Extreme Weather and the Power Grid: A Case Study of Winter Storm Uri

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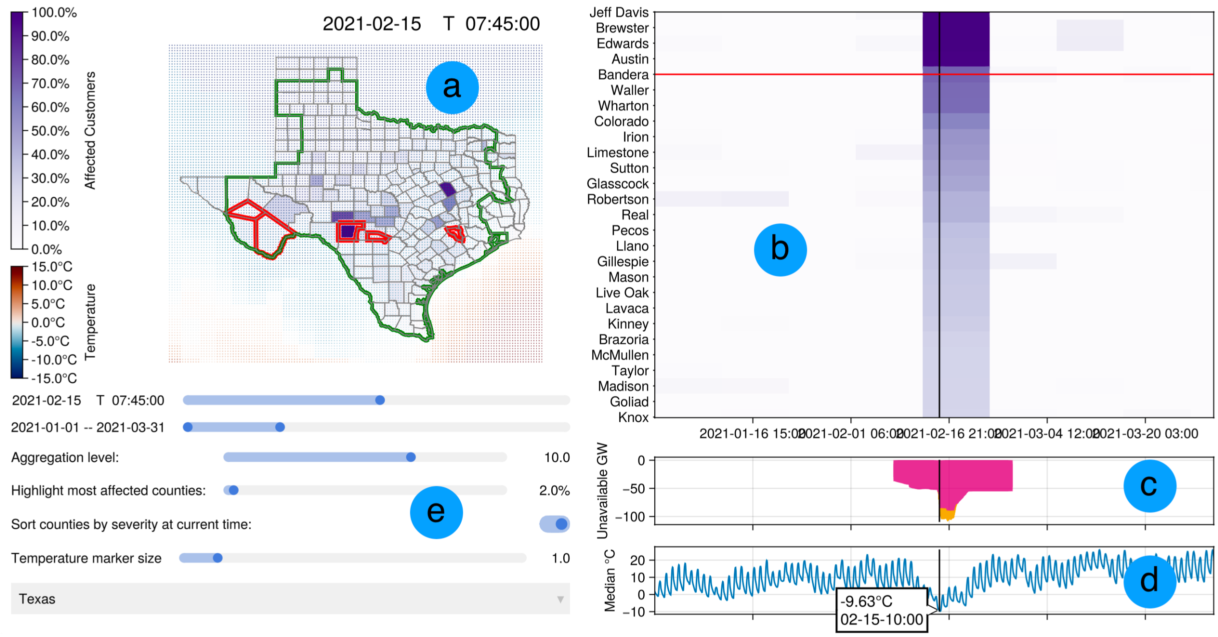

Figure 1: Sample analysis using the OutVis analysis tool. (a) shows the choropleth map of the outage data for a selected state at a specific time, with an optional temperature data overlay. Users can select counties in view (b) and highlight them with red outlines. The Texas Interconnection boundaries are displayed in green. (b) displays the temporal outage *severity* for every county of the state. Counties can be sorted by severity at the specified time (black bar). The red bar indicates the threshold of the $n\%$ most affected counties, as selected by the user. (c) shows power generation shortages and (d) displays the median temperature over time. Finally, the tool provides data exploration options (e) to select the time range, the specific time, the aggregation level for severity, or set the threshold to automatically highlight the most severe outages, control of temperature overlay in (a), and state selection.

Abstract

Weather can have a significant impact on the power grid. Heat and cold waves lead to increased energy use as customers cool or heat their space, while simultaneously hampering energy production as the environment deviates from ideal operating conditions. Extreme heat has previously melted power cables, while extreme cold can cause vital parts of the energy infrastructure to freeze. Utilities have reserves to compensate for the additional energy use, but in extreme cases which fall outside the forecast energy demand, the impact on the power grid can be severe.

In this paper, we present an interactive tool to explore the relationship between weather and power outages. We demonstrate its use with the example of the impact of Winter Storm Uri on Texas in February 2021.

Index Terms: Power outages, weather, severity, exploration.

