A Power Outage Data Informed Resilience Assessment Framework

Michael Abdelmalak[1], Sean Ericson[2], Jordan Cox[2], Mohammed Ben-Idris[1], and Eliza Hotchkiss[2]
[1]Department of Electrical and Biomedical Engineering, University of Nevada-Reno, Reno, NV 89557, USA
[2]National Renewable Energy Laboratory, Golden, CO 80401, USA
Emails: mabdelmalak@nevada.unr.edu, sean.ericson@nrel.gov, jordan.cox@nrel.gov,
mbenidris@unr.edu, eliza.hotchkiss@nrel.gov

***Abstract*—Catastrophic impacts to power systems due to disruptive events have increased significantly during the last decade. These events highlight the need to develop approaches to assess the resilience of power systems against extreme events. However, the availability of data that capture power system performance during and after disruptive events is scarce. This paper proposes an assessment framework to evaluate the performance aspects of the grid system during extreme outage events using the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) data. EAGLE-I includes information related to the number of impacted customers, duration, and location of power outages in the United States. Statistical analyses were conducted to extract resilient-based outage data and derive probability distribution functions of their impact and recovery characteristics. A list of extreme events is identified based on few predetermined threshold values. Metrics from other power outage assessments were used to measure the characteristics of each event, including impact rate and duration, recovery rate and duration, and impact level. A probability distribution function is obtained for each metric. The obtained results provide a representation of national grid performance during extreme events, which can be applied as a framework to evaluate various resilience enhancement techniques.**

***Index Terms*—EAGLE-I, extreme weather event, power outage, resilience.**

I. Introduction

Modern societies have been heavily relying on electricity access and availability. When electricity is unavailable, individuals, communities, and countries are subject to economic and physical harm, especially when an electricity outage occurs during an extreme weather event (e.g., extreme heat or cold). Reliability has long been an important indicator for electricity grid operators, but as the frequency and intensity of extreme weather events have increased in recent years, yielding prolonged outages and significant economic losses [1], [2], resilience has become a larger focus for grid operators and communities. For example, Hurricane Sandy caused over eight million customers to lose power across 15 states in the United States [3]. In 2021, the winter storm Uri caused widespread power outages in Texas during extreme cold, which resulted in 246 recorded deaths and more than four million customer without power for a few days [4]. During the last seven years, the U.S. has been exposed to seven wildfires, eight droughts, 75 severe storms, 19 tropical cyclones or hurricanes, 16 floods, five winter storms, and one freeze event with more than one billion-dollars in estimated costs [5]. Fast and efficient restoration of grid systems, after disruptive events occur, is one of the most important attributes to achieving resilient operation of power systems. Quick recovery of grid infrastructure reduces associated economic and community impacts [6], [7]. These challenges require the development of resilience evaluation methodologies to quantify the behavior and characteristics of extreme events on power systems.

Many definitions for power system resilience exist. For the purposes of this paper, the authors define resilience as “The ability of a system to prepare for, absorb, adapt to, and recover from disruptive events” [8]. Attributes of resilience include preparedness, recovery, adaptability, and reliability, just to name a few. Electric reliability is the likelihood that electricity will be available during normal operating conditions and grid operators have a long history of using reliability metrics. There is no single metric for resilience, however [9]. In order to compare resilience across infrastructure domains and jurisdictions, there is a need for publicly available datasets with transparent metrics for, or attributes of, resilience. Having reliable and accurate data is the first step toward understanding the behavior and performance of electric power systems during extreme events. These datasets can be used by (a) individuals and communities to perform cost benefit analyses on resilience measures, such as backup power systems or islandable microgrids, and mitigation strategies, such as hardening transmission and distribution lines, and (b) by government entities to compare resilience performance across infrastructure systems. Also, datasets can be leveraged to extract system features and extreme event characteristics for resilience analyses. Therefore, robust statistical analysis can be carried out using extreme event data and quantifying their characteristics.

