

U.S. Resilience to Large-Scale Power Outages in 2002–2019

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Abstract

Prolonged power outages debilitate the economy and threaten public health. Existing research is generally limited in its scope to a single event, an outage cause, or a region. Here, we provide one of the most comprehensive analyses of large-scale power outages in the U.S. for 2002–2019. This analysis is based on the outage data collected under U.S. federal mandates that concern large blackouts, typically, of transmission systems and exclude much more common but smaller blackouts, typically, of distribution systems. We categorized the data into four outage causes and computed reliability metrics, which are commonly used for distribution-level small outages only but useful for analyzing large blackouts. Our spatiotemporal analysis reveals six of the most resilient U.S. states since 2010, improvement of power resilience against natural hazards in the south and northeast regions, and a disproportionately large number of human attacks for its population in the Western Electricity Coordinating Council region. Our regression analysis identifies several statistically significant predictors and hypotheses for U.S. resilience to large blackouts. Furthermore, we propose a novel framework for analyzing outage data using differential weighting and influential points to better understand power resilience. We share curated data and code as Supplementary Materials.

Keywords: power outage, reliability, natural hazard, cyber attack, sabotage, operational maintenance

1. Introduction

Although power outages affect everyone, it severely impacts those whose access to electricity is so critical that a lapse in the electrical infrastructure

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can be fatal or cause permanent damage [1]. For instance, there is an increasing prevalence of diabetes in Puerto Rico [2] and many of them depend on electricity-powered dialysis machines, but when Hurricane Maria struck in 2017, it left virtually all residents without power [3] and was not restored to normal levels until after 10 months [4]. Another power outage induced by 2021 winter storms in Texas over two weeks cost over 200 lives [5]. These incidents solemnly call for a comprehensive analysis of historical data about large-scale U.S. power outages. This study uses U.S. federal data currently available from 2002 to 2019 to examine the past and identify the trends that remain in force.

There are numerous studies on the impact of extreme weather on above-ground electrical infrastructure [6–11] or on energy systems in general [12–17] and the aftermath of power outages caused by extreme weather events [18–21]. There are also studies that discuss the reliability of the electrical grid in other countries such as Fiji [22] and Japan [23], analyses of reliability metrics in Switzerland [24], and research on the reliability of electrical supply in the face of climate change in the U.S. and Europe [25]. However, these studies mainly focus on outages caused by natural hazards or effects of climate change. In our paper, we expanded this scope to also include power outages caused by human attacks, mechanical failures, and operational maintenance. Studies on cyberattacks and deliberate physical attacks are often qualitative and do not discuss in depth outages caused by natural hazards or mechanical failures [26, 27] or are limited to microgrids [28].

Many studies investigate power outages using mathematical [29] and statistical models such as support vector regression [30]; support vector machine-random forest [31]; ANOVA, ARMA, and Poisson regression [32]; and linear modelling [33], but they either have a significantly different scope and approach from our work, do not incorporate the Institute of Electrical and Electronics Engineers (IEEE) 1366 reliability metrics, use a smaller data set that does not encompass the entire U.S., contains much less than 18-years of data, or was specific to a certain type of outage. In addition to statistical modeling, understanding the resilience of the country at scale requires a large data set and evaluation of multiple outage causes simultaneously using meaningful metrics in the subject matter [34–36].

This study’s main contribution is an objective evaluation of the U.S. electrical grid’s resilience to large blackouts, analyzed in two ways. First, we analyze three IEEE 1366-2012 reliability metrics—System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and Customer Average Interruption Duration Index (CAIDI)—for all 50 states over a 18-year time period (2002–2019). This analysis resulted in three key discoveries: 1) we found that, since 2010, Alaska, West Virginia, Montana, Wyoming, South Dakota, and Nebraska are overall the most resilient states for all types of large-scale outages, 2) North American Electric Reliability Corporation (NERC) region Western Electricity Coordinating Council (WECC) has a disproportionately large number of human attacks for its population, 3) the south and north-east regions of the U.S. have improved their resilience to extreme weather over time when compared to outages caused by human attacks, mechanical failures,

and operational maintenance. Second, our regression analysis of the reliability metrics with 41 explanatory variables revealed two additional discoveries: 4) states with higher population density in urban areas tend to experience fewer large blackouts per customer served, 5) numerous strong predictors that will inspire future research hypotheses. We conclude our analysis by proposing a new framework for interpreting the reliability metrics, which includes weighting outages and using influential points to identify anomalies that provide new insight into power resilience.

