Historical Power Outage of the US and Social Vulnerability Index

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***Abstract*—Several works have been documented in the literature to study the societal impact of power outages through the Social Vulnerability Index (SVI) and power outage data correlation analysis. Since SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events. This work performs a detailed societal vulnerability analysis of power outages by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry (CDC/ATSDR). We have performed the power outage analysis with and without an extreme weather outage threshold to study their relation with SVI themes. Although there is some relation between power outages and the SVI themes in the results, there is no strong distinction between the power outage duration and low vs High SVI values.**

***Index Terms*—CDC/ATSDR, EAGLE-I, NWS, Power outage, and Social Vulnerability Index**

I. Introduction

Extreme weather events have been causing significant disruptions in the power grid system, resulting in widespread power outages and severe infrastructure (e.g., substations, transmission and distribution lines, and power generation plants) damage, leading to inconveniences in critical services (e.g., health care, transportation, and national security), severe economic losses, and adverse effects on the well being of the community [1]–[3]. Monetary losses of major power outage events are billions of dollars every year (25 to 70 billion [4]) to the US economy. Therefore, their social, economic, and technical impact analysis is important to develop the appropriate emergency response and mitigation measures.

To analyze the impact of the major events, the US Department of Energy (DOE) collects power outage data for major power system events [5]. DOE mandates that utility companies in the United States submit major power outage information, which DOE publishes in the OE-417 report. Major events have been defined as events that cause power outages to more than 5,000 customers or more than 300 MW of power demand disruption. Using DOE's major power outage information, several analyses have been documented in the literature studying the impact of weather events on power systems. For example, authors in [6] studied the impact of these events on the power delivery of the United States. The seasonal pattern of power outages has been analyzed in [7].

In addition to the literature on the impact analysis of power outage on power delivery in the United States, numerous work has been documented in the literature to study the societal impact of power outages through SVI and power outage data correlation analysis. Work presented in [8] performs socioeconomic vulnerability impact analysis of severe weather-related power outages. Authors of [8] perform analysis only with Atlantic hurricanes, it does not perform nationwide analysis with other types of weather events such as severe thunderstorms, heat waves, cold waves, snow storms, and flooding. The analysis of [8] is conditioned based on the assumption that outages are caused by extreme outages, ignoring operation-related causes of power outages. The social vulnerability of power outages has been studied in [9]. The work [9] analyzes the power outages caused by all events (weather and nonweather events) and does not perform a detailed social analysis with several social vulnerability themes. The data sources used in [8], [9] are also not available publicly, limiting their replicability for other similar analyses.

In this work, we work around some of the existing problems by mapping weather data obtained from the National Weather Service (NWS) with the publicly available power outages dataset. We used this mapping to develop a threshold to distinguish the power outages caused by extreme weather events. Also, this work performs a detailed societal vulnerability analysis of power outages nationwide at county level resolution by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry(CDC/ATSDR SVI). Analyzing each of these individual SVI themes is important as overall SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events and may shadow the relevant themes.

The rest of the paper is presented as follows. Section II provides the overview of the data source and data processing. Section III provides a methodology and the results of the proposed work along with the discussion. Finally, concluding

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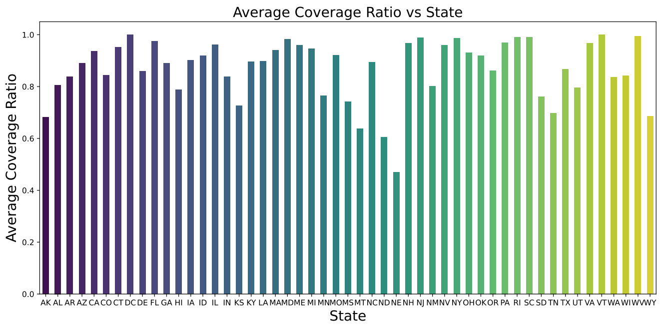

Fig. 1. Average coverage ratio (of coverage ratio between 2018–2022) for different states.