Though different approaches have been proposed to distinguish between outages that belong to reliability analysis and those that belong to resilience analysis, gaps still exist. For instance, a time-based threshold has been used in [10] to identify prolonged outage events for resilience evaluation framework. In [11]–[13], a temporal perspective is presented where a twenty-four hours mark has been used as a threshold to differentiate between short- and long-duration outages. Also, a quantitative threshold has been used based on the amount of customers without power or the amount of lost energy to identify extreme outage events, as proposed by the Department of Energy (DOE) [14]. Other approaches include assessing lifeline infrastructure restoration behavior using predefined extreme weather events [15], similar to a description of power outages using retrospective analyses (e.g., outages between 2000 and 2016) [14]. Most of these methods have conducted basic analysis of the existing data for specific weather events or defined geographical regions. The importance of extracting distribution functions governing the behavior of extreme outage events has not been deeply investigated, highlighting a research gap in resilience evaluation processes.

The goals of this paper are to examine a publicly available dataset to evaluate power outages due to extreme weather events, propose threshold values to measure the power outage duration, number of customers affected, and restoration time. Quantifying the characteristics of extreme outage events was conducted to provide probability distribution functions (PDFs) of extreme outage event characteristics. Several threshold values were calibrated against event data from several extreme weather events to create metrics that could be used to compare the resilience performances of jurisdictions and electricity providers for the entire U.S. A list of metrics is included to measure the characteristics of extreme outages, including event frequency and duration, impact and recovery duration, and impact level. Curve fitting was used to determine the best-fit PDF for each metric. This method was then applied to the aggregated outage data across the entire U.S.

The remainder of this paper is organized as follows. Section II describes the methodology developed to quantify extreme power outages. The implementation procedure and results are provided in Section III. Some concluding remarks are provided in Section IV.

II. Methodology

The methodology developed in this paper consists of five steps. The first step involved cleaning and aggregating a publicly available dataset related to power outages (i.e., EAGLE-I data). Second, the outage data was filtered based on defined threshold values. Event characteristics were calculated in the third step, then curve-fitting the outage event progression to a PDF was conducted in the fourth step. The fifth step required calculating the sensitivity of results against the threshold values used for the original resilience event filtering. This process is described in more details in this section.

A. Data Processing

A publicly available dataset called the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) is chosen for the purpose of this analysis. The EAGLE-I dataset is collected and managed by the U.S. Department of Energy's (DOE) Oak Ridge National Laboratory (ORNL) [16]. This dataset spans November 2014 to the present and is collected by scripted scrapers that check publicly available outage maps from utilities. The data is used to estimate the number of customers without power, by utility, in a given county, and is updated every 15 minutes. Since the dataset is based on the number of utility websites that can be scraped, the number of utilities in the dataset and their geographic granularity has changed since the data was first collected. For example, in 2015, the EAGLE-I dataset lists 2,153 unique utilities, whereas in 2020 the dataset lists 3,014 unique utilities. This shows that more utilities are making their power outages publicly available since 2014.

To utilize the EAGLE-I data, the "non-float" values were removed and a linear smoothing between noncontinuous time steps was assumed. The "non-float' values are defined to be the data records that show large momentary drop in outage record due to missing an outage record by a single or set of scrapers. Second, years 2015 to 2020 are included such that only complete years are studied in the analysis period. Data was then aggregated for the entire U.S. for all utility customers without power at the same time interval. The data was also aggregated by utility, county, and state, though only the nation-wide aggregation was used for this analysis.

The following figures illustrate the outputs of this data scrubbing and aggregation process. Fig. 1 visualizes the aggregation for an example duration (i.e., between October 7^{th} and October 16^{th}, 2016). Fig. 1(a) shows the electric power outage for all electric utilities in a specific county, whereas Fig. 1(b) shows the aggregated values for all counties in a specific state. The aggregated power outages on the state level is shown in Fig. 1(c), followed by the aggregated outage on the national level.

B. Resilience Thresholds

The electric power outages in the EAGLE-I dataset represent the number of customers without power, which varies from zero to a maximum value of almost ten million customers (i.e., during Hurricane Irma in 2017). A customer is defined as any entity that purchases energy from a utility via a tariff. This means that 'customer' should not be interpreted as 'persons'. Residential households with only one tariff often have multiple residents, and commercial entities sometimes have multiple tariffs for a single site. Notwithstanding the incongruity between persons and customers, the DOE identifies extreme outage events as those exceeding 300 megawatts (MW) or 50,000 customers [14], and other thresholds can also be identified with the data.