2. Methods

2.1. Data

The U.S. Department of Energy (DOE) mandates that, among others, major transmission and distribution system interruptions and failures or shutdowns of transmission and distribution systems be reported federally through Form DOE-417 [37]. The DOE uses Form DOE-417 for bulk (transmission level) outages as well as distribution level outages since at least 2001 [38]. The form is used by electrical utilities, local utilities, some generating utilities, balancing authorities, reliability coordinators, and computer centers and physical security departments [37]. The DOE collects this information through form DOE-417 for national security, energy emergency management responsibilities, and other analytical purposes [39].

The mandated criteria for filing Form DOE-417 *within one hour of incident* are as follows [37]:

1. *Physical attack that causes major interruptions or impacts to critical infrastructure facilities or to operations.*
2. *Reportable Cyber Security Incident [defined in [40]].*
3. *Cyber event that is not a Reportable Cyber Security Incident that causes interruptions of electrical system operations.*
4. *Complete operational failure or shut-down of the transmission and/or distribution electrical system.*
5. *Electrical System Separation (Islanding) where part or parts of a power grid remain(s) operational in an otherwise blacked out area or within the partial failure of an integrated electrical system .*
6. *Uncontrolled loss of 300 Megawatts or more of firm system loads for more than 15 minutes or more from a single incident.*
7. *Firm load shedding of 100 Megawatts or more implemented under emergency operational policy.*
8. *System-wide voltage reductions of 3 percent or more.*
9. *Public appeal to reduce the use of electricity for purposes of maintaining the continuity of the Bulk Electric System.*

Seventeen additional criteria require filing within longer time frames, including

12. *Loss of electric service to more than 50,000 customers for 1 hour or more [to be reported within six hours of incident]*

20. *Uncontrolled loss of 200 Megawatts or more of firm system loads for 15 minutes or more from a single incident for entities with previous year's peak demand less than or equal to 3,000 Megawatts [to be reported "by the later of 24 hours after the recognition of the incident OR by the end of the next business day"]*
21. *Total generation loss, within one minute of: greater than or equal to 2,000 Megawatts in the Eastern or Western Interconnection or greater than or equal to 1,400 Megawatts in the ERCOT Interconnection. [ditto]*

These criteria indicate the magnitude of impact and seriousness of incidents that are covered in the analyzed data. The qualified incidents are often too large to be included in the calculations of IEEE 1366-2012 reliability metrics for distribution systems.

Form DOE-417 includes information about the date and time the event began and restored (the time and date of outage and its restoration), the area affected (state and, if applicable, the specific county), the North American Electric Reliability Corporation (NERC) region, alert criteria, event type (cause of outage), the demand loss in megawatts, and the number of customers affected. These values are recorded then uploaded as Excel files to the DOE website [41]. The records date back to 2000, but for this study we are using records from 2002 and beyond because 2000 and 2001 datasets are in PDF format instead of in Excel or CSV format.

The second source of data used is from the U.S. Energy Information Administration (EIA). The purpose of the EIA is to collect and analyze independent and impartial information regarding energy. The EIA collects surveys on electric power data. A specific form EIA-861 is used to record electric power sales, revenue, and energy efficiency data, customer counts, etc. from each utility company. These files are available in Excel formats from the years 1990–2019 [42].

DOE-417 provides us with the details surrounding the outage including the number of people affected, duration, and cause. EIA-861 provides us with the information regarding how many customers were sold electricity by a breakdown of state. We limited our period from 2002–2019 since 2002 was the oldest published and parseable dataset that the DOE had records for DOE-417.

The data can be combined to calculate the percentage of customers affected and for how long. Supplementary Tables 2 and 3 show useful information that can be extracted from DOE-417 and EIA-861, respectively. The reported outage duration is subject to variations in different definitions and to reporting errors, thus requiring extensive data cleaning and cross-referencing effort [43]. Before combining the two datasets using the Area Affected column from DOE-417 and the State column from EIA-861, we took several steps to clean the dataset. For the DOE-417 dataset, we added a column for time elapsed (days) regarding the duration of the outage and deleted rows where the number of customers affected was missing. After doing this calculation, we observed 11 data points where the time elapsed values were negative. We reviewed these observations on a case-by-case basis. If we determined with high confidence that it was pos-

sible for the operator to mistakenly input AM when they meant PM or vice versa we manually made the proper adjustment to reflect the possible actual value otherwise the observation was removed. We verified these with reported news articles or alerts around the time of the event. There were 8 observations in which the number of customers was negative. We found no explanation for negative values in this column, so we made the assumption that such observations were meant to be positive but were mistakenly inputted as negative after cross-checking with other sources such as news articles from that time to ensure that changing the negative values to positive values aligned with estimates from other sources. If we were not able to verify, then the data points were removed.

