180 documents, with key word searches including but not limited to:

- Energy efficiency resilience
- Demand response resilience
- Demand flexibility resilience
- Social vulnerability power outages
- Social vulnerability power outages resilience
- Resilience measurement
- Energy resilience measurement
- Power sector resilience measurement
- Resilience valuation
- Energy resilience valuation
- Power sector resilience valuation.

[1] In this paper, we use the term "disruptive event" rather than "natural disaster." Multiple articles have emphasized that the "disaster" element of natural hazards is often a product of human design, engineering, planning, and construction (Chmutina and von Meding 2019; Kelman 2018; Chmutina, von Meding, and Bosher 2019).

Given the rapidly evolving landscape of research related to energy resilience measurement and valuation, this review necessarily provides a snapshot of the most relevant literature as of mid 2023.

1.2 Defining Resilience

In this paper, resilience is defined as "a system's ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions" (Hotchkiss and Dane 2019; White House 2013). NREL has used this definition of resilience since 2014, and U.S. legislators included a similar definition in the Bipartisan Infrastructure Law/Infrastructure Investment and Jobs Act (U.S. Congress 2021). The Infrastructure Investment and Jobs Act includes investments in resilience to lessen the risk and impact of extreme weather and climatic events, in terms of both acute shocks (e.g., hurricanes, floods, and wildfires) and chronic stressors (e.g., drought). Resilience refers to the ability of the energy system to avoid, withstand, and recover from the impacts of extreme weather and other disruptive events.

The need for resilience is a pressing national issue across all infrastructure types, communities, and economic sectors (Hotchkiss and Dane 2019). Recent increases in the number and severity of acute weather events (e.g., storms) and human-caused incidents (e.g., cyberattacks) resulting in widespread, long-duration, and costly outages have brought resilience to the fore (Lin, Wang, and Yue 2022). A systems approach toward resilience is essential for capturing the linkages among environmental, social, economic, and security considerations (Fastiggi, Meerow, and Miller 2021; Roege et al. 2014). NREL's definition of resilience captures this systems approach and recognizes the need to adapt to changing conditions in planning and design processes or approaches (like an increased emphasis on decarbonization). This expanded view of resilience is supported by several studies that highlight the need for flexibility and adaptation in achieving long-term resilience goals (Murphy et al. 2020; Anderson et al. 2019; Hassler and Kohler 2014). Identifying the built environment's risk factors and protective variables is necessary to enhance and maintain critical functions in the face of disruption.

1.3 Historical Threats

Since 2010, every county in New York State has been affected by at least one federally declared weather disaster. From 2010 through 2023, New York State has experienced 46 extreme weather events costing the U.S. $1 billion or more after Consumer Price Index adjustments—including 26 severe storms, 9 winter storms, 7 tropical cyclones, 2 droughts, and 2 flood events (NOAA 2023a). Across all states impacted by these 46 extreme weather events, the total estimated Consumer Price Index-adjusted cost is approximately $357 billion, and the number of deaths amounts to almost 1,250 people. Table 1 summarizes these extreme weather events for the northeast region.[2] Tropical cyclones accounted for approximately 55% (~$197 billion) of the total costs across this period, severe storms for approximately 17% (~$60 billion), winter storms for approximately 14% (~$51 billion), droughts for approximately 13% (~$45 billion), and flood events for approximately 1% (~$4 billion), just to highlight a few impacts.

Table 1 is not an exhaustive list of all weather hazards that impacted New York State during this period and does not show the costs mitigated by preventative measures, but it helps provide an estimate of the potential value of investing in resilience. For example, of the 46 extreme weather events tallied in Table 1, seven tropical cyclones accounted for over half the costs. Given this insight, an organization or entity (in

[2] Note that these cost estimates and death rates are not specific to New York State—the "Total CPI-Adjusted Cost" and "Deaths" columns in Table 1 represent an aggregate across all impacted states. Deaths associated with drought are the result of heat waves. All data current as of August 3, 2023. For more information and to view the relevant data, visit: https://www.ncei.noaa.gov/access/billions/.

this case, New York State government organizations) might consider targeting future resilience investments toward the threats associated with tropical cyclones.

Table 1. Weather and Climate Billion-Dollar Disasters That Affected New York From 2010–2023 (Consumer Price Index-Adjusted)

Event Name	Event Type	Month/Year	Total CPI-Adjusted Cost (Millions of Dollars)	Deaths
Northeast Flooding	Flooding	March-10	$2,582	11
Midwest/Northeast Severe Storms and Flooding	Severe Storm	July-10	$1,328	0
Groundhog Day Blizzard	Winter Storm	February-11	$2,476	36
Hurricane Irene	Tropical Cyclone	August-11	$18,082	45
Tropical Storm Lee	Tropical Cyclone	September-11	$3,367	21
Northeastern Winter Storm	Winter Storm	October-11	$1,239	1
Southern Plains/Midwest/Northeast Severe Weather	Severe Storm	May-12	$3,041	1
Hurricane Sandy	Tropical Cyclone	October-12	$85,202	159
U.S. Drought/Heat Wave	Drought	July-05	$40,205	123
Midwest/Plains/East Tornadoes	Severe Storm	May-13	$3,144	27
Midwest/Plains/Northeast Tornadoes	Severe Storm	May-13	$2,376	10
Midwest/Southeast/Northeast Winter Storm	Winter Storm	January-14	$2,825	16
Midwest/Southeast/Northeast Tornadoes and Flooding	Severe Storm	April-14	$2,222	33
Rockies/Midwest/Eastern Severe Weather	Severe Storm	May-14	$4,753	0
Michigan and Northeast Flooding	Flooding	August-14	$1,321	2
Central and Eastern Winter storm, Cold Wave	Winter Storm	February-15	$3,851	30
Central and Northeast Severe Weather	Severe Storm	June-15	$1,488	1
Southeast and Eastern Tornadoes	Severe Storm	February-16	$1,331	10
Rockies and Northeast Severe Weather	Severe Storm	July-16	$1,847	0
West/Northeast/Southeast Drought	Drought	July-05	$4,408	0
Midwest Tornado Outbreak	Severe Storm	March-17	$2,720	2
North Central Severe Weather and Tornadoes	Severe Storm	May-17	$1,167	1
Midwest Severe Weather	Severe Storm	June-17	$1,871	0

Event Name	Event Type	Month/Year	Total CPI-Adjusted Cost (Millions of Dollars)	Deaths
Central and Eastern Winter Storm	Winter Storm	January-18	$1,283	22
Northeast Winter Storm	Winter Storm	March-18	$2,677	9
Southern and Eastern Tornadoes and Severe Weather	Severe Storm	April-18	$1,595	3
Central and Northeast Severe Weather	Severe Storm	May-18	$1,682	0
Central and Eastern Severe Weather	Severe Storm	May-18	$1,658	5
Southeast, Ohio Valley and Northeast Severe Weather	Severe Storm	February-19	$1,485	2
Southeast Tornadoes and Northern Storms and Flooding	Severe Storm	January-20	$1,356	10
South, East and Northeast Severe Weather	Severe Storm	February-20	$1,482	3
Southeast and Eastern Tornado Outbreak	Severe Storm	April-20	$4,098	35
Hurricane Isaias	Tropical Cyclone	August-20	$5,566	16
Northwest, Central, Eastern Winter Storm and Cold Wave	Winter Storm	February-21	$26,316	262
Southeast Tornadoes and Severe Weather	Severe Strom	March-21	$1,929	6
Tropical Storm Elsa	Tropical Cyclone	July-21	$1,347	1
Tropical Storm Fred	Tropical Cyclone	August-21	$1,418	7
Hurricane Ida	Tropical Cyclone	August-21	$81,665	96
Southeast, Central Tornado Outbreak	Severe Storm	December-21	$4,268	93
Southeast Tornado Outbreak	Severe Storm	April-22	$1,488	3
Central Derecho	Severe Storm	June-22	$3,343	1
North Central and Eastern Severe Weather	Severe Storm	July-22	$1,380	1
Central and Eastern Winter Storm and Cold Wave	Winter Storm	December-22	$8,614	87
Northeastern Winter Storm / Cold Wave	Winter Storm	February-23	$1,767	1
South and Eastern Severe Weather	Severe Storm	April-23	$1,949	23
Central Tornado Outbreak and Eastern Severe Weather	Severe Storm	March-23	$5,421	33
		Total	$356,631	1248

Table by NREL, data from NOAA 2023a

Historical analyses are one way to quantify the impacts associated with both acute and chronic disruptive events. To understand how to incorporate resilience solutions, it is also important to recognize potential future risks. While impossible to predict fully, the literature points to the ways in which climate change will exacerbate severe weather events in the future. The 2022 Intergovernmental Panel on Climate Change report issues a stark warning that climate change will cause unavoidable increases in multiple hazards, even under the rapidly approaching 1.5°C Paris Agreement goal (IPCC 2022). According to the World Meteorological Organization, there is a 66% probability that annual average near-surface global temperatures will exceed this 1.5°C goal for at least one year between 2023 and 2027 (WMO 2023). Temperatures are likely to reach record levels during this time in part because of a naturally occurring El Niño event, a phenomenon associated with above-average equatorial sea surface temperatures that has historically exacerbated extreme weather events and reduced country-level economic growth (NOAA 2023b; WMO 2023; Callahan and Mankin 2023). The National Oceanic and Atmospheric Administration predicts El Niño conditions to gradually strengthen into the Northern Hemisphere during the winter of 2023–2024 (NOAA 2023). The El Niño predicted for 2023 could alone result in more than $3 trillion of lost global income by 2029 (Callahan and Mankin 2023; Horn-Muller 2023).

The Northeast chapter of the Fourth National Climate Assessment specifically details how extreme weather, higher temperatures, and sea level rise will adversely impact residents of the northeastern U.S. states. Critical infrastructure interdependencies across water, energy, transportation, and telecommunications could lead to cascading failures during climate-related disruptions. For example, the Northeast is projected to experience a significant increase in summer heat and heat waves that will further stress summertime energy peak load demands. The region's high density of built environment sites and aging housing and infrastructure (compared to other regions) also suggest urban centers in the Northeast are especially vulnerable to climate shifts and extreme weather (USGCRP 2018). The Federal Emergency Management Agency's (FEMA's) National Risk Index identifies some of the top hazards and threats facing New York State as flood events, heat waves, hurricanes, and extreme winter weather like ice storms and cold snaps (FEMA 2021a).

All of this means New York State would benefit from increased planning and preparation for the types of events listed in Table 1, accounting for increased event severity and duration. Increased storm wind speeds, larger amounts of precipitation, rising sea levels, and longer-duration heat and cold spells are anticipated, as well as new hazards and threats. It is imperative to include extreme weather events, gradual climate shifts like rising temperatures and humidity, and associated changes in behavior (such as increased power demand) in planning for future program designs, operations, governance, and investments. Research has shown states with more residential customers (e.g., CA, TX, FL, NY, and PA) tend to observe larger unanticipated surges in electricity demand, due to events like swings in temperature change. These states are also becoming more vulnerable to high-impact, low-frequency events because of an increased population concentration in areas prone to extreme weather events (Ankit et al. 2022).

It is important to recognize that power systems must be resilient against non-climate hazards as well. There are four main categories of disruptive events summarized in the literature: (1) natural hazards; (2) mechanical failure; (3) human attack; and (4) operational failure. In recent years, the Northeast region of the United States has improved its power system resilience to natural hazards compared to outages from the other three event categories (Ankit et al. 2022). There must also be an emphasis on improving infrastructure resilience against human and operational events that, like severe weather, can lead to single-component faults or cascading failures (Bie et al. 2017). New York will likely also increase the proportion of renewable energy technologies in its power generation mix to meet the goals outlined in the New York State Climate Act (Hibbard et al. 2020). An increase in solar generation, hydropower, wind generation, and energy storage assets means certain weather and environmental conditions can affect electrical supply and dispatch throughout the grid. Weather events like prolonged cloudy conditions, high temperatures, and lulls in wind could increase the uncertainty of electrical supply, which introduces other sets of considerations for capacity planning and grid flexibility.