In this research, a threshold, α, was created to act as a filtration such that outages exceeding a threshold were considered "extreme outage events" and vary for sensitivity analyses. This filtration threshold is used to select outages with extreme impacts on the power grid. Fig. 2 visualizes the concept of the filtration threshold and the importance of its value for a single month between January 10^{th} to February 10^{th}, 2016. The chosen threshold will have a significant impact on analysis results. For example, a higher threshold value results in fewer extreme events with a shorter event duration. Additionally, from an energy justice perspective, rural communities with fewer than 50,000 customers will never register as having a long-duration outage in the current

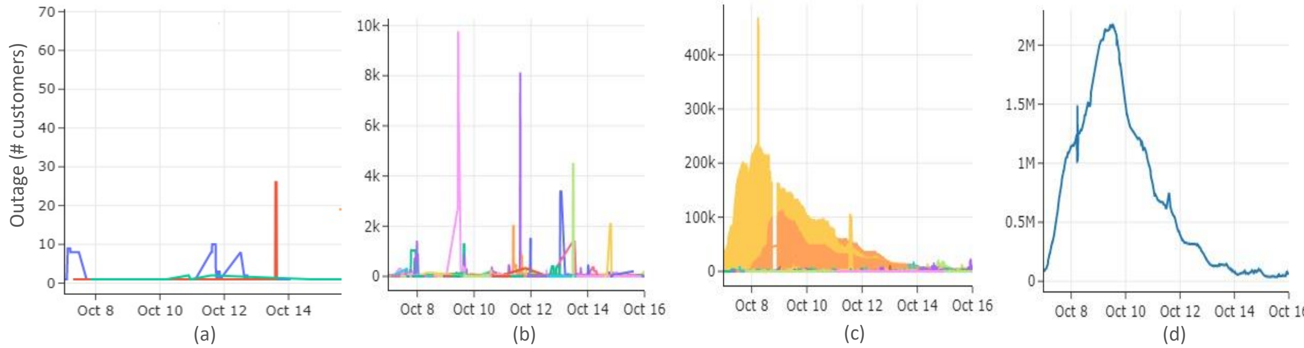

Fig. 1. Power outage records on (a) utility level, (b) county level, (c) state level, and (d) country level

methodology. While odds are low that only one small community would be affected in a natural disaster for a long-duration outage, future work will seek to address this disparity. For the selected period, the threshold filtering resulted in five extreme outages when α equals 100,000 customers and around 15 extreme events for the 50,000 threshold. In this work, a few thresholds were tested to show the importance of the threshold values for resilience-based studies.

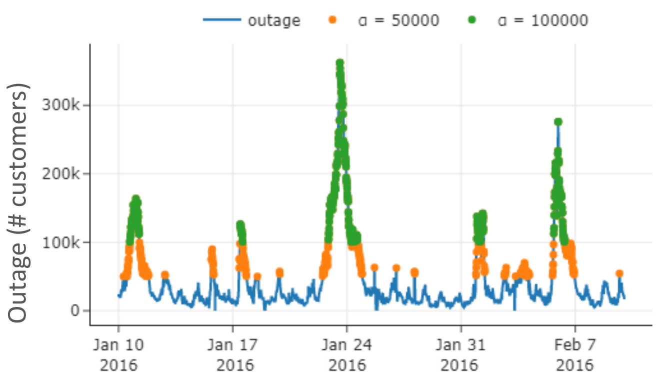

Fig. 2. Resilience-based filtration for α = 50,000 and α = 100,000

C. Event Characteristics

Once the filtration threshold was established and incorporated into the pre-processed EAGLE-I dataset, extreme outage events were identified. For this analysis, an extreme outage event was defined to be the set of contiguous customer outage records bounded by outage level beyond threshold value starting and ending the event, as shown in Fig. 2. Metrics used to quantify the characteristics of each extreme outage event included the event duration, the impact duration, the recovery duration, the post-event duration, and the impact level, as illustrated in Fig. 3. These metrics were determined based on the resilience triangular and trapezoidal curves [1], [17]. The metrics are defined as:

- M_1 Event duration: the total time of an extreme outage event where the outage level exceeds the filtration threshold, α.
- M_2 Impact duration: the total time between the start of an extreme outage event and the maximum outage level within the event duration.
- M_3 Recovery duration: the total time between the maximum outage level within the event duration and the end of the event.
- M_4 Post-event duration: the total time between the end of an event and the start of the proceeding event.
- M_5 Impact level: the maximum number of customers without power within the event duration.