For DOE-417 2002 through 2019, the Event Type column had 46 unique causes. These causes were simplified to four overarching reasons that we determined were still able to capture the category of the cause. The first category was natural hazards, which included all outages directly caused by any natural event such as high winds, damage due to trees, and any type of severe weather and outages indirectly caused by natural events such as voltage reduction and fuel supply emergencies due to unfavorable weather. The second category was mechanical failure, which included all outages caused by fuel supply emergencies due to limited resources, distribution interruptions, transmission interruption, generation inadequacy, and units or transmission trips. The third category was human attack, which included outages caused by vandalism, cyber-attacks, and sabotage. The fourth category was operational maintenance caused by deliberate outages due to islanding, load shedding, public appeal to reduce electricity usage, planned outages, or operational failures caused by uncontrollable outages due to a lack of preparedness in operations.

2.2. Spatiotemporal Analysis

Once we combined the DOE-417 dataset with the EIA-861 dataset, we were able to calculate the percentage of customers affected. To explore the reliability based on different outage causes, we calculated the System Average Interruption Duration Index ($SAIDI = \sum_{i=1}^n r_i N_i / N_T$), System Average Interruption Frequency Index ($SAIFI = \sum_{i=1}^n N_i / N_T$), and Customer Average Interruption Duration Index ($CAIDI = \sum_{i=1}^n r_i N_i / \sum N_i$) for each state considering all causes of outage and for each state considering each cause of outage, where n is the total number of events, r_i is the restoration time of the i -th event in days, N_i is the total number of customers interrupted by the i -th event, and N_T is the total number of customers served in the studied region. IEEE Standard 1366 establishes a list of reliability metrics (including the three most popular metrics SAIDI, SAIFI, and CAIDI) to provide a standard way for all electric utilities to measure electrical reliability and ensure consistency and compatibility. We included all events from the DOE-417 dataset in the reliability calculations because they were significant enough to be recorded at a federal reporting level and as part of the DOE-417 dataset and as such should be included in a national level analysis. The existing literature frequently uses the three metrics, but our approach is unique in that we analyze reliability based on four comprehensive causes. This helps give new insight into the electrical grid as it allows for the

analysis at a clustered level. It is also important to mention that as of January 2017 “only 33 percent of utilities report [SAIDI and SAIFI] statistics” [44] which prompted us to calculate these metrics for all states as well. The reliability metrics are calculated each year, but we also calculated them for longer time periods as well for spatiotemporal analysis and trend identification. With our 18 years of data from 2002 – 2019, we separated the data into two parts of 9 years each: 2002 – 2011 (year range 1) and 2011 – 2019 (year range 2).

2.3. Regression Analysis

We used a total of 41 variables as the potential predictors in our least absolute shrinkage and selection operator (LASSO) regression model [45] to select the variables that best predict the three metrics (SAIDI, SAIFI, and CAIDI) based on the 10-fold cross-validation. The data collected by Mukherjee et al. contains 55 variables that pertain to major power outage events [46]. We used 39 of the variables provided by Mukherjee et al. and combined them with additional two predictors: number of unique companies (from EIA-861) and land area in square miles (from the U.S. Census Bureau). LASSO was chosen over other variable selection methods due to its interpretability and general robustness against collinearity between predictors. We calculated the three metrics for each state and each outage cause category. We then used the selected variables as the predictors in an ordinary least-squares (OLS) regression model and selected the variables that had p -values less than 0.10 before refitting the final OLS model. The chosen p -value threshold of 0.10 allows us to identify potentially meaningful predictors of the reliability metrics. The regression coefficients, intercepts, standard errors, t -values, and p -values of each model are summarized in Supplementary Tables 4–6.

3. Spatiotemporal Analysis of U.S. Power Resilience

This section analyzes how power outage patterns vary across states over time. To organize all the outages into a comprehensive analysis, we simplified 46 reasons for power outages into four overarching causes: natural (including but not limited to hazards and weather events), mechanical failure, human attack, and operational maintenance (see Section 2 for definitions). To explore the resilience based on the four different causes we calculated three IEEE Standard 1366 reliability metrics (SAIDI, SAIFI, and CAIDI) for each state considering all causes of outage and for each state considering each cause of outage.