This paper is organized into two parts: the first section provides an overview of the literature on measuring resilience, and the second section provides an overview of the literature on valuing resilience. "Part I: Measuring Resilience" discusses the similarities and differences between resilience and reliability, different categories of resilience metrics, and a high-level overview of different analysis methodologies that could help evaluate performance enhancements associated with resilience strategies. "Part II: Valuing Resilience" discusses the monetization of resilience, a cost-benefit analysis approach that uses probabilistic risk assessment (PRA), and consequence-focused metrics. Appendices have been included to define key terms and provide additional details on reliability metrics and quantification.

2 Part I: Measuring Resilience

2.1 Resilience vs. Reliability

Reliability measures are often relevant to resilience—especially in the power sector, where reliability has a specific definition. When attempting to quantify the consequences of a disruptive event on grid operations and power delivery, for example, we might use megawatt hours (MWh) of power not delivered because of a storm to measure either reliability or resilience (Petit, Vargas, and Kavicky 2020). Reliability is a long-established concept in the power sector, while definitions of resilience are still evolving. It is important to note, however, that resilience is inherently contextual; systems resilient to one hazard or threat type may not be resilient to another hazard or threat type. For example, a system resilient to hurricanes might not be resilient to earthquakes (Jeffers et al. 2020).

The most common differentiator between reliability and resilience is the probability and impact of the disruptive event under consideration (Cicilio et al. 2021). Reliability typically deals with routine, shorter-term events (like lightning strikes and vegetation encroachment) or the unanticipated loss of system elements from credible contingency events (e.g., electric insulation failure on a generator) (NIAC 2010; NASEM 2017; AEMC 2023). Alternatively, a resilience approach typically focuses on low-probability, high-consequence events like extreme weather or large-scale cyberattacks. Resilience events have the capacity to cause multiple instantaneous or cascading component failures and affect a significant number of customers, often spanning a wide geographic extent (Bie et al. 2017).

Resilience extends and includes reliability, allowing for the evaluation of systems in terms of both minor routine disruptions and major disruptions from extreme events. Considering both routine and extreme disruptions helps to create a more stable, resilient system. Figure 1 shows the different phases of a resilience event and the potential performance of a system both before and after this event. Repair and restoration are typically more complex for resilience events, in part because resilience events tend to result in longer outage durations than reliability events. Low-probability, high-consequence disruptions have the potential to damage numerous system components, prevent timely service restoration to impacted transmission and distribution equipment, and lead to competing priorities for a limited number of field crews and facilities (Liu 2015).

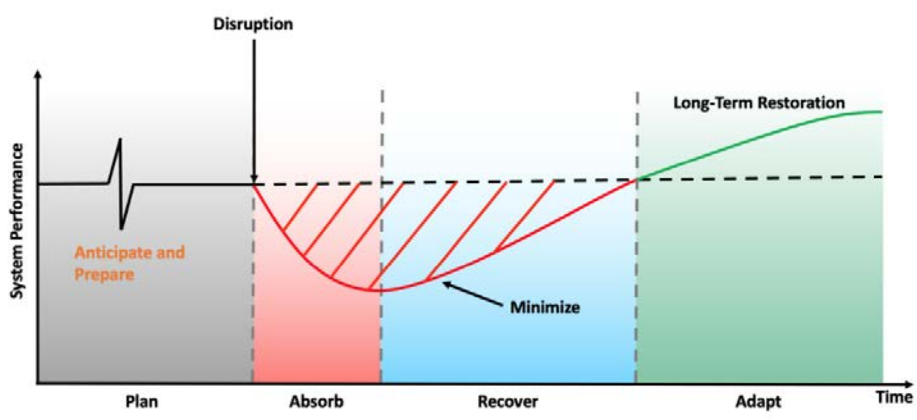

Figure 1. Phases of a resilience event

Figure by NREL, adapted from Linkov, Trump, and Hynes (2019)

Resilience is an expansive concept that extends reliability and includes broader characteristics like economic resilience, readiness for climate shifts, operational flexibility, and the ability to move resources as needed (Stout et al. 2019). Resilient systems employ recursive and adaptive processing that includes sensing, anticipating, learning, and adapting—both following an acute shock or disruptive event and over the long term to address chronic stressors. This process-oriented perspective has important implications for the management of complex engineering systems like the power grid (Ayyub 2014). Reliability might evaluate different power system states (e.g., resilient state, post-event degraded state, restorative state, post-restoration state), whereas resilience is also a function of the transition time between these states. This time-based dimension is an important differentiating feature for resilience (Panteli and Mancarella 2015). Figure 2 summarizes some of the key differences between resilience and reliability.

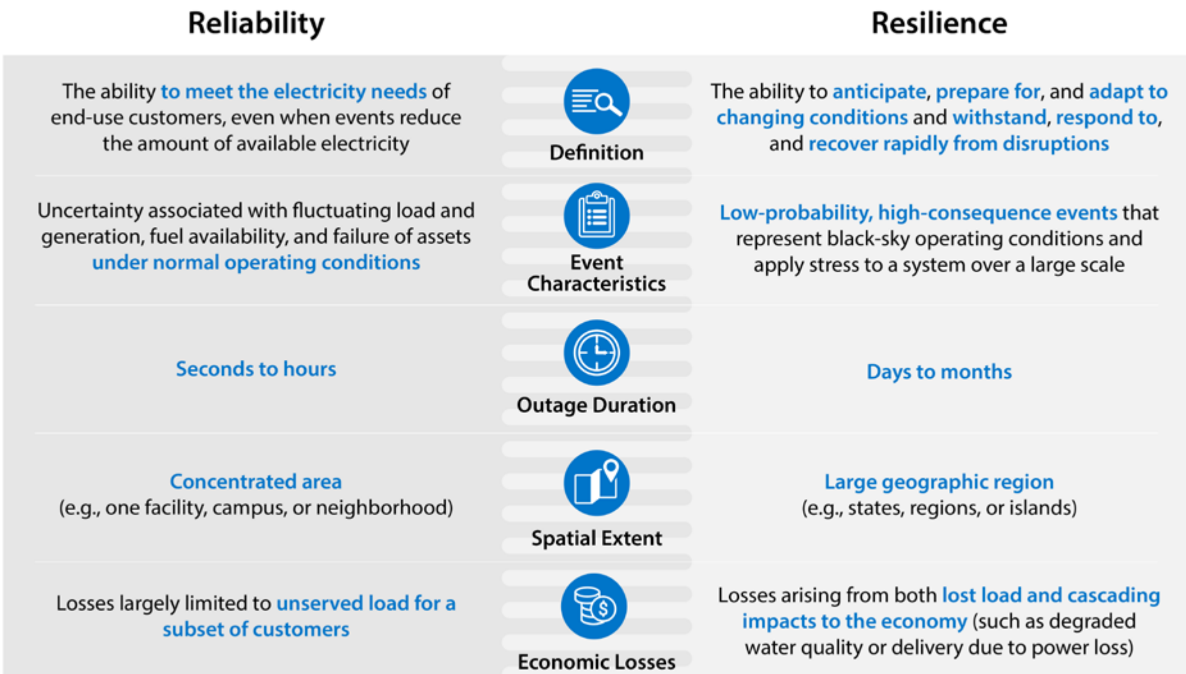

Figure 2. Reliability versus resilience

Figure by NREL, adapted from NIAC (2010); Hotchkiss and Dane (2019); Stout et. al (2019)

Resilience approaches also acknowledge that higher-level consequences to human wellbeing can become extreme for high-impact, low-frequency events—and therefore focus on addressing solutions that could decrease these negative consequences. In some cases, this can mean the most effective resilience investment may not decrease outage risk equally for all customers (Cicilio et al. 2021). Adding more nuance to current valuation methods can help better capture the landscape of possible resilience benefits.

2.1.1 Reliability Metrics

Metrics for reliability are mature and widely adopted at both transmission and distribution levels. Given NYSERDA's interest in bolstering resilience across customer-facing entities, we first highlight distribution-focused reliability metrics before turning to transmission-focused metrics. Since the early 1970s, electric utilities have used reliability metrics from the Institute of Electrical and Electronics

Engineers (IEEE). In 2012, IEEE defined six average-based and two customer-based reliability indices that are now industry standard (IEEE 2012) (see Table 2). Electric utilities use these indices to improve year-over year system reliability, infer infrastructure health, and estimate customer satisfaction.

Appendix D provides additional details on how to calculate these reliability metrics (IEEE 2012).

Table 2. IEEE 1366 Reliability Metrics

AVERAGE-BASED METRICS	System Average Interruption Duration Index (SAIDI)	Indicates total duration of the average customer interruption
	System Average Interruption Frequency Index (SAIFI)	Indicates how often the average customer experiences an interruption
	Customer Average Interruption Duration Index	Indicates average time to restore service
	Customer Average Interruption Frequency Index	Indicates how many interruptions each impacted customer experiences
	Momentary Average Interruption Duration Index	Indicates total duration of the average customer momentary interruption (i.e., interruptions lasting less than five minutes)
	Momentary Average Interruption Frequency Index	Indicates how often the average customer experiences a momentary interruption (i.e., interruptions lasting less than five minutes)
CUSTOMER-BASED METRICS	Customers Experiencing Long Interruption Durations (CELID)	Indicates the ratio of individual customers that experience interruptions with durations longer than or equal to a given time. That time is either the duration of a single interruption (s) or the total amount of time (t) that a customer has been interrupted during the reporting period
	Customers Experiencing Multiple Interruptions	Indicates the ratio of individual customers experiencing n or more sustained interruptions

Table by NREL, adapted from IEEE (2012)

Although traditional reliability metrics are useful for maintaining service subject to low-impact, high-frequency events, these indicators are insufficient for measuring resilience. The IEEE reliability metrics use unweighted data that cannot account for regional differences in policy and regulatory standards, socioeconomic factors, system configurations, customer density, and hazard exposure. The use of unweighted data means these metrics cannot capture disproportionate damages and losses across different regions during the same outage scenario (Ankit et al. 2022). In evaluating average-based metrics (SAIDI, SAIFI, Customer Average Interruption Duration Index), utilities often exclude major outages caused by unexpected or high-impact events. As a result, a highly reliable power system according to these metrics is not necessarily a resilient one (Bie et al. 2017).

Transmission operators use different reliability metrics than utilities. For example, New York Independent System Operator reliability metrics focus on transmission security and resource adequacy, examples of which are included in Table 3. These reliability metrics are under strain from several factors, however. One universal factor is the shift from “normal” weather conditions to more extreme (and less predictable) weather conditions resulting from climate change. Factors specific to New York

State include a reduction in power generators due to the Peaker Rule, a 2019 New York State Department of Environmental Conservation rule that reduces ozone-contributing pollutants associated with New York State-based peaking unit generation. The New York Independent System Operator (2022a) predicts Peaker Rule compliance obligations phased in between 2023 and 2025 will impact approximately 3,300 megawatts (MW) of electricity generation. The Peaker Rule also includes a potential higher-than-planned load level in part due to increased electric vehicle adoption and New York's projected shift to a winter-peaking power system because of an increase in electrification for space heating, water heating, clothes drying, and cooking (NYISO 2021).