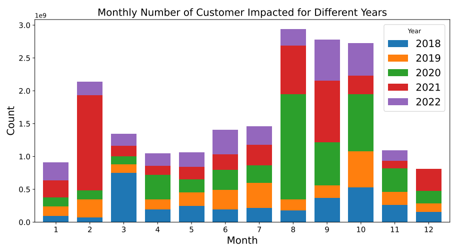

Fig. 2. Number of customers impacted by power outages in the United States from 2018–2022 by month.

remarks are provided in IV.

II. Data Source

This section provides the source of the data and performs data processing for the proposed work. In this work, we have utilized power outage data from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) platform, SVI CDC/ATSDR, and weather data from NWS.

A. Power Outage Data: EAGLE-I Data

This work leverages the publicly available power outage data for the United States obtained from ORNL's EAGLE-I platform[1]. EAGLE-I is an interactive geographic information system that allows users to view and map the nation's energy infrastructure and obtain near real-time information updates concerning the electric, petroleum, and natural gas sectors within one visualization platform. The EAGLE-I platform has been collecting county-level power outage datasets from the US power grid from 2014. EAGLE-I datasets are available for academic research. Since data are more complete from 2018, we are using 2018-2022 EAGLE-I data for our analysis.

EAGLE-I datasets are collected based on the voluntary participation of utility companies in the United States. The participation of electric utilities has been increasing over the years, making the dataset more reliable and useful. Fig. 1 shows the state-wide average coverage ratio. The coverage ratio is the ratio between the total number of electrical customers that share data to the total number of electrical customers.

Fig. 2 shows the monthly number of customers impacted by power outages (caused by any kind of cause: weather, operation, cyber, etc.) in the United States from 2018–2022. (Although EAGLE-I started the data collection in 2014, data for some states were not available until 2017; therefore, we are analyzing only 2018–2022 from the EAGLE-I dataset.) This figure shows that a maximum number of cumulative power outages occurred in August, followed by September and October. The possible reason for this trend could be that the outages coincide with tropical storms, thunderstorms, and heat waves. This could also be due to more industry demand (as businesses ramp up after summer breaks) pushing the infrastructure capacity limits towards or above the limit boundary.

[1]https://eagle-i.doe.gov/

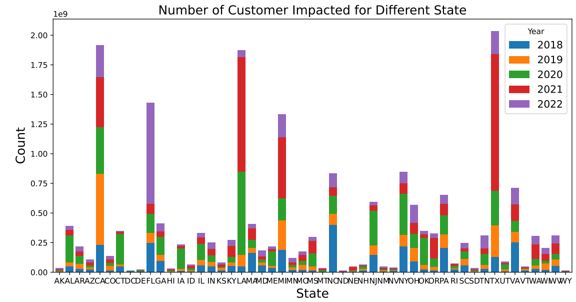

Fig. 3. Number of customers impacted by power outages by state from 2018–2022.

Fig. 3 shows the yearly number of customers impacted by power outages in the United States by state from 2018–2022. This figure shows that the maximum number of cumulative power outages occur in Texas, followed by California and Louisiana. The possible explanation for the maximum number of outages in Texas and California could be because of the significant number of weather events, the power grids running near to or above their capacities, and being significantly more populous states (more population means more customers could be impacted).

Although the number of customers impacted by power outages has changed over the years, drawing conclusions with these limited data from scraping utility websites would be premature. Therefore, more data will be required to draw a concrete conclusion.

B. Social Vulnerability Index Data

SVI data required for our analysis are obtained from the United States CDC/ATSDR SVI [10]. CDC/ATSDR has defined social vulnerability as "Community's ability to prevent human suffering and financial loss in the event of disaster". The main purpose of the SVI is to help the communities to better prepare before, during, and after hazardous events (extreme weather events, disease outbreaks, and chemical exposure). It provides community-specific and spatially relevant information to health officers and emergency responders.