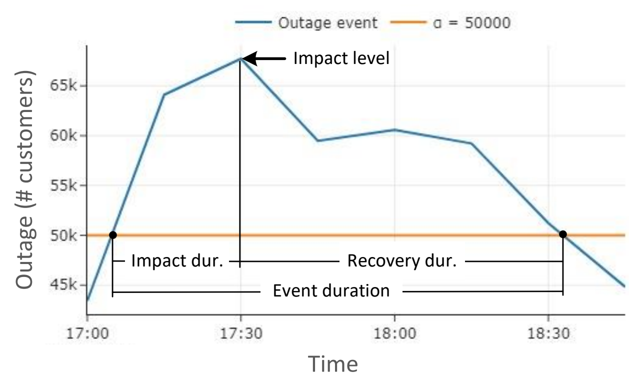

Fig. 3. Event characteristics curve

D. Outage Curve Fitting

Curve fitting was used to determine probability distributions for the proposed event metrics, based on extracted extreme outages from EAGLE-I dataset. These PDFs can be used to simulate diverse extreme outage events for resilience-based studies and estimate the cost versus benefit of resilience solutions and mitigation strategies. For each threshold value, a list of extreme outage events and their corresponding characteristics was obtained. Curve fitting approaches are used to evaluate the best fit PDF governing the behavior of each metric. Various PDFs were proposed and tested including normal, exponential, Pareto, double Weibull, t, gamma, lognormal, beta, and loggamma. Detailed information regarding each PDF has been well documented in previous studies [18], [19]. The residual sum of squares (RSS) criterion was used to evaluate the goodness-of-fit of each PDF. The results were compared across threshold values to show the sensitivity to thresholds of the analysis results.

III. Implementation and Results

The methodology outlined in the previous section was applied to the EAGLE-I dataset, which includes more than 130 million customer outage record values. This section provides detailed statistical analysis for various proposed thresholds. The PDFs governing the behavior of extreme outage events were calculated and evaluated, the results of are detailed in this section.

A. U.S. Extreme Outage Statistics

In this study, the number of customers without power (outage count) was used to measure the outage impact as recorded in the EAGLE-I dataset. Five threshold values were selected for evaluation, as described in Table I, and compared with the DOE defined threshold of extreme outages. It is worth noting that the average outage count for the U.S., as a whole, is 96,682.8 with a standard deviation (st. dev.) of 302,185 customers.

TABLE I
Selected thresholds for resilience-based evaluation of the EAGLE-I dataset

	Value	Description
α_1	50,000	The DOE defined threshold of extreme outages
α_2	247,776	Average plus half st. dev. of outage count
α_3	398,868	Average plus st. dev. of outage count
α_4	2,187,765	20% of maximum outage count
α_5	3,281,647	30% of maximum outage count
α_6	4,375,529	40% of maximum outage count

Table II summarizes the number of extreme outage events, the average, and the standard deviation of outage level for each threshold. The number of extreme outages decreases as the threshold value increases. For example, there were approximately 4,000 extreme outages based on the DOE threshold. Given that the EAGLE-I data capture outage records for a total of six years and four months, this yields an average of 889 extreme outage events per year. Though this number might not reflect the exact extreme outage events per year in the U.S., it provides an accepted estimate of extreme outages based on robust data. The extracted events based on the DOE threshold have an average of 200,000 customers without power per event. Using higher thresholds leveraging the EAGLE-I dataset shows the significant reduction in the frequency of extreme outage events. For instance, almost 200 events exist for α_3 yielding 44 events per year on average. Moreover, α_5 and α_6 have the same number of events, yet different average values result. Since α_6 has higher value than α_5, the average number of impacted customers will be higher but with lower deviation level. Finally, the significantly large average values can be due to the presence of extreme weather-related outages including Hurricane Irma, Winter Storm Uri, and Hurricane Isaias with outages exceeding 10, 4, and 3.5 million customers, respectively. Therefore, different thresholds can be used based on the specified resilience level of the system under study, as well as the geographic location and the type of event being analyzed.