Table 3. New York Independent System Operator Grid Reliability Metrics

Transmission Security Margins	Described as the power margin (MW) by subtracting load (forecasts and operating reserve requirements) from power sources (New York Control Area generation and external area interchanges)
Loss of Load Expectation (LOLE)	Defined as the expected (weighted average) number of days in a given period (e.g., one study year) when for at least one hour from that day the hourly demand is projected to exceed the zonal resources (event day). Within a day, if the zonal demand exceeds the resources in at least one hour of that day, this will be counted as one event day. The New York Independent System Operator criterion is that the LOLE does not exceed one day in 10 years, or LOLE < 0.1 days/year.
Zonal Resource Adequacy Margins	Defined as the amount of "perfect capacity" in each zone that could be removed before the New York Control Area LOLE reaches 0.1 days/year (one-event-day-in-10-years). "Perfect capacity" is capacity that is not derated (e.g., due to ambient temperature or unit unavailability), not subject to energy duration limitations (i.e., available at maximum capacity every hour of the study year), and not tested for transmission security or interface impacts.
Binding Interfaces	Described as when a specific transmission interface impacts system resource adequacy. This is determined by an analysis that removes the limit on various transmission interfaces in resource adequacy models—either one at a time or in various combinations—and observes whether the system results in a decrease in LOLE, indicating that the flow of power across the interface is "binding" due to transmission constraints.

Table by NREL, adapted from NYISO (2021)

Both reliability and resilience help maintain grid operations at an acceptable level of performance, but there are some key differences. For example, reliability metrics typically do not capture or report long-duration outages—which have become increasingly relevant to customer safety and satisfaction, given both the greater frequency of extreme weather events and the widespread adoption of remote work during the COVID-19 pandemic. By focusing on event duration and recovery time through a more qualitative lens, resilience can help contextualize the time-based aspects of grid reliability (e.g., provide information on the total outage duration of specific critical facilities or pinpoint differences in recovery times among certain customers). Reliability metrics are also not designed to capture secondary impacts to systems when power is lost. These secondary impacts include economic consequences, critical infrastructure damages, and effects on local and regional communities (Petit, Vargas, and Kavicky 2020). As we discuss below, resilience metrics do attempt to capture these critical secondary impacts and interdependencies.

In general, reliability metrics do not encompass resilience because they: (1) exclude major event days from the calculations; (2) ignore the consequences resulting from disruptive events, which can create potentially unintended inequities; and (3) ignore the fact that consequences from those events change over time.

2.1.2 Resilience Metrics

Unlike reliability metrics, resilience metrics are still in their nascent stage (Anderson, Hotchkiss, and Murphy 2019). The main challenge for resilience metrics is how to turn the complex concept of resilience into measurable indices, because there is no single metric that applies to all aspects of infrastructure or every domain within the energy sector. Resilience metrics aim to capture the impacts of a low-probability, high-consequence disruptive event. Impact categories include the ability of a system to: (1) avoid a disruption; (2) mitigate the effects of a disruption should one occur; and (3) recover quickly following a disruption (Watson et al. 2015). Recent research has also emphasized the importance of developing metrics to capture the equity-focused components of resilience—like response time, deprivation time, and the social consequences of infrastructure service disruptions (Lin, Wang, and Yue 2022; Clark et al. 2022; Dugan, Byles, and Mohagheghi 2023). We discuss the literature on consequence-focused and social metrics in greater detail in Part II.

There is no one-size-fits-all resilience metric capable of addressing every decision-making requirement (Willis and Loa 2015). The appropriate metric or set of metrics will depend on context like the energy sector, geographic region, or timescale under consideration—as well as the needs of specific individuals, communities, or systems. Resilience metrics should align with adaptation and resilience strategic priorities at the state or local level, which will help narrow down the measurements needed to make progress (California OPR 2022). A multilayer metric system can best incorporate the different perspectives and goals of power sector stakeholders. For example, one layer might be the time-dependence of a given metric over the course of a disruptive event (Murphy et al. 2020).

At the highest level, we can categorize resilience metrics as either attribute-based or performance-based. Attribute-based metrics typically help describe the properties or characteristics of a resilient system. Performance-based metrics can help inform resilience investment decisions and capture the effects of a disruptive event (through consequence-focused metrics, a subset of performance-based metrics) (Anderson et al. 2021). A combination of attribute-based and performance-based metrics can be helpful to comprehensively represent the complexities of resilience, especially because we do not currently have the data to validate a solely performance-based approach.

2.1.3 Attribute-Based Metrics

Attribute-based resilience metrics often take the form of qualities that describe the characteristics of a resilient system. Attribute-based metrics can be helpful in measuring resilience when numeric indicators are unable to provide a complete picture of the system (e.g., because certain data are unavailable, detailed modeling is prohibitively expensive, or when a qualitative lens is helpful) (Schipper and Langston 2015). Resilience attributes enhance a system's ability to perform as intended during major disruptive events (Vugrin, Castillo, and Silva-Monroy 2017).

There are many examples of resilience attributes and attribute groupings. One example is the attribute grouping used by the U.S. Air Force, called the 5 Rs: robustness, redundancy, resourcefulness, response, and recovery. The first three Rs are preventative or planning-based attributes, and the last two are performance or operation-based attributes (Rits 2019; Cicilio et al. 2021). Taken together, the 5 Rs help capture the complex and dynamic nature of resilience and provide an umbrella for other resilience attributes (USAF 2021). We delve further into each of the 5 Rs below. Although each of these attributes is listed independently, they often overlap. For example, system redundancy can help with overall robustness of the system—but like the difference between reliability and resilience, one does not necessarily imply the other. Just because a system has redundancy built in does not automatically make it robust. The 5 Rs are described in more detail in Table 4.

Table 4. The U.S. Air Force 5 Rs Resilience Attributes

Robustness	Robustness refers to a system's ability to withstand disturbances (USAF 2021). It is a physical attribute describing the level to which assets are hardened against disruptions (Anderson et al. 2019). Because robustness addresses a system's ability to tolerate both acute and chronic shocks, it incorporates the concept of reliability. Like resilience and reliability, robustness and reliability are interrelated but not the same. Robustness is "the ability of the system to withstand a given level (of disruption)," and reliability is "the ability of the system…to withstand instability, uncontrolled events, cascading failures, or unanticipated loss of system components" (Francis and Bekera 2014; DOE 2017). Unlike robustness, reliability focuses on the ability of energy systems to provide service during frequent disruptions. A reliable system and system components, however, do offer long-term and robust performance in their intended function (Shandiz et al. 2020). Robust performance describes a system and infrastructure capable of absorbing some level of impact or shock with minimal disruption to customers.
Redundancy	Redundancy describes a system with multiple pathways toward mission assurance (Anderson et al. 2019). Spare capacity and backup systems enable the maintenance of core functionality in the event of disturbances (USAF 2021). Like robustness, redundancy is a primarily physical attribute. For example, adding a backup power line is a physical measure that will improve overall redundancy. Redundancy is essential for resilience. Including additional resources beyond those required for daily operations increases a power system's resilience because these resources can be relied on during other infrastructure failures or fuel shortages. Increasing supplies, routes, or incorporating redundancy to overall systems will reduce the risks of those systems failing (Stout et al. 2019).
Resourcefulness	Resourcefulness refers to a system's flexibility in adapting to new conditions (Anderson et al. 2019). It is an operational measure describing a system's ability to adapt to crises, respond flexibly, and neutralize negative impacts (Shandiz et al. 2020; USAF 2021). Community coordination, available power generation, energy storage, and recurring training exercises all contribute to resourcefulness (Rits 2019).
Response	Response refers to a system's ability to mobilize quickly in a crisis (USAF 2021). It is an operational measure describing the capacity of a system to self-heal, automatically respond to disruption, and manage the adverse effects of an event (Anderson et al. 2019; Petit, Vargas, and Kavicky 2020).
Recovery	Recovery describes the extent to which assets can bounce back from disruption (Anderson et al. 2019). It is an operational measure referring to a system's ability to regain a degree of normality after an event, be flexible, and evolve to deal with new circumstances (Shandiz et al. 2020; USAF 2021). It also captures a system's capacity to return conditions to an acceptable level of operation (Petit, Vargas, and Kavicky 2020). We can also break recovery down into a subset of events, ranging from best (expeditious recovery to a state that is better than before a disruptive event) to worst (recovery to a state that is worse than before a disruptive event) (Ayyub 2014).

Although all the attributes in the 5 Rs are widely accepted resilience attributes, they do not constitute an exhaustive list. Some literature instead emphasizes the importance of resilience stages like preparedness, mitigation, response, and recovery, following the FEMA structure (Bie et al. 2017). Other authors equate resilience with adaptive capacity and attempt to identify the key components of adaptive capacity—like diversity, redundancy, efficiency, and optimal system structure (Molyneaux et al. 2016). Additional related (but separate) resilience attributes found in the literature include anticipation, absorption, adaptation, flexibility and interoperability, rich information and creativity, and system fragility (Roege et al. 2014; Younesi et al. 2020).

Other important attribute-based frameworks define different forms or outcomes of resilience. Resilience can be inherent (i.e., possessing the capacity to respond to disruptive events without special measures) or adaptive (i.e., measures that can reduce the impact of disruptive events—like rescheduling or temporarily relocating power production) (Baik et al. 2021). We can also use qualitative indicators to gauge the resilience of built systems. Examples of these indicators include whether critical lifeline services and facilities are accessible and reliable throughout the lead up to and recovery from a disruptive event, as well as whether plans and codes address climate risk and adaptation (California OPR 2022).

There are also attribute-based metrics that are quantitative. For example, the available MW of spare capacity in a grid system helps describe that system's robustness (Watson et al. 2015; Willis and Loa 2015). To help measure the attribute of response, we can use MW of curtailable load or number of linemen on call to respond to grid restoration (Willis and Loa 2015).

2.1.3.1 Performance-Based Metrics

Performance-based metrics help outline information that utilities, regulators, and other stakeholders can use to monitor and improve the grid performance of resilience investments (Broderick et al. 2021). These metrics are most helpful when evaluating the effectiveness of certain resilience measures or comparing the level of resilience of different systems. Performance-based metrics are most meaningful when applied or evaluated for a specific event (Bie et al. 2017).

Performance-based metrics describe how a system performed, or is expected to perform, during a disruptive event (Vugrin, Castillo, and Silva-Monroy 2017). These metrics are generally quantitative approaches for answering the question "How resilient is my system?" and vary based on the system under consideration (Petit, Vargas, and Kavicky 2020; Raoufi et al. 2020). For example, performance-based metrics for a building can capture passive survivability, while metrics for an electric power distribution network might measure expected energy not served—or the average curtailed energy of the load point when the load point experiences an interruption due to a disruptive event (Ayyub 2014; Schneider et al. 2021).

Performance-based metrics for energy systems are often measured in units (like MWh or Metric Million British Thermal Units) or measurements derived from performance, such as percentage of energy delivered or time until restoration. These metrics draw heavily from historical events, subject matter estimates, and computational infrastructure models. Other examples include MWh of load curtailed, percentage of customer demand met or expected demand not supplied, and average number or percentage of critical loads that experience an outage (Petit, Vargas, and Kavicky 2020; Ayyub 2014).

The temporal component of these metrics is also important to evaluate—for example, how many MW of load is curtailed every hour. Evaluating performance-based metrics over time can help reveal the nonlinearity of impacts across time and space over the course of a disruptive event. Because performance-based metrics can measure the potential benefits and costs associated with proposed resilience enhancements and investments, performance-based methods are often valuable for cost-benefit and planning analyses (Petit, Vargas, and Kavicky 2020). Consequence-focused metrics are an important subset of performance-based metrics for resilience measurement and valuation purposes.

2.1.3.2 Consequence-Focused Metrics

Consequence-focused metrics (often used interchangeably with the term "outcomes-based metrics") are a subset of performance-based metrics that describe the consequences or expected consequences of a given disruptive event. These metrics effectively extend the performance of infrastructure to the consequences for society. Consequence-focused metrics often use economic or health-related units of measurement. Examples include reduction in gross domestic product, cost of repair, value of insurance claims, total value of lost load (VoLL), and number of fatalities.