The definition in the IEEE Standard 1366 guideline for the reliability metrics states that the indices are “intended to apply to distribution systems, substations, circuits, and defined regions” [47]. Deviating from this intention, we incorporate transmission-level data when calculating the reliability indices. Similarly, the study in [43] computes “bulk power system only” SAIDI and SAIFI values while “effectively treating the entire U.S. as a single utility.” Our analysis extends this approach to treat each U.S. *state* as a single utility. As an anonymous reviewer noted, “the areas controlled by reliability coordinators or

independent system operators” could be a more natural choice. This idea merits future work that collects and curates the area-specific data. The same reviewer noted that different results across states (e.g., Alaska vs. other states) could reflect mainly a different balance between transmission and distribution. In addition, note that the standard calculation of the indices for distribution systems exclude large events based on the 2.5 Beta Method [47]. Hence, the power industry does not use the indices for large blackouts, as done in this and other academic studies [43, 48]. The study in [48] uses SAIFI for the year 2000 to estimate that only about 4% of all customer interruptions are recorded in the Form DOE-417 data that only cover the reporting-mandated interruptions, as discussed in Section 2.1. We also used the same assumptions in [43] to calculate the reliability indices using the aforementioned outage data: each event was a distinct event, each reported event represented a single event, and customers affected would decline exponentially over the duration of the event as restoration efforts continue.

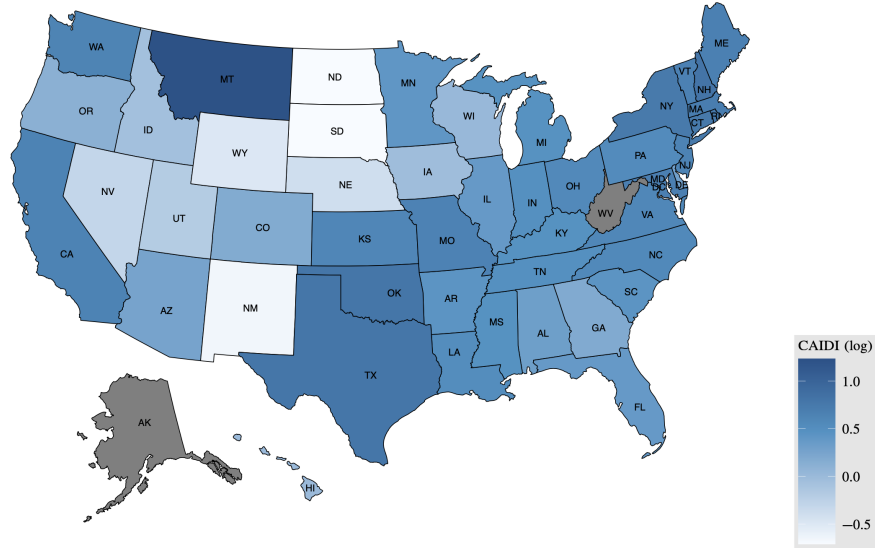


Figure 1: CAIDI values for each state for power outages caused by natural hazards on a log scale (2002–2019).

Figure 1 is a map of the CAIDI values on a log scale for each state for the natural hazard type. Since CAIDI measures the average duration length per outage, a lower CAIDI value translates to a more resilient infrastructure. Immediately, we notice there are two gray states: West Virginia and Alaska. Although the gray states are not on the reliability metric scale (i.e. not a sufficient number of outage observations in DOE-417 to calculate a CAIDI value), note that the lack of a CAIDI value itself is a measurement of reliability. If there were no outages recorded then the electrical structure was robust enough to withstand disruptive natural hazards such that outages never occurred or that the outages

were insignificant (e.g., small flicker in power) because the infrastructure was strong enough to not be affected and was thus not reported in DOE-417 (see Supplementary Note 1.1 for more details including federal reporting mandates on DOE-417).

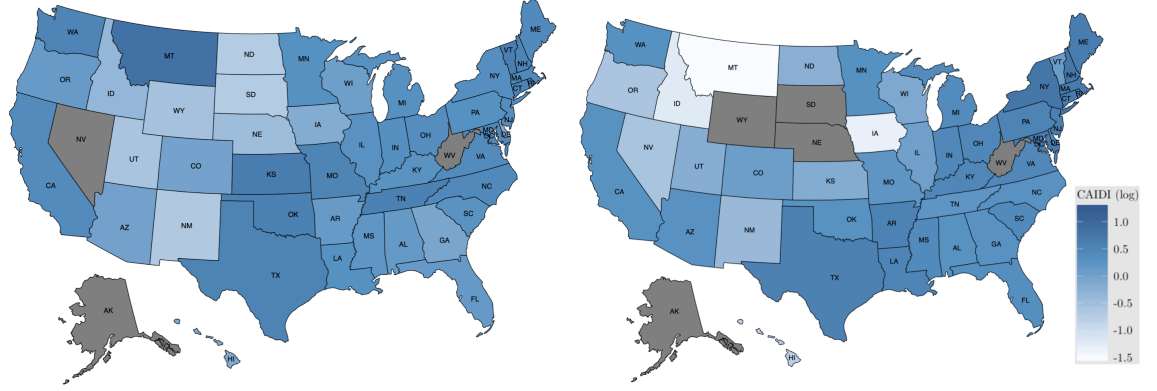


Figure 2: CAIDI values for each state considering all types of power outages in 2002–2010 (a) and 2011–2019 (b) on a log scale.