TABLE II
U.S. extreme outage analysis

Threshold	No. of Events	Average (μ)	St. Dev. (σ)
α_1	3,949	202,983	461,052
α_2	333	795,489	977,399
α_3	193	1,148,286	1,164,232
α_4	12	3,853,089	1,347,568
α_5	9	4,637,203	1,211,036
α_6	9	5,886,450	974,717

B. Event Characteristic Analysis

The methodology described in Section II-C was applied to the extracted events for each threshold. Table III summarizes the average and standard deviation for all metrics used in the analysis, as well as the maximum recorded values for each metric. It is worth stating that all metrics were measured in hours, except for M_5, which was measured in outage count to represent the number of customers without power.

TABLE III
Event statistical analysis summary

		α_1	α_2	α_3	α_4	α_5	α_6
M_1	μ	5.76	10.31	10.29	19.55	15.55	6.36
	σ	22.12	26.63	26.73	26.20	20.57	10.57
	Max	647.00	214.50	191.75	82.75	56.00	33.25
M_2	μ	2.16	3.18	3.18	6.15	3.42	1.70
	σ	6.57	8.13	8.31	9.60	6.34	3.36
	Max	133.75	83.00	80.00	32.00	20.00	10.50
M_3	μ	3.60	7.13	7.10	13.40	12.14	4.67
	σ	17.82	20.46	19.96	19.10	18.13	10.60
	Max	626.00	174.25	157.00	64.75	55.50	32.75
M_4	μ	8.21	153.18	271.38	2,488.34	3,326.89	3,333.81
	σ	22.99	355.56	694.89	6,048.14	8,375.54	9,999.07
	Max	366.25	3,336.00	4,910.50	21,203.75	25,280.00	29,998.00
M_5	μ	88,321	488,809	707,786	3,701,076	6,329,059	7,022,472
	σ	231,132	733,431	914,046	2,430,105	3,093,945	2,488,403

For event duration metric (M_1), the average value was almost six hours for α_1 and 20 hours for α_4. This is due to eliminating many events with lower impacts, but longer durations. In general, relatively close standard deviation values are noticed in M_1 except for α_6, which implies that extracted extreme events exhibit very similar event duration features. Also, the maximum event duration is 647 hours for α_1 and decreases dramatically with increasing threshold values due to ignoring 90% of the events extracted in α_1.

The average value of the recovery duration metric (M_3) is almost double the average value of the impact duration metric (M_2) for all thresholds, which implies that it takes the system more time to return to pre-event conditions. Although standard deviation values are relatively small in M_2 and M_3, maximum values are relatively large. This signifies the presence of very limited numbers of events with extended impact or recovery durations. It is worth noting that M_3 measures the duration until the outage count decreases to below threshold value, rather than returning to normal system operation, which reflects the noticeable reduced recovery duration values.

The post-event duration metric (M_4) increases dramatically with the increase in threshold values, which is expected due to larger timespans between two consecutive events. This metric provides further understanding regarding the frequency of occurrence of extreme outages. Based on the DOE threshold, an extreme outage takes place every 8 hours on average. However, severe outage events are expected to occur separate from one another. This raises a concern regarding the DOE threshold value and requires further investigation to adopt a new value. For α_2, an extreme outage event occurs every week, implying a realistic value that complies with another historical outage dataset hosted by DOE (i.e., Form OE-417 weather-related extreme outage dataset) [10], [20].

With a maximum extreme outage count exceeding 10 million customers, the impact level metric (M_5) shows significantly higher average values and variances. On average, 80,000 customers lost electricity based on the DOE threshold; whereas, 490,000 outage counts were observed for α_1. The very large impact level (more than 1 million customers) for a very limited number of events (around 20 events) during the six year period is the main reason to derive the M_5 to relatively high values.

C. PDF Models of Event Metrics

The aforementioned process in Section II-D was used to determine the best distribution function that fits the histogram behavior of each metric for a single threshold value, α_2. The RSS value was computed for all PDFs and used as an evaluation criteria. The smaller the RSS, the better the distribution function.

Fig. 4 shows the behavior of PDF models relative to the actual data of the event duration metric. The normal and loggamma distribution do not provide well-fitted PDF models. Other PDFs show relatively close behavior of the actual histogram, which can be observed in first column of Table IV. Also, it is worth noting the high number of events with duration less than five hours, which proves that most of the extreme outage events do not show prolonged outage behavior.