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1 Introduction

Energy resilience is becoming an increasingly studied topic. Most renewable energy sources are subject to seasonal variation, such as differences in wind patterns, ideal operating temperatures for solar photovoltaic (cold), and differences in river water volume due to snow melt and droughts. Many renewable and fossil energy sources also depend on the daily weather, including solar photovoltaic and concentrated solar power, which operate best with clear skies, and wind energy on land and offshore. Extreme weather can further affect the electric grid through direct damage, such as frozen natural gas lines [14], melted power lines during heat waves [27], or downed power lines after storms [21]. Extreme weather can also affect the grid more indirectly, e.g., through restrictions on cooling water for nuclear reactors to limit the environmental impact on river ecosystems during a drought [22], as happened during the summer of 2022 in France. Dumas et al. [12] provide a comprehensive overview of how extreme weather events affect the different means of energy production. Novacheck et al. [26] examine how different future weather conditions will affect the operation of diversified power grids that rely primarily on renewable energy sources.

The United States Power Grid consists of three major interconnections [7]. The Western Interconnection includes the western United States and Canada, the Eastern Interconnection includes the central and eastern United States and central Canada, and the Texas Interconnection covers 90% of the Texas customer loads [13].

The advantage of an interconnection is that electricity can be shared within the entire interconnection. For large interconnects that span multiple climate zones, this enables the grid to compensate for production shortcomings in some areas by using electricity produced in unaffected areas. However, if the entire interconnection area is affected by extreme weather, the operations of power systems can be hampered. In this paper, we will focus on the widespread power outages in Texas caused by Winter Storm Uri in February 2021.

Most of Texas lies within hot-humid and hot-dry climate zones, and in highly populated areas, winter temperatures typically remain above freezing. This is relevant for two reasons: first, the Texas Interconnection has relatively homogeneous temperatures, and the entire area was affected by the winter storm. This means that there was little opportunity to balance production and loads across the grid. Second, the majority of the Texas building stock is comprised of buildings that are designed for a warm climate. Texas households rely primarily on electricity (51%), and natural gas (42%) for heating.

During Uri, temperatures dropped $22-28°$C/$40-50°$F below average winter temperatures [14]. These low temperatures led to a sharp increase in electric loads well above typical demand as people tried to keep their homes warm. The loads were further exacerbated as the natural gas pipes froze, which led to a further increase in the use of electricity for heating (e.g., with space heaters), while the electricity production from natural gas decreased, which contributes 52% to the generation. The Federal Energy Regulatory Commission (FERC) performed an in-depth analysis of the Uri outages and found that there were over 70 hours of firm load shedding – forced rolling outages to keep the grid from complete collapse – due to freezing issues (frozen wind turbine blades, frozen equipment in natural gas plants), limited availability of natural gas, mechanical and electrical problems, leading to an overall deficit of 65,622 MW [14].

In this paper, we evaluate the relationship between weather and power outages at the example of the Uri outages in Texas.

2 Related Work

The visualization of geographic data is common practice. In terms of analysis, previous studies show the importance of normalization of the data when using choropleth maps [33, 10, 1]. As time-varying data are a common case in visual analysis, various studies were conducted. The resulting toolbox is extensive and includes approaches ranging from juxtapositions, glyph designs, and data aggregation that enable data exploration [16, 8, 34, 35, 30, 28] and evaluations [18, 20]. More information on the visualization of time series data can be found in the surveys: [2, 24, 31]. To allow for intuitive understanding and exploration of the data, we utilize well-known and studied approaches, e.g., juxtaposed line charts, heatmaps, and choropleth maps.

Previous work on outage analysis has focused on geospatial tools that overlay multiple layers of information on a map [32]. Outside of interactive exploration, research has expanded to the study of the spatial distribution of power outages in relation to social vulnerability [11]. Some works have studied disparities between different counties during Uri on an aggregate scale of total hours of consecutive outages [15], and assessing overall household burden [29]. Although both of these are very interesting works, they are all based on survey data and their focus is static visualization for analysis.

