QUANTIFYING POWER SYSTEM RESILIENCE TO EXTREME WEATHER EVENTS USING STATISTICAL ANALYSIS AND BAYESIAN LEARNING

Apsara Adhikari (Washington State University), Charlotte Wertz *(Washington State University)*, Arslan Ahmad *(Iowa State University)*, Anamika Dubey *(Washington State University)*, Ian Dobson *(Iowa State University)*

WASHINGTON STATE UNIVERSITY

1. BACKGROUND AND MOTIVATION

- Extreme weather events are the leading cause in power outages, causing billions of dollars in damage [1], [2]
- The spatiotemporal nature of these events make them difficult to characterize and predict future outages for mitigation purposes
- Additionally, historical outage and weather data is lacking in this area and difficult to analyze
- We need to formulate a data-driven model to understand the leading cause of outages and their specific magnitude with existing data

2. OBJECTIVES

- Characterize and quantify outage event metrics from extreme weather events
- Understand how different weather variables affect outages
- Develop algorithm to detect outage events based on historical data
- Predict and mitigate future outage events based on mathematical and statistical modeling
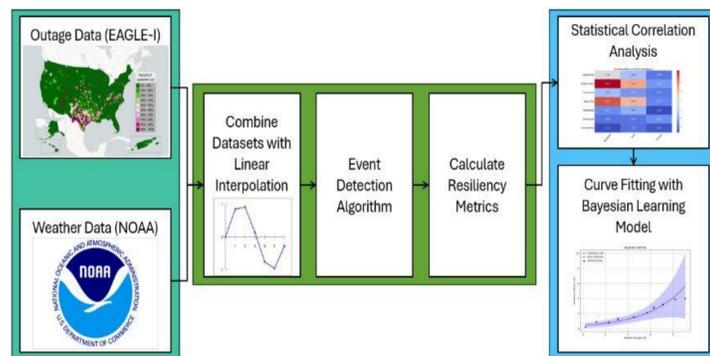
3. PROPOSED FRAMEWORK

Fig. 1: Proposed Framework for grid resilience modeling as a function of weather parameters

- Collect raw 15-minute data from EAGLE-I [3]and NOAA [4]
- Combine the datasets and aggregate individual reported outages into events
- For each event, calculate resiliency metrics
- Use regression models and Bayesian learning to create weather-outage relationship
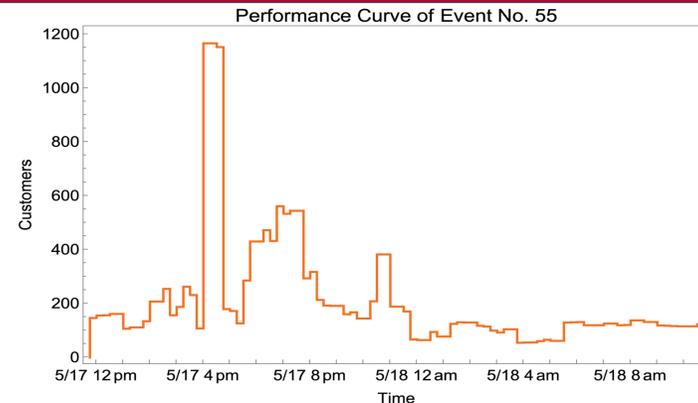
4. EVENT DETECTION AND RESILIENCY METRICS

Fig. 2: Performance Curve of a Sample Event

Metric	Description
Area Under the Performance Curve (AUC)	Measures total impact of outage in customer-hours
Number of Customer Outage	Number of customers affected per unit time
Outage Duration	Time between first and last outage