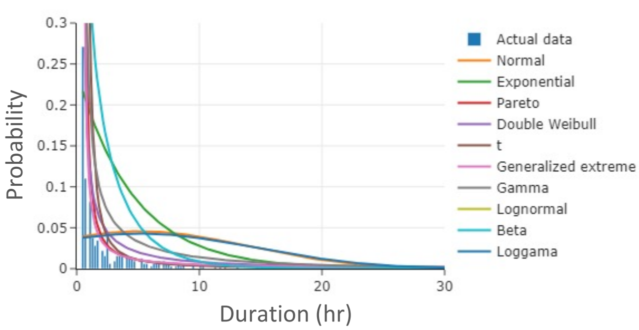

Fig. 4. PDF models for event duration metric

Table IV summarizes the RSS values of all PDFs for each metric. The best-fit PDF representing each metric is highlighted. The three best fit PDFs for M_1 are t, beta, and gamma distributions; whereas M_2 can be represented by Pareto, beta, and exponential distributions. The best-fit PDF for M_3, M_4, and M_5 is beta distribution.

TABLE IV
RSS OF PDF MODELS

	M_1	M_2	M_3	M_4	M_5
Normal	0.242726	0.149186	0.040828	9.21e-05	0.085117
Exponential	0.120749	0.040586	0.014820	3.95e-05	0.007791
Pareto	0.141930	**0.007400**	0.008104	6.60e-05	0.012396
Weibull-double	0.154112	0.128769	0.031670	7.03e-05	0.065992
t	**0.026532**	0.188705	0.048153	0.000113	0.072915
Gamma	0.086719	0.109352	0.024653	4.99e-05	0.106103
Lognormal	0.238728	0.153024	0.035232	0.000111	0.034197
Beta	0.037537	0.020868	**0.007835**	**7.29e-06**	**0.004090**
Loggamma	0.244715	0.151715	0.041152	9.33e-05	0.088438

Table V provides the parameters of the two most-fit PDFs for each metric. Each PDF model was chosen based on their parameter representation in Python distribution flow packages [21], [22]. Each metric is represented by a unique PDF with different parameters. The PDFs can be used to generate extreme outage events with diverse behavior for resilience-based studies.

TABLE V
PARAMETERS OF TWO MOST-FIT PDFS FOR EACH EVENT METRIC

	First PDF		Second PDF	
	Type	Parameters	Type	Parameters
M_1	t	0.49835	Beta	0.73538, 147.92905
M_2	Pareto	1.70799	Beta	0.52797, 660.89838
M_3	Beta	0.45694, 140.85338	Pareto	1.29466
M_4	Beta	0.69853, 294.48884	Exp	153.177
M_5	Beta	0.86561, 613.73911	Exp	2.410

Curve fitting was used to determine probability distributions for the proposed event metrics, however future research could be done on potential discrepancies or nuances in developing PDFs. The PDFs applied to this methodology and using this dataset could potentially be used to simulate diverse extreme outage events for resilience-based studies and estimate the cost versus benefit of resilience solutions and mitigation strategies.

IV. CONCLUSION

This paper has described a framework to evaluate the characteristics of extreme outage events in the U.S. using historical outage datasets, thresholds, and PDFs. The approach extracted extreme events based on recorded outages in the ORNL EAGLE-I dataset. An aggregation process was conducted to sum outages taking place at the same time. A set of thresholds were identified and used to filter out abnormal outages (e.g., different customer numbers or outage time periods). Statistical analyses were conducted to capture the characteristics of extreme outage events including event duration, impact duration, recovery duration, post-event duration, and impact level metrics. Various PDFs were applied to the metrics, dataset, and thresholds to determine the best-fit model to represent the behavior of each metric. The results showed that event duration metric follows a t-distribution model; whereas, a Pareto distribution model fits the impact duration metric. Also, distinct beta distribution models are convenient for recovery duration, post-event duration, and impact level metrics. The framework provides a systematic statistical approach to understand the behavior of extreme weather impacts on the U.S. power grid based on recorded outages across the nation. This also provides researchers with PDFs governing the behavior of extreme outage events for resilience-based studies. Further investigation is needed to expand the analysis to the state and county level across the U.S. and continue to compare results with events as they occur to understand potential discrepancies or nuances.