3 Datasets

3.1 Customer Outages

We use the Environment for Analysis of Geo-Located Energy Information (EAGLE-I) [32] platform. The EAGLE-I outage dataset contains eight years of county-level outages collected at 15-minute intervals. Each time step contains the Federal Information Processing Standards (FIPS) code, the state and county name, and the number of customers without power for each county. Estimated customer counts for each county were provided separately [6].

3.2 Generator Outages and Load Shedding

The power outages during Uri were caused by different factors, including weather, equipment problems, fuel limitations, pre-existing outages, and other problems. To prevent a complete collapse of the power system, ERCOT ordered load shedding to reduce the demand on the network and get it to stabilize. To help illustrate the timeline of events and their relationship with the observed customer outages, we manually sampled data from FERC Report [14] Figures 66b (outages) and 85 (load shedding). This sampling is rather coarse, as it primarily serves illustrative purposes.

3.3 Weather

The weather data were obtained from the Prediction Of Worldwide Energy Resources (POWER) project [25] API. We obtained hourly temperatures (T2M) at 2m above ground for the region that spanned latitude 25 to 37 and longitude -107 to -93 at intervals of 0.1 degrees.

3.4 Geometries

The county boundaries were obtained from Census data. ERCOT boundary generated manually cross-referencing county maps for ERCOT.

4 OutVis

The primary purpose of the OutVis prototype is to allow the user to get a quick overview of power outages, identify times of interest and geographic regions of interest, and analyze power outages and their relationship to weather for these regions at interactive speeds. To that effect, we designed the tool to assist in exploration through an interactive user experience.

The application is written in Julia [5], and we chose the Makie framework [9] to create the user interface and visualizations, as its support for OpenGL and WebGL makes it adaptable and scalable. An overview of the tool can be found in Figure 1.

In this work, we base our analysis on the relative outage count,

$$o(c;t) = \frac{\text{affected customers at time } t}{\text{estimated customer count at time } t}, \quad (1)$$

where c is a county and t is time. Note that $o(c;t)$ can be larger than 1 due to the imprecision in the estimated customer counts. For the sake of brevity, we refer to $o(c;t)$ as *outages*. The *temperature* will be denoted as: $T(t;x,y)$, for location x,y at time t. Note that x and y are discrete locations and that the time resolution of t varies between the outage data (15 minutes) and the weather data (one hour).

4.1 Preprocessing

Browsing the timeline for large datasets at interactive speeds requires appropriate data management. The goal of this preprocessing step is to allow quick access to outages at a specific time step in a specific county. Since outages are sparse by nature, we only need to store data for time steps in which at least one outage has occurred in a specific county. Through experimentation, we found an array of dictionaries, where every dictionary corresponds to a county to be viable. Within each county, we use a numeric representation of

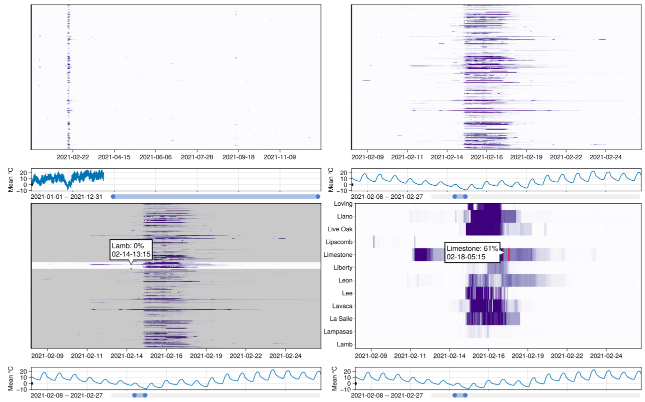

Figure 2: Views on the timeline showing (a) the initial configuration showing all counties for the full time range, (b) focused on a smaller time range, (c) user selection of a subset of counties, and (d) the selection results . For all views, the color indicates the outage severity $o(c;t)$., and the chart below shows the median temperature.

the time step as keys and the outages as values, keeping the memory footprint low. The temperature data was stored using a similar approach. This use of dictionaries facilitates fast and parallel requests for outages $o(c;t)$ and temperatures $T(t;x,y)$ with a rapidly varying value of t. To further improve the interactive experience and avoid recomputing, the data is cached.