SVI is a percentile ranking of 16 different variables such as unemployment, racial and ethnic minority status, and disability which are further grouped into four related themes: socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and trans-

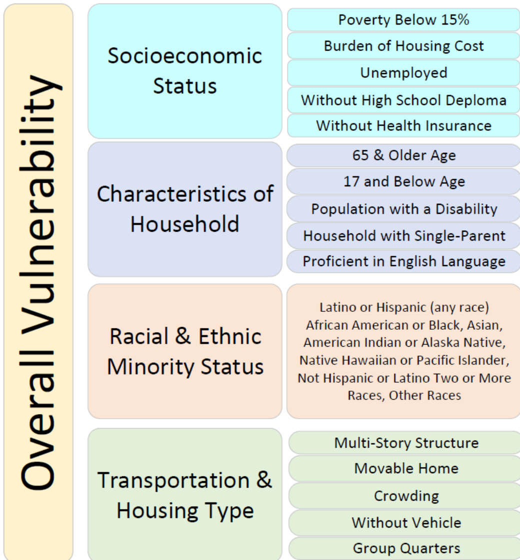

Fig. 4. Themes and variables of the American community survey, used for computing overall SVI. Source CDC/ATSDR SVI [10]

portation as shown in Fig. 4. SVI provides these rankings for each of the counties of the United States. In our analysis following terminologies are used: RPL_THEME1 for Socioeconomic Status; RPL_THEME2 for Characteristics of Household; RPL_THEME3 for Racial &Ethnic Minority Statys; RPL_THEME4 for Transportation Housing Type; and RPL_THEMES for overall vulnerability index. SVI data are available for the years 2000, 2010, 2014, 2016, 2018, 2020. Since we are performing the analysis on power outage data from 2018-2022, we have averaged the SVI data from 2018 and 2020 for this work.

C. Weather Data

Weather datasets are obtained from the National Weather Service (NWS), a federal agency of the United States[2]. The NWS provides information about weather, water, climate data, warnings, advisories, history, and forecasts, as well as impact-based decision support systems to protect human life and enhance the US economy. We used the NWS Valid Extend Code (VTEC) archives dataset processed by the Iowa State University Iowa Environmental Mesonet (IEM). This dataset contains information about the geography and life cycle of weather events that occur in the United States, including watches, warnings, advisories, and others. Please refer to the IEM VTEC achieve website for further details on the data[3]. Since "W" (Watch) and "Y" (Advisory) are the most impactful events, we are filtering only the "W" and "Y" type SV events for our analysis.

III. Methodology and Results

In this section, we provide the power outage and SVI with and without the weather-related outage threshold. In our work, we have mapped the weather outage data with the power outage data to determine the threshold for the outages caused by the extreme weather event. The threshold value is calculated—average power outages from regular causes—to distinguish power outages caused by extreme events from other regular causes (e.g., vegetation and system faults). Fig. 5 displays an example power outage curve. The weather data are only used in this study to calculate the threshold of outages due to extreme weather events. Weather event correlation with SVI is left as future work. The following analysis is performed for this work.

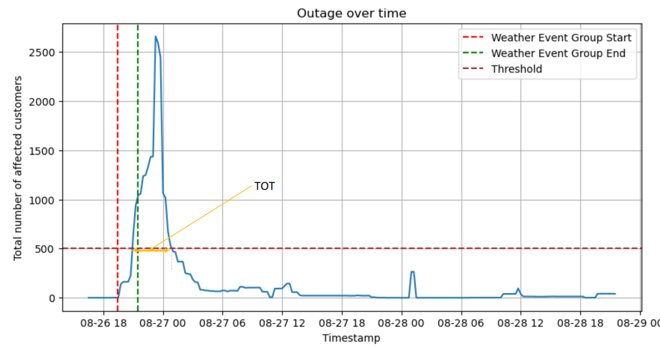

Fig. 5. Power outage pattern of a weather event with the threshold.

A. Power Outage and SVI without Threshold

Figure 6 shows the Power outage count of different durations vs the cumulative customer impacted. Due to the space limit, we have only provided the results for Theme 1 and Theme 2. The rest of the results are provided in the supplementary file [11]. This plot shows that for Theme 1 (socioeconomic status), theme 2 (characteristics of household), theme 4 (transportation and housing type), and overall theme, there is no clear distinction for all outage duration counts (more than 1 hour, more than 8 hours (medically significant [9]), and more than 24 hours events). For theme 3 (Racial & Ethnic Minority Status), there seem to be more cumulative customers impacted and more events of various duration for more vulnerable communities. In general, there is no strong distinction between outage duration of various sizes vs SVI themes.