Figure 2 shows CAIDI values for each state over two large time periods. Alaska and West Virginia remained gray indicating that through the 18 years, there were no outages severe enough to warrant reporting the outage at a federal level. Nevada in Figure 2b is now light blue from gray in Figure 2a indicating a decline in reliability. This change was a result of 13 human attack incidents, two natural hazards, and two incidents for operational maintenance. Nevada is a part of the Western Electricity Coordinating Council (WECC) which sees the highest number of human attacks (38.1% of the human attacks in all NERC regions occurred in WECC) as shown in Table 1.

One may interpret this as a consequence of the large area that WECC oversees (Supplementary Figure 1) and suspect that a higher population will naturally result in more frequent outages to be caused by human attacks. However, this is not true when comparing the population sizes: from 2011 – 2019, WECC oversaw 32,820,380 electrical customers per year on average and SERC oversaw 32,852,013 customers per year on average and yet only had 11 human attacks (5.2% of the total human attacks in all U.S. NERC regions).

In addition, Table 2 shows that SERC has 62.8% more outages of all kinds than WECC (546 compared to 324). Out of all outages that occur, 24.69% of outages were due to human attacks in WECC, but only 2.02% of outages were due to human attacks in SERC. It is clear that WECC has a disproportionately large number of outages caused by human attacks. One possible explanation for this may be that WECC does not prioritize placing preventative measures for physical and cyber-attacks as much as SERC. The reasoning for this can be two-fold. (Hypothesis 1) By deprioritizing the allocation of initial preventative measures that would have stopped outages occurring from human attacks, they

Table 1: Number of power outages caused by human attacks per NERC region

NERC Region	Number of Outages Caused by Human Attack
WECC	80
RFC	64
NPCC	36
SERC	11
TRE	7
MRO	4
SPP	4
FRCC	2
MISO	2
HI	0
AK	0

Table 2: Number of outages by NERC region per type of cause

Cause	SERC	WECC
Human attack	11	80
Mechanical failure	11	17
Natural hazard	495	138
Operations	29	89
Total	546	324

redirect the resources to prevent other types of causes. A reason for this could be that outages caused by human attacks are typically restored more rapidly than outages caused by other types. (Hypothesis 2) WECC conducted its own analysis and determined that it is increasingly difficult to prevent human attacks and thus resorted to allocating resources that would shorten the restoration time instead of allocating resources and money for initial preventive measures such as undergrounding since it is not always cost effective [49]. Both hypotheses could be investigated using financial information and more detailed reports of the systems and rules in place, but Table 3 shows that human attacks in WECC indeed recover faster than any other type of attack as indicated by the CAIDI value. Easily accessible and well-curated data would aid in determining exact root causes instead of hypothesizing. A lack of data makes it difficult to come to exact conclusions and limits further analyses [50].

In Figure 3a, we observe a sudden increase of outages by natural hazards in 2017, which is an outlier from the decreasing trend in the previous eight years. This outlier was caused by Hurricanes Harvey, Irma, Lee, and Maria. The last major increase most similar to that of 2017 was in 2008 due to the 2008 Super Tuesday tornado outbreak, Hurricane Ike, and ice storms. The events in 2008 and 2017 occurred in the same south and northeast regions of the U.S. [51] A

Table 3: CAIDI values (in days) per outage type for WECC 2002–2019

Reason for Outage	CAIDI
Human attack	0.0728
Mechanical failure	0.3296
Natural hazard	4.0848
Operations	1.2837

difference between 2008 and 2017 is that in 2008 SAIDI and SAIFI (Figures 3b and 3c) suddenly increase by 1038% and 343%, respectively, but in 2017 SAIDI and SAIFI increase by 353% and 22%, respectively, while in 2008 CAIDI increased by 157% and 271% in 2017. Over a longer period, it is difficult to say with certainty whether the range that we examine in our dataset can support the hypothesis that large-scale outages are decreasing in size overall, especially noting that Hines et al. found no correlation between blackout frequency and time in previous decades [48], but we can observe that during the recent events in 2017 that caused a sudden increase in CAIDI, the lower percentage increase in SAIDI and SAIFI in 2017 suggests an improvement in the infrastructure and/or preparedness in those particular regions. One argument that is supported by our regression analysis is that states with higher population density in urban areas experience fewer natural hazard-induced large blackouts per customer served. As the general population moves toward urbanization particularly more rapidly in the recent years [52], we hypothesize that utility companies would invest more resources into preventative maintenance to address the growing number of residents.