4.2 Map View

Understanding spatial relationships is vital when analyzing geographic data. This view aims to provide the user with geographical context (cf. (a) in Figure 1) by rendering county boundaries for the selected state. We chose to display the outage $o(c;t)$ for the currently selected time step using a choropleth map where $o(c;t)$ is normalized by the estimated number of customers. Temperature data can be can be blended in to assess the spatial distribution of the temperature between different areas (cf. the top row of Figure 4). In addition, we display the boundary of the Texas Interconnection, as its isolated status played an important role for the specific use case we will investigate. This view is intended for investigating specific times and allows users to quickly find the geographic location of counties that have noteworthy outage behavior.

The map view supports zooming to focus on specific areas, as well as mouse hovering to read precise temperatures if the markers are currently active. The investigated time step can be set in the sliders below (cf. (e) in Figure 1) or in the timeline view.

4.3 Timeline View

The timeline view (cf. (b) in Figure 1) allows the user to explore customer outages in more depth. It uses a heatmap for which the horizontal axis corresponds to time and the vertical axis corresponds to counties. The time frame displayed in this view can be set by using a double slider. The counties are initially sorted alphabetically by name. They can also be sorted by outage $o(c;t)$ at the current time step (indicated by a vertical black line), which can be selected by the user with a slider (e) or by clicking on the heatmap. The horizontal red line indicates the threshold for most affected counties that can be set using a slider (e). A mouse hover reveals the county name, the exact outage percentage, and timestamp for any point on the heatmap. Zooming by mouse selection (locked to the vertical axis) allows the user to focus on specific counties. Zoomed in, county names are appropriately displayed and can be selected, highlighting them in the map view.

To reduce noise and provide a more simplified view of the

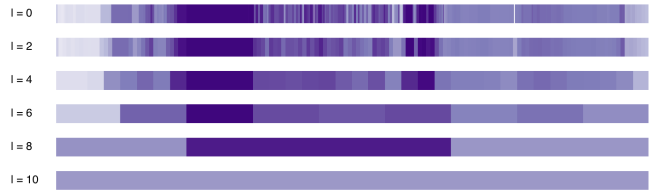

Figure 3: Example different aggregation level settings for Limestone county, Texas, USA for a date range of 2021-02-14 – 2021-02-20. (cf. subsection 4.3)

heatmap, we introduced aggregation level settings, as seen in Figure 3. As $o(c;t)$ is a time domain representation, an extensive toolbox of smoothing approaches from signal processing theory is available. For this work, we utilized the wavelet transform, which shares commonality with the more widely applied Fourier transform. As the resulting frequency domain representation applies the frequency components to the whole signal, we lose information about the signal variation over time. This is a fundamental drawback of techniques related to frequency domain representation, as signals cannot be localized in the time and frequency domains simultaneously [19]. As $o(c;t)$ can vary greatly, especially as in the present case study, these variations express themselves locally. The wavelet transform mitigates the issue of locality by estimating the frequency domain locally using a decaying weight function. Using wavelets, our smoothing technique can robustly filter locally expressed high-frequency outages $o(c;t)$ as shown in Figure 3. In this work, smoothing refers to the aggregation of the temporal high-frequency content of $o(c;t)$. Haar wavelets [17] are sufficient and provide a fast computation for an interactive modification of the filtering level. In the following, refer to the values of the aggregated outage signals as (outage) *severity*.

Initially, this aggregation is turned off, and users can make a conscious decision to examine the aggregated data instead of the raw numbers. When aggregation is active, it also affects sorting by outage severity. This allows for a comparison of the higher-level outages. We assume the aggregation to be particularly useful when the data is unknown as it allows the user to reveal large-scale outage fluctuations in long time intervals, thus providing an overview.