B. Power Outages and SVI with Threshold

In this case, we have analyzed the power outage duration (in minutes) with different values of the SVI index for different sizes of the counties in terms of their population. The results are as shown in Fig 7, in this figure TOT denotes the time duration over the threshold. The average value of county-level TOT calculated is 495 minutes. TOT as shown in 5, is visually indicated by the length of time the power outage curve remains above the threshold line. TOT provides information about the duration of power outages experienced by customers due to extreme events. Lower TOT signifies the power system takes less time to recover from power outages. Q1 and Q4 represent

[2]https://www.weather.gov/

[3]https://mesonet.agron.iastate.edu/info/datasets

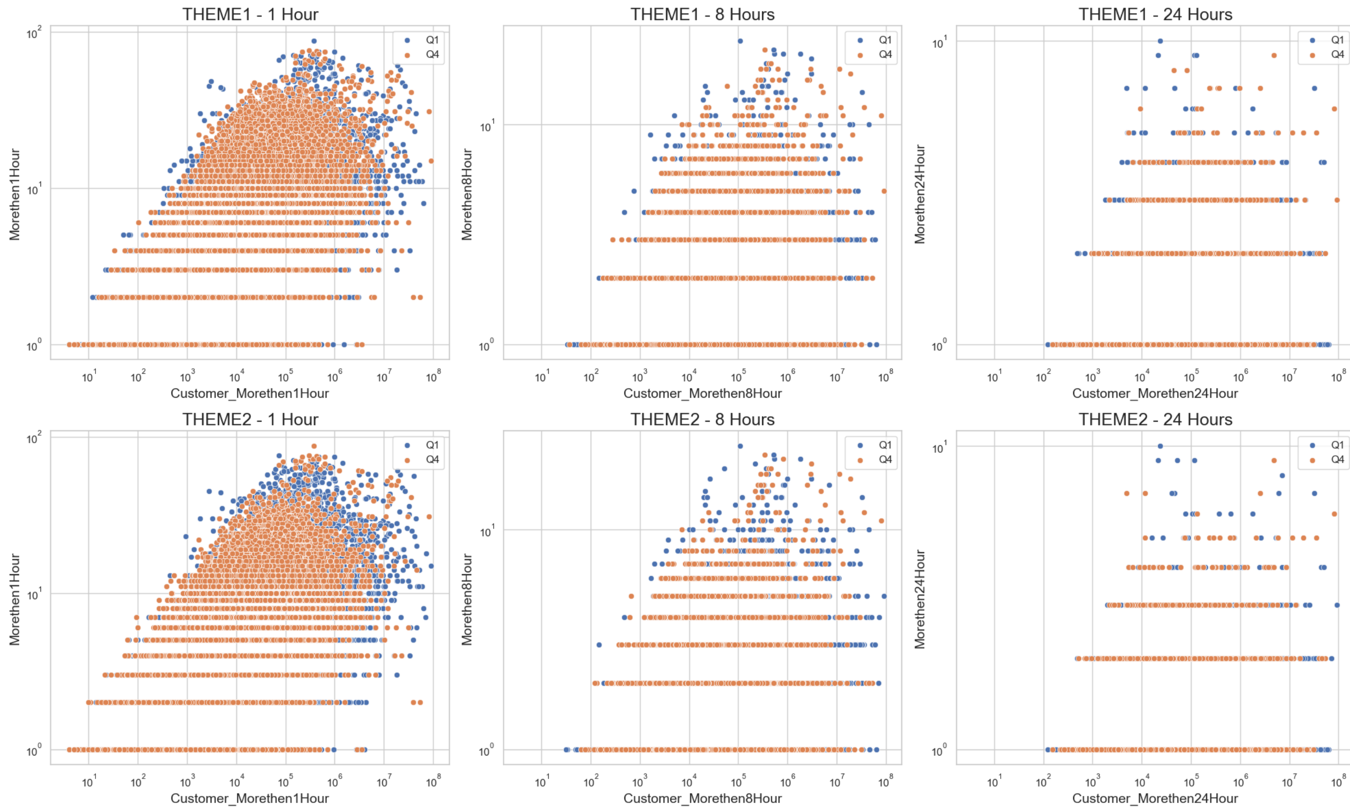

Fig. 6. Outage Duration of More than Various Hours vs SVI Themes. Both low and high SVI counties have higher outage duration, hence do not show a high correlation.

the first(low SVI: 0-0.28: less vulnerable) and fourth (high SVI: 0.77-1: more vulnerable) quartile values of respective SVI themes.