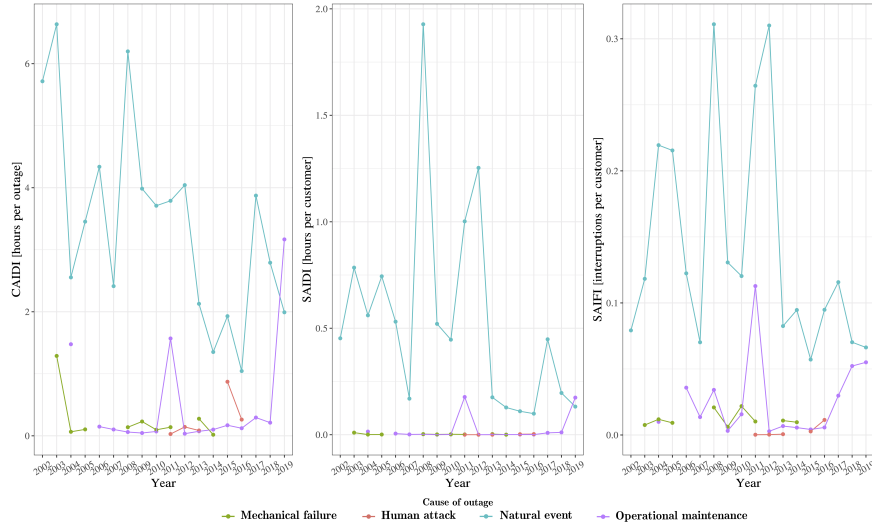


Figure 3: CAIDI (a), SAIDI (b), and SAIFI (c) for 2002–2019 by outage type.

4. Regression Analysis of U.S. Power Resilience

We conducted a regression analysis to identify multiple hypotheses on U.S. power resilience based on 41 potential predictors. Recall that a regression analysis can identify a significant *association* between a predictor and a response variable (while controlling for other predictors’ associations with the response variable). The significant associations reported below should not be construed as definite *causation*. Our stated hypotheses implying causal relationships are meant to inspire future work for testing the hypotheses or investigating the associations further (e.g., collinearity with other predictors not included in our analysis). In this study, the response variables are IEEE reliability metrics for each state

- considering all causes of outage (denoted, for example, as “SAIFI state”) or
- considering each cause of outage (denoted, for example, as “SAIDI mechanical” for SAIDI calculated with respect to mechanical failures only).

Below we discuss major findings and defer additional analysis results to Supplementary Notes 1.2 - 1.4.

Our analysis found that SAIDI mechanical was positively correlated with the number of residential customers (regression coefficient: 9.739×10^{-10} , standard error: 4.208×10^{-10} , p -value: 0.02510). By definition, SAIDI mechanical measures the system-wide (in this case, state-wide) average interruption duration due to mechanical failures (e.g., generation inadequacy and transmission trips). The states with a higher number of residential customers (e.g., CA, TX, FL, NY, PA) tend to observe larger unforeseen surges in electricity demand, e.g., due to temperature changes [53]. A hypothesis is that a greater unprepared surge demand leads to a greater SAIDI in these states. An example is 2021 February blackout in Texas due to severe winter storms, although this incident is not covered in this study’s data that spans through 2019. This incident is attributed to the unexpected surge demand for electricity and natural gas for heating, met by failures in electricity generation, transmission, and distribution due to lack of winterization [54].

For SAIFI state, states with higher urban population and density have fewer interruptions per customer. The two significant predictors chosen by LASSO were population percentage in urban areas (regression coefficient: -3.2903×10^{-2} , standard error: 1.4777×10^{-2} , p -value: 0.03091) and population density of urban clusters (regression coefficient: -2.2244×10^{-3} , standard error: 7.104×10^{-4} , p -value: 0.00302). Both predictors had a negative correlation with response variable. A hypothesis is that preventive measures and restoration resources are better in places with larger urban populations with higher population density, allowing for better prevention and responses than states with lower “operational agility” [55]. Note that faster responses (e.g., thanks to the sufficient repair crew and equipment) can contain an incident to the extent that it does not require mandatory reporting on Form DOE-417. Also, recall that

the equation for calculating SAIFI had the total number of customers served in the denominator, which means that in regions that have large population (large total number of customers served), such as urban areas, will result in lower SAIFI values. Because of large populations in urban areas, we also expect their electrical infrastructures to be large enough or larger to support the growing population and demand. Due to their more advanced infrastructure, urban areas may use their power transmission systems to sell their power to supplement utility companies in nearby regions [16]. This secondary income would further incentivize investing in robust restoration resources because it may also affect nearby regions that rely on buying electricity.