Acknowledgement

This work was supported by the U.S. National Science Foundation (NSF) under Grant NSF 1847578.

References

[1] N. Bhusal, M. Abdelmalak, M. Kamruzzaman, and M. Benidris, "Power system resilience: Current practices, challenges, and future directions," *IEEE Access*, vol. 8, pp. 18 064–18 086, 2020.

[2] R. J. Campbell, "Weather-related power outages and electric system resiliency," Congressional Research Service, Tech. Rep., 2012.

[3] W. House, "Economic benefits of increasing electric grid resilience to weather outages," Executive office of the president, Washington, DC, USA, Tech. Rep., Aug 2013.

[4] P. Svitek, "Texas puts final estimate of winter storm death toll at 246," Jan. 2022. [Online]. Available: https://www.texastribune.org/2022/01/02/texas-winter-storm-final-death-toll-246/

[5] Billion-dollar weather and climate disasters. [Online]. Available: https://www.ncdc.noaa.gov/billions/events/US/2013-2021

[6] A. Kavousi-Fard, M. Wang, and W. Su, "Stochastic resilient post-hurricane power system recovery based on mobile emergency resources and reconfigurable networked microgrids," *IEEE Access*, vol. 6, pp. 72 311–72 326, 2018.

[7] A. Gholami, T. Shekari, and S. Grijalva, "Proactive management of microgrids for resiliency enhancement: An adaptive robust approach," *IEEE Trans. on Sust. Energy*, vol. 10, no. 1, pp. 470–480, Jan 2019.

[8] E. L. Hotchkiss and A. Dane, "Resilience roadmap: a collaborative approach to multi-jurisdictional resilience planning," National Renewable Energy Lab.(NREL), Golden, CO (United States), Tech. Rep., 2019.

[9] E. Vugrin, A. Castillo, and C. Silva-Monroy, "Resilience Metrics for the Electric Power System: A Performance-Based Approach," p. 49, Feb. 2017.

[10] M. Benidris, N. Bhusal, M. Abdelmalak, M. Gautam, M. Egan, S. Groneman, and T. Farkas, "Quantifying resilience value of solar plus storage in city of reno," in *2021 Resilience Week (RWS)*, 2021, pp. 1–6.

[11] M. J. Sullivan, M. T. Collins, J. A. Schellenberg, and P. H. Larsen, "Estimating power system interruption costs: A guidebook for electric utilities," Tech. Rep., 07/2018 2018.

[12] L. Lawton, M. Sullivan, K. Van Liere, A. Katz, and J. Eto, "A framework and review of customer outage costs: Integration and analysis of electric utility outage cost surveys," 2003.

[13] M. Sullivan, M. Perry, J. Schellenberg, J. Burwen, S. Holmberg, and S. Woehleke, "Pacific gas & electric company's 2012 value of service study," May 2012.

[14] S. Mukherjee, R. Nateghi, and M. Hastak, "Data on major power outage events in the continental us," *Data in brief*, vol. 19, p. 2079, 2018.

[15] M. Martell, S. B. Miles, and Y. Choe, "Review of empirical quantitative data use in lifeline infrastructure restoration modeling," *Natural Hazards Review*, vol. 22, no. 4, p. 03121001, 2021.

[16] ORNL. (2022, May) EAGLE-I emergency response tool development. [Online]. Available: https://csmd.ornl.gov/project/eagle-i-emergency-response-tool-development

[17] A. F. Snyder and S. Morash, "Toward developing metrics for power system resilience," in *2020 Clemson University Power Systems Conference (PSC)*, 2020, pp. 1–7.

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

[19] R. Nateghi, S. D. Guikema, and S. M. Quiring, "Comparison and validation of statistical methods for predicting power outage durations in the event of hurricanes," *Risk Analysis: An International Journal*, vol. 31, no. 12, pp. 1897–1906, 2011.

[20] D. of Energy, "Electric emergency incident and disturbance report," http://www.oe.netl.doe.gov/oe417.aspx , 2019.

[21] M. Mayo. (2022, April) Best fit pdf using python. [Online]. Available: https://www.kdnuggets.com/2021/09/determine-best-fitting-data-distribution-python.html

[22] E. Taskesen. (2022, May) distfit documentation. [Online]. Available: https://erdogant.github.io/distfit/pages/html/index.html