Results in Fig. 7 show that for Theme 1 (socioeconomic status) and Theme 2 (characteristic of household), higher-population cities are more vulnerable. On the other hand for Theme 3 (Racial and Ethnic minority status) and Theme 4 (transportation and housing type), high-population cities are less vulnerable. In terms of power outage duration, there is no clear pattern distinction between the high and low values of SVI themes for different sizes of counties in terms of population. This means there is no clear discrimination between the low SVI counties and high SVI counties in terms of power restoration after a weather event. However, when we look at the individual data points (individual counties), we see the statistics as shown in Fig. 8. The rest of the counties are in the "Q2:[0.28-0.53]" and "Q2:[0.53-0.77]" range (averagely vulnerable) and are not included as we are comparing the more vs less vulnerable counties in terms of SVI themes.

Power outage and SVI on the Continental US map are provided in Fig 9 and Fig 10. The first information that can be extracted from these figures is that even for the same quartile ($Q1[0-0.28]$ or $Q2[0.77-1]$), different SVI themes cover different counties. The Counties with white color in these map indicates that the respective SVI (Theme1, Theme2, Them3, Theme4, and overall) values do not fall in those counties. Fig 9 provides the TOT with low SVI values, this indicates that power outages are generally high in highly populated cities. The result is similar for high SVI values in Fig 9 as well. The possible reason for this is that outage events of the same duration in general impact more population in dense areas resulting overall longer power outage duration. With more power system infrastructure in a densely populated area also has, there is the probability of more infrastructure being damaged due to an event resulting in more power outage duration.

These results show that there is no strong correlation between power outages due to extreme events (distinguished based on the calculated threshold) and the SVI index. Note that the results can expanded to other geographical regions (e.g. Alaska, Hawaii, etc.) of the USA comfortably, although we have provided the results only for the continental US.

IV. Conclusion

This work performed a detailed societal vulnerability analysis of power outages by analyzing several vulnerability themes such as socioeconomic status, characteristics of the household, racial and ethnic minority status, and housing type and transportation provided by the CDC/ATSDR. This analysis is important as SVI is calculated based on the summed rank of multiple vulnerability factors to disaster, it may include factors that are not relevant to power outages due to extreme events

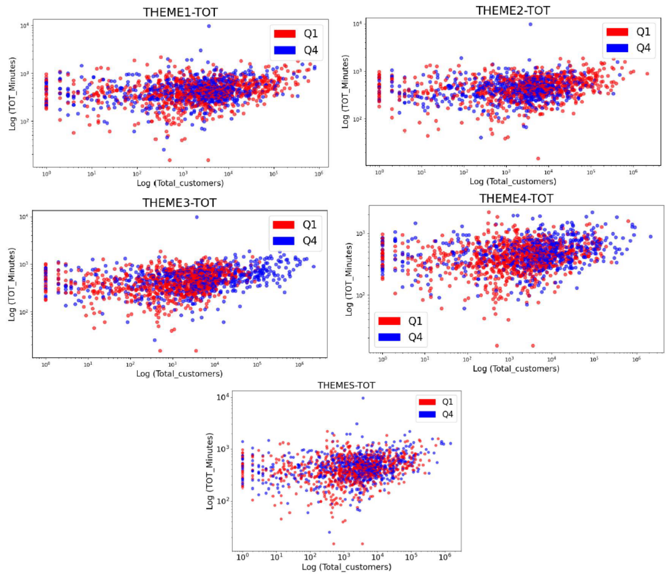

Fig. 7. County level TOT vs Customers. TOT represents the time over the threshold line of the power outage curve as shown in Fig 5. Q1 and Q4 represent the first(0-0.28) and fourth (0.77-1) quartile values of respective SVI themes. Both low and high SVI counties have high TOT with the increasing number of customers impacted.