Consequence-focused metrics attempt to quantify the effect of system performance on diverse aspects of society. Raoufi et al. (2020) identify consequence-focused metrics across four key categories: economic, social, geographic, and safety and health. An economic consequence-focused metric might be the cost savings of loads served by a microgrid (Anderson et al. 2017), while a social consequence-focused metric could be the social vulnerability index (Flanagan et al. 2018). Geographic metrics identify the physical areas lacking electricity, while safety/health-related metrics might include number of hospitalizations or the loss of human life. Other categories of consequence could include environmental and national security (or military).

We also see some authors take a service-based approach to consequence-focused metrics, attempting to emphasize the impact of a disruptive event on critical services like electricity, heating, cooling, and water (Shandiz et al. 2020). Resilience events are more likely than reliability events to have exponentially increased consequences, due to the nonlinear effects associated with extremely long-duration or widespread outages (Broderick et al. 2021). We discuss the literature on consequence-focused and social metrics in greater detail in Part II.

2.1.3.3 Combining the Metrics

Metrics categories are useful for understanding the resilience measurement landscape. To capture resilience as accurately as possible, however, it is often helpful to combine available metrics. Because resilience metrics describe events with a low probability of occurrence, these metrics would ideally be expressed in risk-based terms. A risk-based resilience approach considers interactions between the likelihood of an event occurring and the severity of that event's consequences should it occur. For example, a risk-based resilience approach would calculate the expected resilience benefits of a microgrid across the entire range of potential outages over a predetermined time horizon. There are limitations to this approach, however, given the challenges associated with calculating risk-based metrics. A lack of data on outage durations for the power grid and a rapidly shifting hazard profile due to climate change often make it difficult to determine the likelihood and consequences of major disruptive events.

A scenario analysis, which uses "what-if" or counterfactual analyses, provides another potential pathway for combining resilience metrics. For example, a scenario-based method could consider the expected resilience savings of a microgrid given a weeklong outage (instead of considering the full range of potential outages). Scenario-based metrics are limited when determining costs and benefits, whereas risk-based metrics are highly sensitive to the potential range of assumed probabilities.

The literature points to other potential methods for combining resilience metrics. Bhusal et al. (2020) and Cicilio et al. (2021) combine attribute-based and performance-based metrics into two main categories of resilience strategy: operation-based and planning-based. Operation-based resilience strategies implement protection schemes and keep the system operational during and following a disruptive event, while planning-based methods target electrical grid expansion and hardening to withstand predicted disturbances. There can be some overlap between these categories as well—some planning-based measures might focus on operational improvements, such as developing a procedure for pre-positioning supplies when an event is forecasted.

Petit, Vargas, and Kavicky (2020) propose a comprehensive resilience metrics capability based on both multi-criteria decision analysis (an attribute-based approach) and performance-based techniques. Multi-criteria decision analysis supports the development and ranking of high-level resilience enhancement alternatives, while performance-based metrics support cost-benefit analysis and help calculate the decrease in risk associated with each identified alternative. In the context of electric utility planning, for example, planners could use the attribute-based approach to conduct a high-level gap analysis of where their system could benefit from resilience investment. This gap analysis would then feed into the performance-based approach, which could calculate a baseline risk and produce more refined alternatives. Utility planners could then conduct as many iterations of this process as they see fit.

The exact choice of metric or metrics for a resilience analysis will always depend on relevant baseline and intended upgrades. For example, a performance-based metric (like increased hours of survivability) could help measure resilience upgrades at a single location but might lack applicability for broader regional upgrades. Conversely, a metric such as MWh of load shed can be valuable for measuring broader grid upgrades but insufficient for capturing the nuances of a single site. We discuss potential analysis methodologies for resilience below.

2.2 Analysis Methodologies

Analytical methods to assess reliability, resilience, risk, and mitigation techniques are as diverse as the systems they model. As with resilience metrics, there is no one-size-fits-all analytical method. Some analytical methods are also better suited to reliability than to resilience. Because reliability focuses on low-impact and high-frequency events, deterministic methods (e.g., N-1 contingency evaluations) can reasonably quantify the preparedness of the system. Resilience instead focuses on high-impact and low-frequency events, and so probabilistic methods are required to account for the likelihood of these events. It is important to note, however, there is a lack of clear criteria to delineate a rare versus frequent event—especially as the frequency of once "rare" events (like a 100-year-flood) increases due to climate change (Cicilio et al. 2021). In this section, we provide a high-level overview of several analytical approaches for both resilience and reliability that are potentially relevant to New York State, both from energy and non-energy perspectives. Before describing the methodologies, we raise several caveats.

First, many analytical methods rely on historical or a priori data. Climate change, novel or young technologies, and evolutions in human behavior create an environment where historical data are not always accurate predictors of future events. For example, climate change has the potential to exacerbate the intensity of historic events like heat waves, winter storms, and hurricanes (USGCRP 2018). Climate change also has the potential to introduce new risks to previously unaffected areas. Wildfires are one example of an expanding climate hazard that would have been highly unlikely in some areas without climate-induced increases in ambient temperatures and decreases in precipitation (Dennison et al. 2014). Focusing on changes to human behavior, relatively novel technologies such as personal cellular phones, social media, and public information campaigns[3] have all changed how humans react during extreme events (Simon, Goldberg, and Adini 2015; EL Khaled and Mcheick 2019). A critical look at all analysis methodologies that rely on historical or a priori knowledge is vital to considering how future trends can impact current results and conclusions.

Second, many analysis methods assume a system is “coherent.” A coherent system is one that increases its resilience as each system component is hardened (Zio 2007; Haarla et al. 2011). We often see the assumption of a coherent system in engineered systems, where a reduction in the failure rate of an individual component reduces the system failure rate by a quantifiable amount. This correlation between failure rates leads to a clear cost-benefit optimization for hardening an individual system component (Stamatelatos and Dezfuli 2011). The assumption of a coherent system is not always valid from the perspective of state- and city-scale systems, however, because these include both engineered and social systems. For example, strengthening components that reduce risk to flooding can increase risks for other catastrophes (e.g., levies designed to protect city centers can push flood waters into surrounding areas) (Heine and Pinter 2012).

An adaptation for one hazard that leads to increased vulnerabilities for other hazards is often termed a “maladaptation.” Poorly designed climate adaptation strategies can result in such maladaptation, where exposure and sensitivity to climate change impacts increase due to action taken. Maladaptation is thus more impactful than simply wasting time and money; it results in creating conditions worse than those the original strategies were attempting to address (Schipper 2020). Climate change literature specifically calls for planners to prioritize anticipation of the risk of maladaptation, methodologies for better assessing maladaptation, and systems thinking when evaluating and mitigating risk (Magnan et al. 2016; Schipper 2022; Noble et al. 2014).

Third, many analysis methods do not fully account for cascading failures. Cascading failures—or failures in which interconnectedness leads to the malfunction of other parts—can span energy, water, food, communications, and human systems (Govindan and Al-Ansariet 2019; Busby et al. 2021). The ability of an analysis to capture cascading failures is usually a trade-off for the simplicity or complexity of an analysis, the availability of data, and the time or funding scope of the analysis period. Even so, planners conducting an analysis should understand that cascading failures are an important consideration in modern analysis frameworks, even if project constraints do not allow their full investigation.

Considering these caveats, the analysis frameworks below can be used for estimating the reliability, resilience, risk, and potential benefits of mitigation techniques. For example, N plus M redundancy can examine systems experiencing routine failures due to aging equipment (reliability) or systems experiencing climate-related shocks and stresses (resilience). The methodology does not predetermine reliability or resilience analysis, and the calculated risk can serve as the estimated risk to a system based on either a reliability or resilience event. For this report, the focus will be on how these frameworks can help inform resilience analyses.

2.2.1 N Plus M Redundancy

N plus M (N+M) redundancy is a deterministic method of evaluating redundancy or resilience. N represents the minimum number of independent components needed to operate. M is the number of redundant components kept available to replace the failure of a component N. The more components

[3] Public information campaigns are not novel, but their implementation method has greatly changed in the past 20 years.

kept in reserve that can perform the same function and replace a failed component, the more redundant and potentially more resilient the system (White and Miles 1996; Barringer 1996). In computer server systems, electric grids, and backup power situations, it is common to have at least one backup component for each critical system—leading to "N+1" as a common level of redundancy. Many utilities, however, are going beyond the N+1 concept to add additional levels of redundancy.

When failure is the result of a common cause failure (CCF), redundancy does not necessarily increase resilience. A CCF is an event in which multiple failures occur in a short period of time due to a common cause, or when two or more elements fail due to a shared cause. For example, if a site only requires one diesel generator but has two available diesel generators, it is estimated to have N+1 redundancy. If the site has a constrained fuel supply during the disruptive event and runs out of diesel fuel, however, adding more generators to the site will increase N+M redundancy metrics without increasing resilience to fuel-constraining disruptions.

2.2.2 Network-Based Methods

Power systems and human systems are becoming more interconnected through communication systems. The resilience of power and communication networks can be examined via complex network theory (Jiang, Gao, and Chen 2009; Saleh, Esa, and Mohamed 2018). Complex network theory is a statistical branch of mathematics built upon graph theory. A series of nodes represents system components in network theory, and edges are the link between nodes where energy or data can be transferred (for a power and communication-type network). Mathematical methods to express the resilience of a network include: (1) the "connectedness" of the system; (2) the average path length between any two nodes; (3) the number of nodes that can be removed before complete system failure (like N plus M redundancy); and (4) the critical nodes that, if removed, isolate part of the system.

Adding edges or nodes can help increase system resilience in a quantifiable way. By mapping an existing network onto complex network analysis, as shown in Figure 3 and even by adding in weights for the nodes and edges, system upgrades can be evaluated from a network theory perspective to see if and how network upgrades improve resilience. Network-based methods can also encompass complex systems and systems-of-systems work. For example, Dobson (2012) uses a branching process model and standard utility data to quantify the effect of cascading failure on blackout extent at the transmission level.

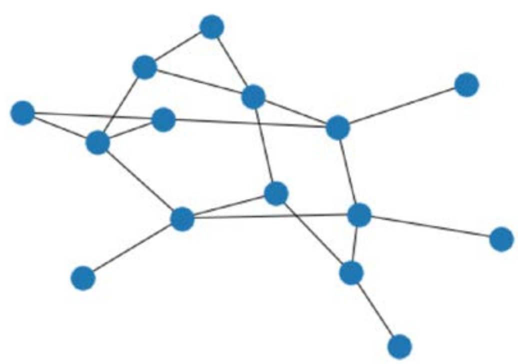

Figure 3. 15-node network

Figure by NREL

2.2.3 Layer-of-Protection Analysis

The analysis methods discussed thus far have largely been technology- and system-agnostic. N + M redundancy and network-based methods are mathematical methods to describe a system, and adding redundancy or nodes changes the system layout and estimated resilience but is often blind to case-specific analysis events (unless the nodes contain specific technology attributes). Layer-of-protection analysis (LOPA) is considered a low-cost and low-data analysis methodology to bring technology and hazard awareness to systems analysis. LOPA begins by identifying major events, usually CCF events, that could cause severe disruption to the system. Using these events, the weakest link in the system is identified (usually through mixed qualitative-quantitative methods) and a protection layer is designed to specifically address the weakest link (Willey 2014; Markowski and Kotynia 2011).

Different industries employ LOPA, and each industry has specific methods for implementing it. An example found in literature from the chemical industry includes the "bowtie" model shown in Figure 4 where the potential causes of system faults are organized on the left of the bowtie and consequences are arranged on the right (Markowski and Kotynia 2011). At the center is the CCF that could lead to system consequences.