4.4 Generation Outage and Temperature View

The generation outage view displays the time series of generation outages (pink) and load shedding as a stacked chart. Together, these two add up to the total unavailable energy.

Below the Timeline View, we display a temperature plot, which shares the same timeline as its x-axis. On this timeline, we plot the temperatures of the entire observed area (bounding box around Texas). We chose to use the median temperature because temperatures in southern Texas and surrounding areas (Mexico and Gulf of Mexico) are substantially higher than in the rest of the area (cf. Figure 4), and the median was more robust to those temperature differences than the mean. The alignment of this view with the heatmap above allows the user to evaluate the impact of temperatures on power outages.

5 Case Study

We demonstrate OutVis at the example of the Uri outages and summarize relevant visualizations in Figure 4. Note that the time steps (a,b,d,e,f) were chosen on the basis of the FERC report, while (c) was determined based on the median temperature. The week of February 8 started with a generation deficit for 35 GW due to ongoing planned and forced outages, as well as seasonal shut-downs. Cold temperatures and freezing rain on February 10 and 11 caused

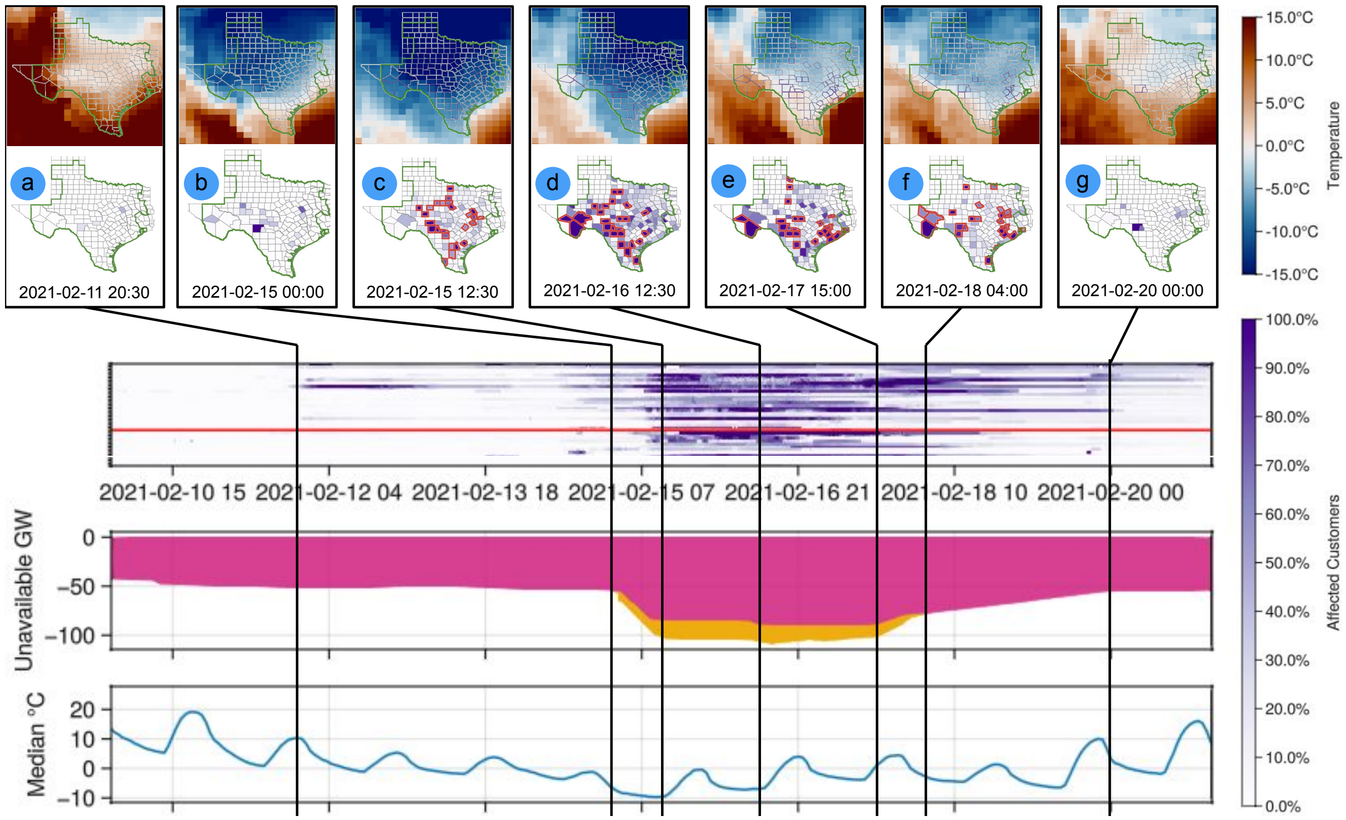

Figure 4: UI elements from different stages of the Uri outages, combined into an illustration. The bottom section shows parts of the timeline view (selecting the 10% most affected counties above the red line), the generation outages view, and the median temperature for the entire timeseries, with vertical lines marking seven significant times. The upper section shows the temperatures and outages in each of the time steps.

ice buildup on wind turbine blades and other equipment and increased that outage to 48 GW [23]. At 20:30 on the second day (a), we begin to see outages in some counties, specifically Limestone (below the red line) and Edwards (near the top). Over the next few days, natural gas production and processing started to fail (not shown here) due to freezing, slowly depleting the reserves needed for direct heating and natural gas-based power generation. As temperatures continued to plummet, and energy consumption increased dramatically in response, resulting in an all-time winter peak load of 69,871 MW. This resulted in a series of cascading failures and load shedding, beginning in the early hours of February 15 (b). The fuel shortage triggered several generator failures and ERCOT began manual load shedding procedures [14] in small increments of 1 GW at a time. With energy demand nearing supply to the point of depleting the entire safety buffer, the network frequency became so unstable that it triggered automated load shedding (shut-offs) in