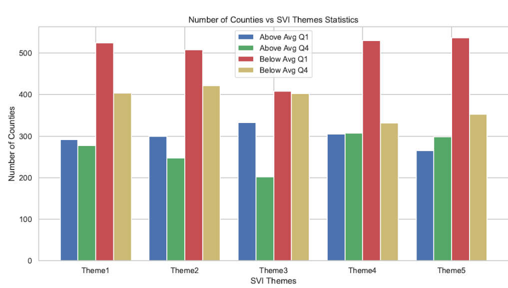

Fig. 8. Number of Counties vs Average TOT Statistics. Q1 and Q4 represent the first(0-0.28) and fourth (0.77-1) quartile values of respective SVI themes.

and may shadow the relevant themes. We performed the power outage analysis with and without an extreme weather outage threshold to study their relation with SVI themes. Although there was some relevance between power outages and the SVI themes in the analysis, there is no strong correlation between the power outage due to extreme events and SVI themes.

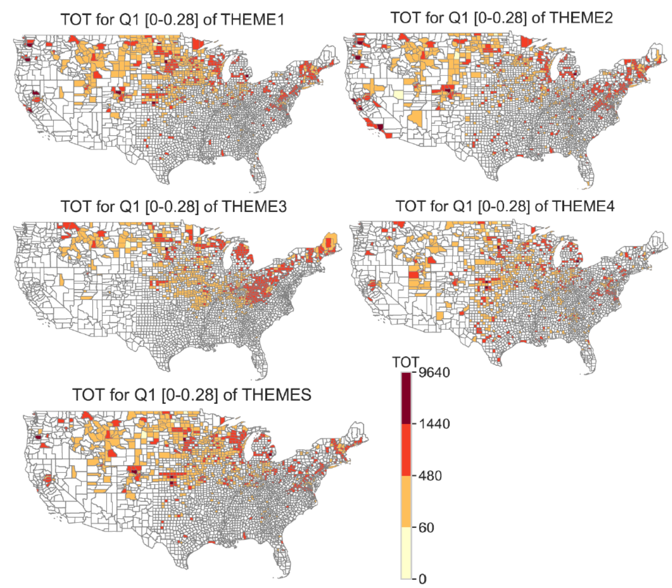

Fig. 9. TOT (in minutes) with Low SVI for Various Theme. TOT represents the time over the threshold line of the power outage curve, see Fig 5.

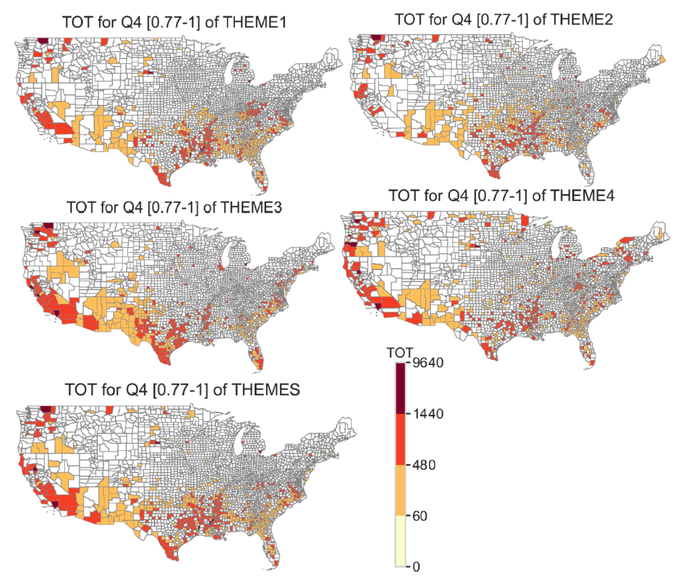

Fig. 10. TOT (in minutes) with High SVI for Various Theme. TOT represents the time over the threshold line of the power outage curve, see Fig 5.

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