SAIFI mechanical had the percentage of inland water area as its most significant predictor (regression coefficient: 2.703×10^{-3} , standard error: 1.033×10^{-3} , p -value: 0.0119). This relationship may be attributed to corrosion and debris flow that can cause the electrical infrastructure to require replacement or cleaning. For example, floods can affect the electrical equipment, and they may still be functional at the time of the flood, but the damage could be realized weeks or months later due to corrosion thus classifying it as a mechanical failure versus a natural hazard-induced failure. Corroded material may also have a cascading effect [56] which can affect a large network of customers, hence increasing the SAIFI values, but it is difficult to measure which of the subsequent outages, if any, were related to prior damage on the system, especially because they are not documented with such high specificity [57].

CAIDI natural's most significant predictor was the population density of rural areas (regression coefficient: 0.02044, standard error: 0.01186, p -value: 0.09140). The positive association between the population density of rural areas and CAIDI natural may be attributed to overhead distribution networks, which are common in rural areas and vulnerable to wind hazards, especially, in close proximity to trees [58]. Furthermore, if the rural population density was low then it would not be significant enough of an outage to make an impact to the CAIDI metric and thus would not be present as a significant predictor in LASSO. Since rural areas are more likely to have radial distribution systems [31], which are more prone to failures, an increasing rural population density would increase the CAIDI metric.

5. A Novel Power Resilience Analysis Framework

When answering questions and investigating data related to power resilience, it is insufficient to only analyze strictly outage related data; there must be an effort made to incorporate a more interdisciplinary curation and analysis of the data that may provide more than just a surface level analysis [59]. All metrics in IEEE Standard 1366 are calculated using unweighted data without regard for differences in policies throughout regions, socio-economic factors, regulatory standards, system configuration, customer density, hazard exposure such as residential proximity to forest and natural vegetation [60], and various other factors that differentially affect the metrics [44, 61]. For example, it is not fair to measure power resilience in all regions equally if the damage and economic loss

during the outage affects different regions disproportionately [62]. We propose a flexible framework to assign any type of quantitative weight to each observation or groups of observations (all observations for a state) to account for the differences and standardize the reliability metrics. This would also allow metrics to be divided into categories such as “consequence-based” or “service-based” [11]. The objective of this framework is to also address a shortcoming of the 2.5 Beta Method used to identify Major Event Days (MEDs), which serve as identifiers for unexpected large-scale events that have a low probability of occurring based on past data [47]. One shortcoming in the 2.5 Beta Method is the degree of influence outliers can have on the value of the threshold resulting in events that were major in one year, but considered normal the next [63] or vice versa. Our proposal of using influential points in combination with weighting the outage data mitigates this issue.

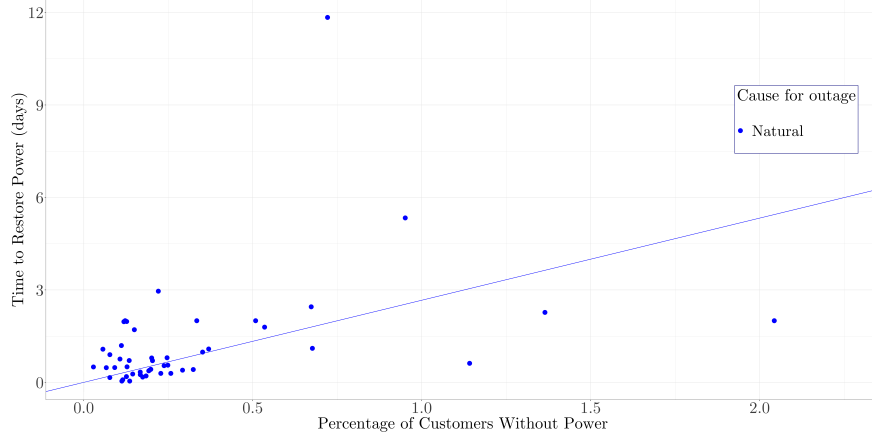


Figure 4: Natural hazard-induced power outage events with a regression line for the state of Alabama for 2002–2019.