Figure 4. LOPA

Figure by NREL, adapted from Markowski and Kotynia (2011)

LOPA is a strong methodology for several reasons. First, it can use semi-quantitative or even qualitative data (often taken from front-line personnel) to provide feedback on the weakest component of the system. Second, LOPA can be used across different hazards and threats (e.g., floods, hurricanes, winter storms) to identify a single CCF—perhaps a power outage for a hospital—such that if the single CCF can be mitigated through backup diesel generators, as an example, the worst consequences of the event might never be realized. In the case of a hospital, LOPA can be used to quantify the value of keeping a critical load subset (such as life support systems) running during various disruptive events. More recently, researchers have begun applying LOPA to cyber-physical systems like the electricity grid. Tantawy, Abdelwahed, and Erradi (2022) propose a new safety design method called "cyber layer of protection analysis" that extends the LOPA framework to include failures caused by cyberattacks. In cyber-LOPA, there is an additional security resilience requirement for the safety instrumented system under consideration: an upper bound on the probability of a successful cyberattack.

2.2.4 PRA

PRA is an extension of the "risk equals probability multiplied by consequence" framework. The PRA is a well-established risk assessment methodology commonly used in the aerospace and nuclear industries (Stamatelatos and Dezfuli 2011; Fullwood and Hall 1988). It is also very well aligned with the performance-based resilience metrics discussed earlier. To perform PRA, an event tree is constructed, as shown in Figure 5. The initiating event and compounding events are all given a probability, often based on component failure rates, such as a pump failing to start or valve failing to open. The probability of arriving at the j^{th} end state is the intersection of initiating and compounding events.

$$P_{es-j} = P_{ie} \cap P_a \cap P_b$$

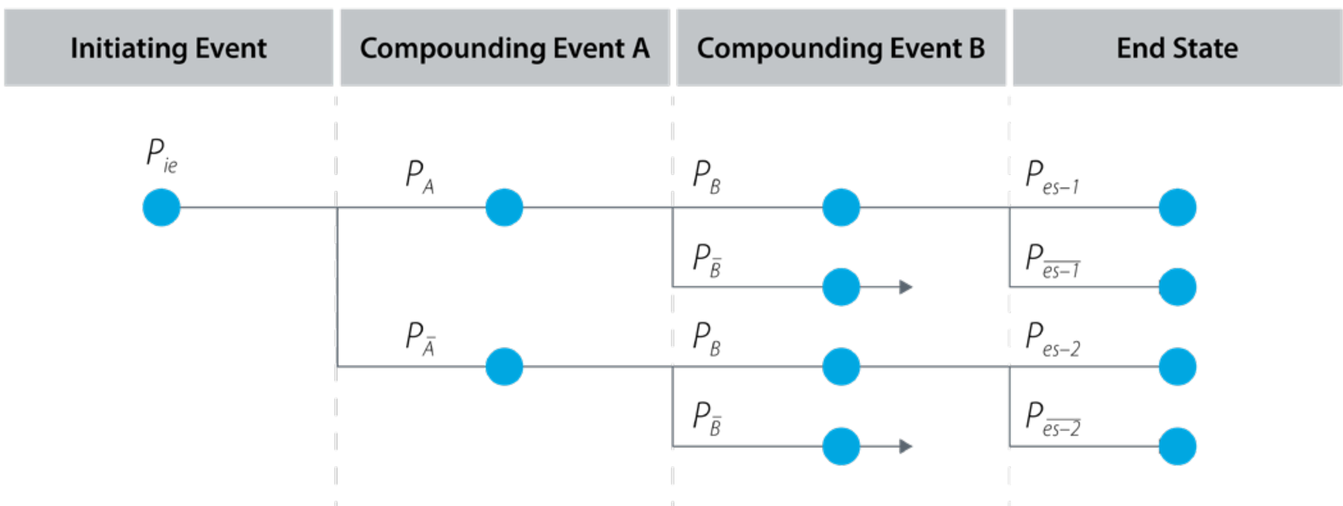

Figure 5. Framing the PRA

Figure by NREL, adapted from Stamatelatos and Dezfuli (2011); Fullwood and Hall (1988)

Using the PRA methodology provides an estimate of the overall risk to a system based on engineered safety features for all designed scenarios. The advantage of PRA is that the change to the failure rate of an individual component can help update the overall change in risk to the system. For example, if a single pump is a critical component in preventing a building from flooding, the risk reduction of adding a redundant pump can be calculated based on the probability of each pump failing to start simultaneously.

The disadvantage of PRA is its need for highly characterized components, which makes it commonly suited only for engineered safety systems. The failure rates of valves and pumps can be easily quantified, while the failure rates of more dynamic systems (like social systems) are more complex. It can also be difficult to quantify the probability of a disruptive event. To apply PRA to resilience events, we need a meaningful probability that X component will, for example, be in the path of a hurricane. Historical data can help provide a starting point for estimating this probability, but such data are typically insufficient on their own for generating a meaningful number.

2.2.5 Flaws in Traditional Techniques

A variety of industries have used the above methodologies to analyze resilience, risk, and mitigation approaches. Before describing how to use these analysis tools for increasing resilience and reliability, it is important to detail their flaws. Three shortcomings are relevant for NYSERDA and are part of the analysis frameworks presented here.

1. Most analysis methods only account for single failure modes and exclude cascading failures.
2. Most analysis methods employ static probabilities, as they relate to system performance and do not dynamically update assumptions based on changing conditions.
3. Most analysis methods do a poor job of capturing irrational human behavior and connecting human behavior to engineered systems and environments.

These shortcomings can be addressed, and examples of this are already starting to appear in the literature. For example, as illustrated by the work of Dobson (2012), systems analysis is increasingly incorporating dynamic or cascading failures into coupled energy, water, and communications networks. PRA is also being updated to include dynamic probabilities that change as the system evolves. These dynamic probability updates can include situations where the failure of a subsequent event changes based on the failure mode of the preceding event. Dynamic probabilities can also include new events that only occur after a failure. For example, the reconfiguration of power flows in the electricity grid following a disruptive event can increase the temperatures of overhead lines, underground cables, and transformers—potentially leading to cascading thermal failures and even blackouts (Henneaux, Labeau, and Maub 2013). Finally, many LOPA methods are incorporating more data from on-the-ground experts who have worked or lived through an event and can provide personal knowledge of how systems failed (Parhizkar et al. 2021; Riddle et al. 2021). As stakeholders examine these and other analysis approaches for resilience, personnel must think through similar solutions for addressing inherent flaws.

3 Part II: Valuing Resilience

3.1 Monetization

Monetization is a major component of resilience valuation. From an investment perspective, the value of resilience is the present value of either: (1) avoided costs from disruptive events over the investment's lifetime; or (2) the avoided cost of alternative investments (like diesel generators or an alternative system, such as a photovoltaic-battery system). To accurately measure resilience, we must be able to measure the reduction in risk between old and new systems (i.e., before and after completion of enhancements that improve resilience). An inability to determine a dollar value for resilience makes it difficult for utility owners and operators to illustrate attractive payback periods to end users. A key challenge in New York State, for example, is in compensating microgrids for the resilience value they offer the electrical grid and provide to customers (Cook et al. 2018).

Like resilience metrics, the exact choice of monetization method will vary by specific circumstance. How we value resilience depends on the type of resilience investment that system planners intend to implement. Types of resilience investments range from system hardening measures to strategies aimed at improving recovery time and processes (Zamuda et al. 2019). We focus below on the following resilience investments and their valuation potential: system hardening and backup power systems, demand response and flexibility measures, energy efficiency investments, and risk management strategies. We then provide an example of how to conduct a cost-benefit analysis for potential resilience enhancement strategies using PRA, before closing with a discussion of valuation methods for consequence-focused and social metrics.

3.1.1 System Hardening and Backup Power Systems

System hardening and backup power systems are some of the most traditional resilience investments. Line hardening is often one of the most effective methods for improving power system resilience at a relatively low cost (Wang et al. 2017). Research has shown that 90% of power outages originate in the distribution system, so hardening is an integral first step in helping create distribution systems with resilient and reliable loads (Bie et al. 2017). Grid hardening on transmission and distribution systems is key to reducing the most consequential outages. Hardening system components can include pole, wire, transformer, circuit, feeder, and substation upgrades or replacements (Kallay et al. 2021).

Backup power systems are a fundamental resilience investment from the customer side, and so resilience valuation methods to date have often focused on backup systems. Backup generation resilience investments could include diesel and natural gas generators, fuel cells, or renewable energy paired with storage that provides a secondary or alternate source of power during a resilience event (Kallay et al. 2021). The literature points to emerging black-start technologies, like collective black start, that can help achieve greater system resilience. Collective black start implies a combination of smaller storage units rather than one fully rated storage unit (Jain et al. 2020). One challenge for resilience valuation will be diversifying away from an overemphasis on backup power while also adequately monetizing emerging backup technologies like collective black start.

3.1.2 Demand Response and Flexibility

Although less studied to date, the literature also points to how demand response and flexibility programs can strengthen power system resilience, including within buildings by way of grid-interactive efficient buildings (Neukomm et al. 2022). Demand response methods are an efficient tool for dealing with the uncertainty of distributed generation and improving overall system resilience (Kahnamouei, Shakeri, and Lotfifard 2021; Khalili, Bidram, and Reno 2020). Demand response programs can help reduce maintenance costs at critical lines and maximize the use of available generation and distribution resources (Rahgozar et al. 2022; Kopsidas and Abogaleela 2018; Mousavizadeh, Haghifam, and Shariatkhah 2018). On the distribution side, leveraging distributed energy resources and microgrids as active system assets rather than boundary conditions can enable greater system flexibility to address all hazards (Schneider et al. 2021). Greater flexibility on the demand side results in a faster adaptation to climate variations and return to normal conditions, thus indicating greater climate resilience (Nik and Moazami 2021).

3.1.3 Energy Efficiency

We see some literature characterizing resilience and energy efficiency as fundamentally conflicting objectives. For example, Zhou (2022) emphasizes that considering energy resilience and energy efficiency together often requires trade-off solutions between enhancing one and decreasing the other. A helpful explanation of this comes from optical networks research, in which (like power systems) energy efficiency prioritizes power minimization and resilience prioritizes the maximization of available resources (Ye et al. 2015). A case study from the buildings sector on trade-offs between energy efficiency and passive survivability found that—although all energy-saving strategies led to better passive survivability in old buildings—there were differences in the relative performance ranking of strategies for energy and resilience objectives (Baniassadi and Sailor 2018).

Energy efficiency measures, however, can also have important resilience benefits—it is not always a zero-sum choice between the two. A more recent buildings study from the DOE (2022) found that improving envelope efficiency in residential buildings nearly always saves lives during extreme temperature events. More specifically, increasing envelope efficiency to meet code requirements in existing single-family buildings extended habitability by as much as 50% during extreme cold and by up to 40% during extreme heat. It is important to note that energy efficiency measures do not automatically result in resilience benefits. Stakeholders can achieve co-benefits only by taking advantage of specific efficiency benefits while simultaneously focusing on resilience.

Ribeiro et al. (2015) find energy efficiency to have positive resilience implications across a suite of technologies beyond buildings, ranging from combined heat and power to microgrids. For example, combined heat and power is an energy efficiency measure in that it recovers heat wasted in conventional power generation as useful fuel; combined heat and power has resilience implications in that it can serve power and thermal needs when the grid is down, as well as reduce overall net emissions and potentially increase cost savings. The authors also provide a case study detailing how the Little Ferry Water Pollution Control Facility in Little Ferry, NJ, was able to use backup generators and a biogas-powered combined heat and power system to continue processing sewage in October 2012 during outages from Hurricane Sandy.

Aside from these immediate technical resilience advantages, Ribeiro et al. (2015) argue energy efficiency could also result in higher-level resilience benefits for communities. Community-level resilience benefits from energy efficiency measures include: (1) better response to and recovery from disruptive events; (2) reduced vulnerability to energy price volatility; and (3) reduced greenhouse gas emissions from the power sector. For example, regarding response and recovery, energy efficiency measures can help reduce electricity demand and thus facilitate increased resilience and reliability during times of stress on the power system. One key challenge for resilience valuation moving forward will be in developing metrics for these types of community-level resilience advantages.