more generators, further escalated the problem. The load shedding was increased up to a maximum of 20 GW (c) in order to prevent further frequency-related outages, which could have caused a complete blackout of the Texas Interconnection. This sharp increase can be seen in the heatmap, where outages jump from very low to large percentages of each county. This level of load shedding was maintained for several days until temperatures increased and gas supplies began to stabilize (d). Many counties continued to be heavily affected, but as temperatures began to increase, some of them saw a decrease in outages. The stabilized grid with decreasing loads allowed ERCOT to reduce load shedding slowly at first (e) and then entirely (f). When the temperatures finally returned to typical winter temperatures (g), the majority of customers returned to full service.

6 Conclusion and Future Work

In this work, we proposed a tool to interact and explore the outage data in the context of the winter storm Uri. While the timeline view provides an overview over the temporal dynamics of normalized outages energy availability and temperature, the user is able to interactively investigate the details. The interactive wavelet-based aggregation allows the user to explore general trends in outages indicating severity. The temporal correlations between temperature, power generation, and outages are clearly identifiable. The usefulness of the prototype is showcased in the case study presented.

In the future, we will also include a timeline for gas production and processing to contextualize the present data in terms of heating demands. We will also investigate how well the wavelet-based severity related to metrics related to major outages. To our knowledge, there is currently no formal definition of a major outage. As power generation could also be impacted by other weather scalars than temperature, we will add additional features, for example, wind which is useful for hurricanes. Improvements to the map view to more easily see temperature data in conjunction with outage data will also be investigated. We also want to investigate techniques related to the concept of episodes. As discussed in the work by Andrienko et al. [3], episodes are sets of time series of multiple attribute values. Using this concept, we will investigate adding different information related to local weather and visualizing these appropriately with a focus concurrency with the timeline. In addition, the uncertainty of estimated customers in relation to the EAGLE-I data needs to be quantified and communicated. Finally, since population behavior has an influence on power demand and, by extension, supply, we plan to integrate a more detailed analysis of human mobility [4].

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