This framework is grounded in an intuitive visualization of outage data (publicly available according to U.S. regulations). This visualization plots each observation on a graph as demonstrated in Figure 4 where the duration of the outage (time elapsed in days) is on the y -axis and the percentage of customers without power is on the x -axis. Then, the slope of the regression line created by ordinary least squares is related to CAIDI ($= \sum r_i N_i / \sum N_i$), SAIFI ($= \sum N_i / N_T$), and SAIDI ($= \sum r_i N_i / N_T$) as follows:

$$\begin{aligned}
\text{Slope} &= \frac{\sum_{i=1}^n r_i N_i}{\sum_{i=1}^n N_i^2} N_T \\
&= \left(\frac{\sum_{i=1}^n r_i N_i}{\sum_{i=1}^n N_i} \right) \left(\frac{\sum_{i=1}^n N_i}{N_T} \right) \frac{N_T}{\sum_{i=1}^n N_i^2} N_T \\
&= (\text{CAIDI}) (\text{SAIFI}) \frac{1}{\sum_{i=1}^n (N_i/N_T)^2} \\
&= (\text{SAIDI}) \frac{1}{\sum_{i=1}^n (N_i/N_T)^2},
\end{aligned}$$

where n is the total number of events, r_i is the restoration time of the i -th event in days, N_i is the total number of customers interrupted by the i -th event, and N_T is the total number of customers served in the studied region. Thus, the regression slope characterizes the electrical reliability. Note that N_i/N_T is the proportion of customers interrupted by the i -th event in the studied region. This normalized quantity facilitates comparisons across differently populated regions. Its larger value influences the slope more. Similarly, the larger the r_i , the greater its influence to SAIDI and thus the slope.

When examining the data in this manner, we can apply a different weight on the i -th observation for $i = 1, 2, \dots, n$ to reflect its normalized effect on the slope and thus the reliability according to various weighting schemes (e.g., the weight may be proportional to the proportion of population older than 65 in the affected region to reflect social vulnerability).

Using this framework conducive to regression modeling, we can algorithmically evaluate the influence of each point (or event) on the regression slope (or electrical reliability). To illustrate this, we used California data. As shown in Supplementary Table 1, we determined influential points using commonly used measures in the regression literature. For example, with Cook's Distance (which is arguably the most widely used measure in practice), there is one influential point in the dataset of 62 observations (see Supplementary Figure 2). This observation corresponds to an event that occurred on May 16, 2014 in San Diego and Orange Counties. The outage due to a natural hazard (wildfire) affected 1,400,000 people and lasted approximately 0.4 hours. Table 4 shows the calculated reliability metrics with and without the identified influential point where the total number of outage events was three in 2014.

We might expect that upon removal of an influential point (i.e., a significant power outage event that was deemed the worst in its group), the CAIDI would decrease. If the MED algorithm were not able to identify this observation as an outlier due to an abnormally high threshold value caused by outliers in the previous year, then we would not know the impact of the event in the reliability calculation as the influential point had the shortest outage duration, but the highest number of customers affected of all observations in California in 2014 caused by natural hazards. Influential points serve as a robust method for identifying high impact events that deviate from the norm while retaining the

Table 4: Three reliability metrics with and without the influential point in California where three outage events due to natural hazard were observed in 2014.

IEEE 1366 reliability metric	With influential point	Without influential point	% change
SAIDI [hours per customer]	0.0559	0.0171	- 69.41%
SAIFI [interruptions per customer]	0.1009	0.0100	- 90.09%
CAIDI [hours per outage]	0.5551	1.702	+ 206.6%

purpose of using past observations to measure a typical baseline as used in the MED algorithm.

Examining power outage using weighted data is advantageous for a number of reasons. For example, socio-economic factors of different regions can normalize observations. Normalizing can help give further insight into different regions' electrical infrastructures because some observations may have been previously considered noisy or outliers but in reality were a true reflection of the electrical system. Another possible factor to weight the observations by can be a state or NERC region-specific metric like per capita real Gross State Product (GSP), which would normalize economic differences between the regions.

6. Conclusion

The hypotheses stated in Section 4 in combination with the proposed framework for measuring reliability in Section 5 established fertile grounds for future research. Our spatiotemporal and regression analyses revealed the trends in U.S. resilience to large blackouts and their potential determinants. These analyses also raised questions that may be addressed by future studies. Future work can adopt and expand on our methods to better understand the in-depth effects of population size and density, GSP, number of utility companies in a region, budget allocation, outage restoration procedures, and unique features of a region. Once our hypotheses are tested, policymakers, regulatory and governmental agencies, and utility companies will have a better understanding of creating policies and procedures that result in fewer outages for smaller periods of time. Our power resilience analysis framework's flexibility to incorporate quantitative and qualitative data can help energy researchers probe socio-technical issues underlying power resilience [64]. Furthermore, while this study focused on the U.S., similar data in other countries can allow researchers and policymakers to compare infrastructures across countries, creating the opportunity to learn from one another. Our study further confirmed how a lack of standard in data collection can be a hindrance in understanding power resilience, and we hope that decision-makers will consider our recommendations to improve the quality of data collection and the power resilience.

Data Availability

All the curated data and R code of this study are shared as Supplementary Materials to ensure full reproducibility.

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