3.1.4 Risk Management and Resilient Operations

Resilience is as much a characteristic of processes as infrastructure, so strategy and operations are essential topics for further valuation research. A short-term, process-oriented resilience investment might be resilience-oriented scheduling (such as prepositioning line workers in strategic locations to provide rapid response), while a longer-term plan could incorporate fundamental corrections like hardening and equipment upgrades (Younesi et al. 2022). Other types of planning could include facility management planning, community emergency preparedness, and cyber and physical system response, restoration, and recovery planning (Kallay et al. 2021). Differentiating vulnerability from functional resilience (i.e., service delivered when components fail) could also help identify current gaps in resilience monetization and provide greater clarity to the roles of risk management and service delivery in overall system resilience (Schweikert and Deinert 2021). Training, workforce development, and diversity in workforce can all contribute to more resilient operations as well. Training could include classroom instruction for key staff and practice drills on threat response (Kallay et al. 2021).

3.2 Cost-Benefit Analysis

The value of resilience is an integral component for any cost-benefit analysis of resilience upgrades. Cost-benefit analysis is a systematic approach for assessing investments that allows consistent comparisons across different investment types. Demonstrating cost-effectiveness through cost-benefit analysis is often required to receive government funding (such as FEMA hazard mitigation assistance grants, where a "benefit-cost analysis" is utilized). The application of cost-benefit analysis to investments in grid resilience is still in its early stages. Although we increasingly see resilience cited in connection with grid investment proposals and plans, typically the resilience-related costs and benefits of these investments are not fully identified, quantified, or monetized. To apply cost-benefit analysis more accurately to resilience investments, we need to include considerations such as the probability of event occurrence, temporal and locational variability, and interactive effects (Kallay et al. 2021).

One issue we see currently with cost-benefit analysis for grid resilience investments is the inclusion of all relevant costs, but not all potential benefits (Kallay et al. 2021). Cost-benefit analyses can incorporate any number of benefit categories. Some of the most common for the power sector are: (1) avoided utility costs; (2) avoided customer interruption costs; and (3) non-interruption-related societal benefits. Examples of avoided utility costs could include avoided legal liabilities and vegetation management costs. Examples of avoided customer interruption costs could be the avoided costs of both short-duration and long-duration interruptions. Lastly, examples of societal benefits could include sustained access to critical services, avoided emissions, and broader ecosystem benefits (Zamuda et al. 2019). The societal benefits category, with its necessarily indirect measurements, points to the need for methods to better calculate the total economic valuation of resilience (Ayyub 2014).

Kallay et al. (2021) provide eight principles to improve the application of cost-benefit analysis for grid resilience investments. These principles are:

1. Treat utility resources consistently to avoid bias
2. Align with jurisdiction-specific policy goals
3. Ensure symmetrical treatment of benefits and costs associated with a resource
4. Account for relevant impacts (including those that are difficult to quantify or monetize)
5. Conduct forward-looking, long-term, and incremental analyses

6. Avoid double-counting impacts
7. Ensure transparency in assumptions, methodologies, and results
8. Conduct cost-benefit analyses separately from rate and bill impact analyses.

Developing and establishing performance metrics for resilience (as discussed in Part I) can help enable the quantification of resilience benefits (Kallay et al. 2021). We will now discuss one potential framework for PRA based on a cost-benefit analysis.

3.2.1 PRA for Resilience Valuation

Using the National Academies of Sciences, Engineering, and Medicine framework for PRA, the costs of disruptive events stem from three questions: (1) What disruptive events can occur? (2) How likely are they to occur? and (3) What are the associated costs? (NASEM 2017). The first question considers the underlying hazards that determine which disruptive scenarios to model. The second question considers occurrence frequencies for a given scenario. The third question has two performance-based components: the impact of a given scenario measured using an infrastructure-focused metric, and the consequence of a given scenario measured using a consequence-focused metric (Willis and Loa 2015). NREL folds this PRA process into its resilience assessment methodology to help standardize the assessment process across a diverse set of resilience stakeholders (Anderson et al. 2019).

There are five steps to determining the cost of disruptive events and, in turn, the value of resilience, which are similar to the NREL resilience methodology:

1. Identify hazards
2. Determine relevant scenarios
3. Determine occurrence frequency of each scenario
4. Calculate the impact of each scenario
5. Quantify the consequence of impacts.

Step 1: Identify Hazards

Hazards, which are also referred to as threats, are defined by NYC Emergency Management (2019) as "a source of potential danger or an adverse condition that could harm people, our socioeconomic systems, or our built and natural environments." Hazards are anything that can damage, destroy, or disrupt the energy system and can be natural, technological, or caused by human activity (Anderson et al. 2019). The seven most relevant natural hazards for New York City are (NYC Emergency Management 2019):

- Coastal erosion
- Coastal storms
- Earthquakes
- Extreme heat
- Flooding
- High winds
- Winter weather.

Hazard identification is necessarily location-specific. Before beginning, it can be helpful for utilities and regulators to develop spatial segmentation of their service areas. One way to do so is to categorize existing geographic segments as having a high, medium, or low level of expected consequence

(Broderick et al. 2021). Once a specific location has been established for the analysis, policymakers should also identify key characteristics such as infrastructure types and locations, system topology, and critical mission and community functions. Examples of critical mission functions could include communications, cybersecurity, and logistics; examples of critical community functions could include emergency logistics, evacuation, and medical services (Jeffers et al. 2020).

There are several publicly available sources of hazard or threat data to help guide policymakers. FEMA,[4] the U.S. Geological Survey,[5] and the National Oceanic and Atmospheric Administration[6] all provide open-source data for the United States. For natural hazards, the U.S. Department of Homeland Security's Hazus tool could offer a useful starting point.[7] Hazus provides a standardized methodology for estimating potential losses from earthquakes, floods, hurricanes, and tsunamis (Jeffers et al. 2020).

Step 2: Determine Relevant Scenarios

A scenario consists of the timing, duration, size, and intensity of a relevant or likely hazard. Examples of scenarios include a Category 4 hurricane, a severe flood event, and a 2-day power outage. Considerations for timing and duration could include a hurricane that hits highly populated areas as opposed to more sparsely populated ones, or if the hurricane is fast-moving or stalls above a localized area. A site should select hazard scenarios based on which hazards are most impactful and likely to occur, as well as which hazards the proposed resilience investment is intended to mitigate. The number of scenarios to model depends on trade-offs between the work required to analyze each scenario and the knowledge gained from such analysis.

Step 3: Determine Occurrence Frequency of Each Scenario

Frequency is the annual likelihood that a given scenario will occur. For instance, a one in one-hundred-year event would have a frequency of 0.01. In general, more intense scenarios have a lower frequency of occurrence. We can ascertain frequencies from historical likelihoods or from simulations, although some hazards (like cyberattacks on the grid) do not have historical records and are less well-suited to frequency estimation via simulation. Determining the frequency of occurrence is a key challenge for resilience valuation—particularly for low-frequency events that are difficult to model. An additional challenge in using historical likelihoods is that these can no longer adequately inform what will occur in future, given the rapidly intensifying effects of climate change. It is no longer sufficient to rely on past data to predict future scenarios.

Step 4: Calculate the Infrastructure Performance Impacts of Each Scenario

Infrastructure performance impacts are the physical damages that occur following a disruptive event. Examples of impacts include the number of homes damaged in a storm, the indoor temperature during a heatwave, or the number of customers without power during a blackout. A site can determine impacts from geospatial information (e.g., the number of customers in a flood zone), engineering tolerances (e.g., the expected damage to a home from hurricane-force winds), and simulations (e.g., indoor temperatures during a heatwave) (FEMA 2021b). Outputs from this step could include the hazard

[4] https://www.fema.gov/flood-maps.
[5] https://www.usgs.gov/programs/earthquake-hazards/seismic-hazard-model-maps-and-site-specific-data.
[6] https://www.nhc.noaa.gov/nationalsurge/.
[7] https://www.fema.gov/flood-maps/products-tools/hazus.

magnitude for each threat and location (as either a probability density function or a fixed probability), as well as failure modes and probabilities of failure for specific infrastructure assets (Jeffers et al. 2020).

Step 5: Quantify the Consequence of Impacts

Consequences are the final damages that occur due to an event. Consequences extend performance-based metrics (measured in physical units such as MWh) to focus on event impacts more broadly, including social and economy-wide consequences (generally measured in health-related units like mortality or economic units like dollars) (Jeffers et al. 2020). There are several approaches to quantifying consequences, which we can broadly categorize as bottom-up versus economy-wide and which vary in terms of granularity versus simplicity. We delve further into current methodologies for valuing consequences—including social consequences—in the next section.

Dollars are the most common unit of measurement for consequence-focused metrics because it is relatively straightforward to assign dollar values to impacts like building damages. However, it is more difficult to assign a dollar value to impacts like increased health risks. An ability to measure resilience benefits in dollars is essential because investment costs are also measured in dollars—monetizing resilience thus facilitates cost-benefit analysis. Because the impacts of disruptive events are site-specific, industry-specific, and often business-specific, there is no single consequence-focused metric applicable to all circumstances. Instead, just like with resilience metrics overall, it is important to adopt a multilayered approach.

3.3 Consequence Valuation

As discussed in Part I, consequence-focused metrics extend performance-based metrics to capture the societal impacts of disruptive events. There are several methods for consequence valuation via consequence-focused metrics. The simplest and most common consequence-focused metric is a fixed value per impact. Power outage studies often use a fixed VoLL, measured in dollars per MWh of lost load. For example, FEMA calculates a VoLL for hospitals based on the average cost of transporting and treating patients at the nearest hospital. Using this VoLL in combination with assumptions on outage probabilities,[8] FEMA has estimated the benefits of generator hazard mitigation projects in hospitals at $6.95 per building gross square foot in urban areas and at $12.62 per building gross square foot in rural areas. Other examples of fixed-value consequence-focused metrics include the average cost of repairs per building from hazards like frozen pipes or flooding and the cost per person per day for displaced populations.

Unlike the static VoLL metric, customer damage functions (CDFs) demonstrate how the magnitude of customer economic losses (per kilowatt interrupted) changes over an outage period. This is an important first step in considering how a duration-dependent value of resilience can influence investment and operations decisions. With support from the DOE's Federal Energy Management Program, NREL has developed the Customer Damage Function Calculator[9] to help facility owners and resilience planners understand the costs of an electric grid outage at their site (NREL 2023).

[8] These calculations assume a 5-year recurrence interval for 1-day outages and 50-year recurrence intervals for 4-day outages. These values seem to be based simply on guesses of outage frequency, underscoring the difficulty of finding outage duration data.

[9] https://cdfc.nrel.gov/

As mentioned previously, there are two main approaches for valuing consequences: bottom-up and economy-wide. Bottom-up approaches use aggregations of estimated specific outage impacts to determine the combined impact of a disruptive event. For bottom-up approaches, we often see the DOE's Interruption Cost Estimate calculator,[10] customer surveys, or CDFs used. Economy-wide approaches use economic models such as input-output models or computational general equilibrium to estimate the impact of large-scale events on economic activity. Examples of economy-wide models for power outage costs include IMPLAN[11] and REAcct.[12]

Consequence-focused metrics can also incorporate customer-specific attributes and nonlinearities in the cost of impacts. Although these additions are often more complicated to calculate, they provide useful information. Consequences can increase nonlinearly with impact size, impact area, and impact duration. This means it is most crucial to account for nonlinearities in cost with events that are widespread, high-impact, and extended duration. Consequences can be nonlinear in impact size due to damage thresholds, like replacing an entire roof once more than 5% of the roof sustains damage (FEMA 2021c). Consequences can be nonlinear in impact area due to interactions between individual impacts—like widespread disruptions leading to traffic jams, supply disruptions, or constraints on recovery resources. Finally, consequences can be nonlinear in impact duration due to damage thresholds (e.g., food spoilage, negative health impacts, or inability to go to work) that lead to increasing consequences over time or to mitigation strategies (e.g., backup generators) that reduce consequences over time. Two of the most important types of consequences for power sector resilience are customer interruption costs and social consequences.

3.3.1 Customer Interruption Costs

Power outages are typical in the aftermath of a disruptive event, and can interfere with infrastructure that serves essential operations and lead to economic consequences. The costs that power interruptions impose on both customers and society have become key pieces of the resilience puzzle. While the direct costs of localized and short-duration power interruptions are relatively well understood, we still know little about the full impact of widespread and long-duration power outages—especially in terms of indirect costs and economy-wide impacts. As a result, utility planning activities are often unable to consider the costs of these widespread and long-duration interruptions (Baik et al. 2021).

There are myriad potential electricity-related costs following a disruptive event. The literature identifies five main categories of these costs (Zamuda et al. 2019; Meyer et al. 2013; Baik et al. 2021):

1. The cost of damage to utilities' physical infrastructure
2. The cost of interruptions to electricity customers, including lost production
3. Indirect costs to local or regional economies
4. Intangible costs that can be monetized, including health risks, environmental damage, and legal liabilities
5. The costs of risk reduction and resilience enhancement investments.

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[10] https://icecalculator.com.

[11] https://implan.com.

[12] Vargas, Vanessa N., and Mark A. Ehlen. 2013. "REAcct: a scenario analysis tool for rapidly estimating economic impacts of major natural and man-made hazards." *Environment Systems & Decisions* 33: 76-88. https://doi.org/10.1007/s10669-012-9430-5.

Figure 6 depicts the components associated with direct customer power interruption cost assessments, overall power interruption cost assessments, and damage assessments for power disruptions. The costs of power interruptions for electricity customers (the light green box in Figure 6) include the costs brought about either directly or indirectly by power disruptions.

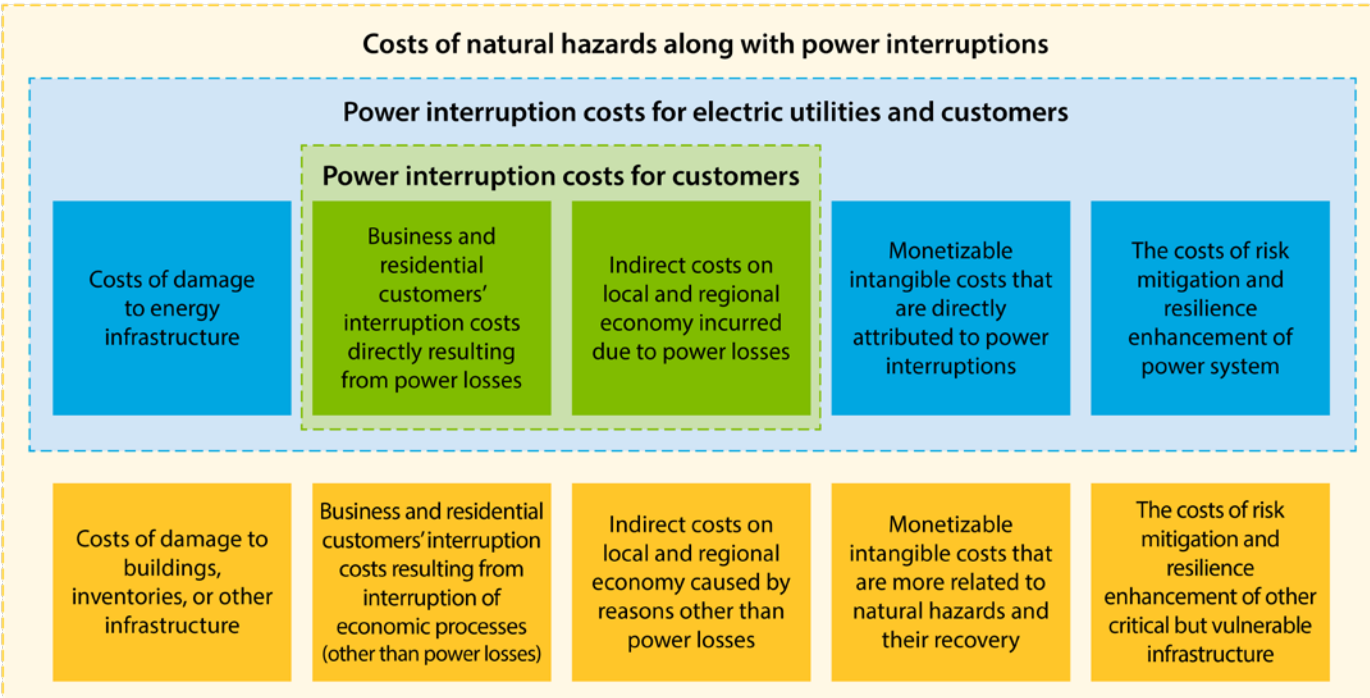

Figure 6. Diagram of natural hazards and power interruption cost components

Figure by NREL, adapted from Baik et al. (2021)

Interruption costs stem from both the actual outage and how it affects users, and these costs are often a function of how long the outage lasts. Calculating interruption costs incorporates the CDF framework. The actual damage caused by an interruption can vary depending on the classes of customers whose power is cut off, the length of time the power is out, the circumstances in which the interruption takes place (like the day of the week, the time of day, the customer's activity at the time of interruption), and whether the event was forecasted (which determines if the customer could prepare for the outage ahead of time). When calculating customer interruption costs, it can be helpful for utilities and regulators to identify one or more classes of "critical customers" that provide critical community services. Examples of critical customers could include hospitals, urgent care facilities, community cooling centers, water and sewer treatment and pumping facilities, vehicle fueling stations, or grocery stores (Broderick et al. 2021).

Current methods for estimating customer interruption costs include customer surveys (the bottom-up approach), regional economic modeling approaches (the economy-wide approach), and hybrid approaches that combine the two. Customer interruption cost surveys are the most common method because they can estimate direct costs for a variety of power interruption scenarios, but regional economic modeling can complement traditional survey methods in the estimation of indirect costs of disruptions (Baik et al. 2021; Sanstad 2016). Baik et al. (2021) describe the development of a Power

Outage Economics Tool that uses survey-based information to calibrate a regional economic model. Including more accurate estimates of customer interruption costs will enhance the effectiveness of utility planning decisions, especially vis-à-vis grid-hardening strategies and other capital-intensive resilience investments (Baik et al. 2021).

Further research is needed to help capture the broader social costs of disruptive events, as well as the impacts of power interruptions on interdependent critical infrastructures. Broader social costs might include injuries and deaths, especially in more vulnerable segments of the population (Baik et al. 2021). The nature of the disruptive event, the infrastructure network under consideration, and the relative vulnerability of those served by this infrastructure are inseparable dimensions when considering direct impacts on human suffering during a power outage. The reality that the effects of power loss on human suffering are spatially diverse speaks to the need to incorporate social vulnerability and equity metrics in resilience valuation methods (Boyle et al. 2022).

3.3.2 Social Consequences

Although power outages ostensibly affect everyone, they do not affect everyone equally—so there is necessarily an equity dimension to power sector resilience. There are also both monetary and nonmonetary costs associated with power outages for residential customers (Ericson and Lisell 2020). Power outages have been linked to a variety of negative outcomes for people's health, including carbon monoxide poisoning, hospitalization for conditions like heart disease or kidney disease, illnesses like gastroenteritis, and other temperature-related conditions up to and including death (Casey et al. 2020).

Outages often disproportionately affect those whose access to electricity is so critical that any interruption can be fatal or cause permanent damage. For example, there is an increasing prevalence of diabetes in Puerto Rico, and many residents there depend on electricity-powered dialysis machines—but when Hurricane Maria struck in 2017, it left virtually all residents without normal levels of power for 10 months. Winter storms in Texas in 2021 resulted in a severe power outage that left 200 dead over a 2-week period due to carbon monoxide poisoning, extreme cold, and the aggravation of preexisting conditions (Ankit et al. 2022; Dugan, Byles, and Mohagheghi 2023). Many of the victims were either already medically vulnerable or relied on electricity-dependent equipment like oxygen concentrators (Dugan, Byles, and Mohagheghi 2023).

Research has also shown the Texas winter storm and its associated blackouts were especially hard on low-income families and communities of color. Overburdened and underserved communities are more vulnerable in part because they have fewer resources to prepare for and cope with extreme weather and climate events. In the case of the Texas storm, for example, communities of color had already been disproportionately affected by the COVID-19 pandemic in terms of disease burden and unemployment rates (Busby et al. 2021).

Vulnerable communities could also include the poor, elderly, language-isolated, and recent immigrants (USGCRP 2018). Dugan, Byles, and Mohagheghi (2023) find that various socioeconomic and demographic characteristics contribute to different levels of health risk, outage preparedness, and willingness and means to evacuate if necessary during a long-duration power outage. For example, being above 65 or under 5 contributes to increased health vulnerability, speaking limited English contributes to increased outage preparedness vulnerability, and identifying as a female adult contributes to increased evacuation vulnerability. The authors argue these relationships highlight the need to proactively identify socially vulnerable groups and communities to provide targeted information, assistance, and resources during disruptive events. Broderick et al. (2021) recommend utilities and regulators consider identifying a specific customer class that includes vulnerable residential customers who require additional individual attention due to higher health risks or lower mobility.

The literature includes a wide range of other potential social vulnerability indicators. Zuzak et al. (2023) use the Centers for Disease Control and Prevention's Social Vulnerability Index[13] for FEMA's National Risk Index, while Dugan, Byles, and Mohagheghi (2023) group vulnerability into the three dimensions of health, preparedness, and evacuation discussed above. Households at or below 200% of the federal poverty level, Black and Hispanic households, and rural households tend to struggle most with everyday energy insecurity and longer power outages (Memmott et al. 2021; Mitsova et al. 2018). Other socioeconomic variables that could indicate vulnerability to power outages include: (1) belonging to a minority group; (2) possessing a sensory, physical, or mental disability; or 3) being unemployed. Further research is also needed to deepen our understanding of how power restoration after disruptive events contributes to and is impacted by the socioeconomic vulnerabilities of communities (Mitsova et al. 2018).

Social burden is another equity-focused metric that can complement social vulnerability. According to Clark et al. (2022), social burden attempts to capture the consequences of infrastructure service disruptions on households. Theoretically informed by the Capabilities Approach theory of human development (which emphasizes outcome-based understandings of what people can do and be), social burden quantifies the burden of post-event adaptations households take to maintain their basic capabilities (e.g., ability to access food and water) and fulfill important household activities (e.g., maintain health and well-being). It does so by measuring social burden as the total hours spent fulfilling needs, calculated by dividing the relative need of a population group to achieve a capability type by the accessibility of the population group to that capability type. The authors argue that by taking this human-centric approach to consequence valuation, we can more objectively and accurately quantify the consequences of disruptive events.

Social vulnerability and social burden metrics can—and should—help inform resilience investments. For example, Jeffers et al. (2018) conducted an equity-informed microgrid siting analysis for Puerto Rico following Hurricane Maria in 2017. The authors based their analysis on a social burden metric that quantified the difficulty community members faced in accessing necessary services in the event of a major disruption. By using this social burden metric, planners could gain quantitative insight into how grid improvements impact the community, especially those residents with fewer means to access services in general. The analysis results provide microgrid siting recommendations explicitly designed to improve a community-focused, risk-informed resilience metric.

The indirect and intangible costs associated with power outages also make relevant the concepts of social community and disaster resilience. The concept of resilience applies to a broad spectrum of system types—including both electric grids and social systems like communities. It is even more difficult to apply monetization methods in the realms of social and community resilience, given the complexity at play in the varied and nuanced interconnections among people, places, and things.

Social and community resilience are subsets of resilience that warrant further attention for measurement and valuation purposes, especially in relation to the power sector. Achieving resilience at the community

[13] https://www.atsdr.cdc.gov/placeandhealth/svi/index.html.

level can lead to massive savings through risk reduction and speedy recovery (Bie et al. 2017). Social resilience is “the ability of groups or communities to cope with external stresses and disturbances as a result of social, political and environmental change” (Adger 2000). It incorporates capacities like social capital, community functions, connectivity, and planning—as well as the capacity to cope, adapt, and transform (Cutter 2016; Keck and Sakdapolrak 2013).

Community resilience can be defined as “the capacity of a community or region to prepare for, respond to, and recover from large multi-hazard threats with little impact on public safety and health, the economy, and national security” (Wilbanks 2007). It can include attributes such as resistance, recovery, and creativity (Maguire and Hagan 2007). Johansen, Horney, and Tien (2017) find that many of the existing metrics for community resilience (like Arup and the Rockefeller Foundation’s City Resilience Index,[14] the U.N. Disaster Resilience Scorecard for Cities,[15] and the U.S. Resiliency Council Building Performance Ratings[16]) are limited to providing general assessment frameworks for communities. The authors conclude that social and community-level resilience metrics should provide place-based methodologies for communities to assess their preparedness for various types of disruptive events, and that there should be a focus on creating metrics with explicit or quantitative outcomes. Like resilience writ large, a combination of metrics will be helpful in adequately capturing social and community resilience to widespread and long-duration power outages moving forward.

Disaster resilience is a related concept that encompasses the social, economic, institutional, infrastructural, community-based, and environmental dimensions of resilience (Burton 2015). Disaster resilience considers the impact of equitable restoration activities on interdependent infrastructure networks, and it combines both social equity and social vulnerability concepts with measures related to critical interdependent infrastructure network restoration scheduling (Karakoc et al. 2020). Disaster resilience is an important concept for the power sector because, as mentioned above, we need to better understand how post-event power restoration both contributes to and is affected by issues of social equity and vulnerability (Mitsova et al. 2018). Improved indicators of social, community, and disaster resilience are a priority area for future metrics research, from both an attribute-based and performance-based standpoint (Maguire and Hagan 2007).

[14] https://www.cityresilienceindex.org.
[15] https://www.undrr.org/publication/disaster-resilience-scorecard-cities.
[16] https://www.usrc.org/usrc-rating-system/.

4 Conclusion

The research landscape in electric power sector resilience measurement and valuation is rapidly expanding. The resilience measurement field appears slightly more robust than the resilience valuation field, although the two are closely interrelated. This could in part be due to the development and evolution of increasingly robust metrics and methodologies for analyzing both resilience and risk mitigation strategies. In general, we need to start applying the available metrics and methodologies, validating them, and demonstrating their use for utilities, regulators, and policymakers.

There are some areas of divergence in the literature, especially on the subject of resilience metrics. Although there is general consensus on attribute-based and performance-based metrics, consequence-focused metrics were less well-developed and sometimes had different emphases. The categories of risk-based and scenario-based metrics also warrant further study. The names of the different resilience metrics categories, however, are less important than their content. Authors largely agreed on a multilayered and context-specific approach toward resilience metrics, as well as the need to better expose and handle the inevitable uncertainty in PRA and other current resilience valuation methodologies.

The subjects of consequence-focused metrics, customer interruption costs, and social consequences point to several opportunities for future research, including in the important areas of social vulnerability and equity-based resilience metrics. The indirect economic and health-related costs of power outages on customers with different socioeconomic and demographic characteristics involve the important concepts of social and community resilience. It is more difficult to monetize these types of resilience than it is physical infrastructure resilience, but social systems are even more in need of resilience than engineered systems like our electricity grid. One especially important avenue for future power sector research in this regard will be how to design and expand resilience improvement projects that support more equitable systems—including during the planning process for power restoration after disruptive events, which must take into account both equity concerns and interdependencies among critical infrastructure networks (Cicilio et al. 2021; Mitsova et al. 2018).

Other future research themes that emerged from the literature review include:

1. Greater focus on how human activities tie into both disruptive events and the response to those events (i.e., how human behaviors can increase or decrease a system's risk, vulnerability, or ability to withstand acute shocks)
2. Better understanding the linkages between resilience and energy efficiency and how the two objectives can support one another
3. How to methodologically keep up with the pace of climate change and associated rapid shifts in disruptive event likelihoods.

As Roege et al. (2014) point out, the human element of resilience also includes the need for technical experts to supplement data where it is impossible to obtain physical measurements. The human element of resilience acknowledges both the positive and negative ways in which people can impact the ability of a system to prepare for and respond to disruptive events.

There is also the need for critical assessment of the power sector's current methods for resilience measurement and valuation. This includes thinking through how we account for cost-benefit ratios when determining the value of resilience investments and understanding the drawbacks of how we measure and value operationally avoided losses or damages. We need to understand what types of consequences are appropriate for ratepayers to buy down (through state Public Utility Commission and utility planning processes) and what types of consequences are more appropriate for a tax base to buy down. Within that, we need to better understand the roles of federal, state, and local governments in helping make these determinations. Another direction for future resilience valuation research could be in better quantifying the insurance value of resilience (Li et al. 2018). We also require new methods for calculating the broader economic valuation of resilience, including both the indirect costs and economy-wide impacts of widespread and long-duration power outages (Ayyub 2014, Baik et al. 2021). Although the power sector has made great strides toward more accurate and meaningful measurement and valuation in recent years, we still have a way to go in putting the right price on resilience.

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Appendix C: Glossary of Terms

Community Resilience: The capacity of a community or region to prepare for, respond to, and recover from large multi-hazard threats with little impact on public safety and health, the economy, and national security (Wilbanks 2007).

Customer Damage Function (CDF): Represents customer interruption costs as a function of an outage duration. For electricity, CDF can be represented as a value in $/kilowatt peak of an outage cost obtained from the CDF curve for a specified duration of an interruption, and represents damages over the outage duration, typically by stock costs, fixed costs, and incremental costs (NREL 2023).

Common Cause Failure (CCF): Multiple dependent component failures within a system that are a direct result of a shared root cause or common cause, such as sabotage, flood, earthquake, lightening, power outage, sudden changes in environment, design weaknesses, or human errors (Hokstad and Rausand 2008).

Coherent System: A system that increases its resilience as each system component is hardened (Zio 2007; Haarla et al. 2011).

Disruptive Event: An event in which operations of the electric grid are disrupted, preventively shut off, or cannot operate safely due to extreme weather, wildfire, or a human cause (42 U.S. Code § 18711 2021)

Hazard: Anything that can damage, destroy, or disrupt the power sector. Hazards can be natural, technological, or human-caused. Hazards are typically not within the control of power systems planners and operators and can include wildfires, hurricanes, storm surges, system malfunctions, and cyberattacks. This term is often used interchangeably with the term "threat" (Stout et al. 2019).

Human-Caused Hazards: Resulting from accidents or the threats or intentional actions of an adversary (e.g., cyber, acts of terror) (Stout et al. 2019; Hotchkiss and Dane 2019).

Layer-of-Protection Analysis (LOPA): A low-cost and low-data analysis methodology to bring technology and hazard awareness to systems analysis (Willey 2014; Markowski and Kotynia 2011).

National Risk Index: A publicly available data source produced by FEMA that seeks to illustrate the communities most at risk from 18 natural hazards based on historic damages (FEMA 2023a).

Natural Hazards: Environmental phenomena that have the potential to impact societies and the human environment. These should not be confused with other types of hazards, such as man-made hazards. For example, a flood resulting from changes in river flows is a natural hazard, whereas flooding due to a dam failure is considered a man-made hazard (FEMA 2023b).

Outage: Period of time after disruption that a service, system, process, or business function is expected to be unusable or inaccessible.

Probabilistic Risk Assessment (PRA): A well-established risk assessment methodology commonly used in the aerospace and nuclear industries (Stamatelatos and Dezfuli 2011; Fullwood and Hall 1988).

Resilience: A system's ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions through sustainable, adaptable, and holistic planning and technical solutions (Hotchkiss and Dane 2019).

Reliability: The ability to meet the electricity needs of end-use customers, even when events reduce the amount of available electricity (NIAC 2010).

Reliability Metrics: Designed to capture events which are expected to occur and disruptions that tend to be limited in time and geographic scope.

Resilience Metrics: Designed to capture lower-probability, higher-consequence events that can last an extended period and impact a large area.

Resource Adequacy: Ability of the electric system to supply the aggregate electrical demand and energy requirements of the firm load at all times, considering scheduled and reasonably expected unscheduled outages of system elements (NYISO 2022b).

Risk: Risk is a function of the likelihood of a hazard, the probability of a vulnerability occurring given a hazard, and the consequence of the vulnerability (Anderson et al. 2019).

Social Resilience: The ability of groups or communities to cope with external stresses and disturbances as a result of social, political, and environmental change (Adger 2000).

Technological Hazards: Result from accidents or failures of systems and structures (e.g., bridge collapse, grid outage) (Hotchkiss and Dane 2019).

Value of Lost Load (VoLL): The costs associated with electric grid outages, represents an approximate price that consumers are willing to pay for uninterrupted electricity; typically measured in units of dollars/kilowatt-hour and can be multiplied by the lost load to estimate the total cost of an outage (Anderson, Hotchkiss, and Murphy 2019).

Appendix D: Calculation Methods for IEEE Reliability Metrics

Average-Based Metrics

(IEEE 2012)

SAIDI: Calculated by multiplying the average duration of customer outages by their total number and dividing by number of customers.

$$SAIDI = \sum \text{Customer Minutes of Interruption} / \text{Total Number of Customers Served}$$

SAIFI: Calculated by dividing the number of customers that have experienced an interruption by the total number of customers.

$$SAIFI = \sum \text{Total Number of Customers Interrupted} / \text{Total Number of Customers Served}$$

Customer Average Interruption Duration Index: Calculated by dividing the total minutes of customer interruption by the total number of customers interrupted.

$$\text{Customer Average Interruption Duration Index} = \sum \text{Customer Minutes of Interruption} / \text{Total Number of Customers Interrupted}$$

Customer Average Interruption Frequency Index: Calculated by dividing the number of interruptions by the number of customers experiencing interruptions.

$$\text{Customer Average Interruption Frequency Index} = \sum \text{Total Number of Customer Interruptions} / \text{Total Number of Distinct Customers Interrupted}$$

Momentary Average Interruption Duration Index: Calculated using the same method of SAIDI but only using momentary interruptions, defined as interruptions lasting less than 5 minutes.

$$\text{Momentary Average Interruption Duration Index} = \sum \text{Customer Minutes of Momentary Interruption} / \text{Total Number of Customers Served}$$

Momentary Average Interruption Frequency Index: Calculated using the same method of SAIFI but only using momentary interruptions, lasting less than 5 minutes.

$$\text{Momentary Average Interruption Frequency Index} = \sum \text{Total Number of Customer Momentary Interruptions} / \text{Total Number of Customers Served}$$

Customer-Based Metrics

(IEEE 2012)

CELID: Describes ratio of customers that experience interruptions with durations longer than the duration of a single interruption or the total amount of time (t) that a customer has been interrupted during the reporting period. The CELID-s is calculated by the total number of customers that have experienced an interruption of s or more hours in duration divided by the total number of customers served. The CELID-t is calculated by the total number of customers that experienced t or more hours of interruption duration, divided by the total number of customers served.

<u>Single Interruption Duration</u>

CELID-t = Total Number of Customers that experienced S or more hours duration / Total Number of Customers Served

<u>Total Interruption Duration</u>

CELID-t = Total Number of Customers that experienced T or more hours duration / Total Number of Customers Served

Customers Experiencing Multiple Interruptions: Calculated by the total number of customers that experienced n or more sustained interruptions divided by the total number of customers served.

Customers Experiencing Multiple Interruptions = Total Number of Customers that experienced n or more sustained interruptions / Total Number of Customers Served