- Event detection algorithm uses a threshold approach based on the percent of electric customers in a county[5],[6]
- Weather data is overlayed on the event to calculate the impact of weather data into resiliency metrics
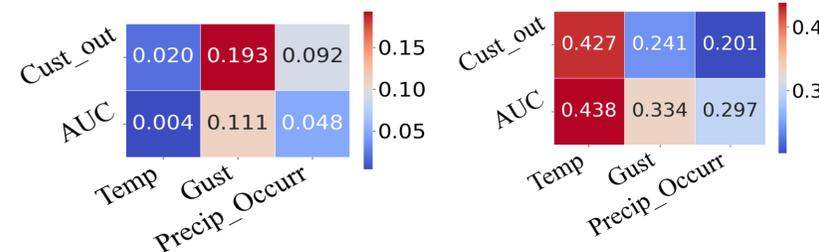
5.WEATHER-OUTAGE REGRESSION MODEL

Fig. 3: Correlation of Weather and Outage Metrics for Cook County(left) and Miami Dade County(right)

- Determine whether weather parameters have strong (if any) correlation to outage metrics and their dependencies
- Plot to find relationships – additive, multiplicative, quadratic, etc

6.BAYESIAN FRAMEWORK

$$R_i = ae^{bW} + c$$

Where:

R_i is the resiliency metric for the i-th observation

W is the weather parameter

a, b, c are the model parameters learned via Bayesian inference

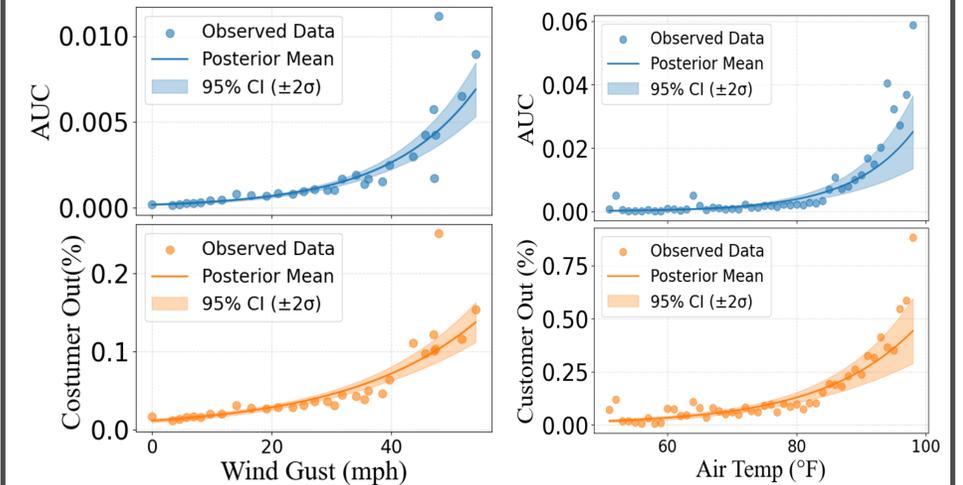- Allows us to incorporate uncertainty quantification

7.RESULTS

Fig. 4: Relationship between Wind gust and Resiliency Metrics for Cook County(left) and Air temperature Vs Resiliency Metrics for Miami-Dade County(right) with 95% Credible Interval

POSTERIOR SUMMARIES FOR MIAMI-DADE AND COOK COUNTIES

Parameter	Miami–Dade Mean	Miami–Dade Std	Cook Mean	Cook Std
a	0.00411	0.0288	0.0167	0.1177
b	0.03943	0.00581	0.06808	0.00363
c	−5.1492	6.9940	−4.5666	7.0566

Metric	Cook County	Miami-Dade County
Root Mean Square Error (RMSE)	0.6034	0.6692
Mean Absolute Error (MAE)	0.4429	0.5315
Mean Absolute Percentage Error (MAPE)	5.9964%	8.4809%

- Exponential fit for wind speed and temperature on Cook and Miami-Dade county
- Shows wind gust and temperature resilience on power system in given regions

8. CONCLUSION AND FUTURE WORKS

- Resiliency Metrics have significant relationship with the weather variables
- Miami-Dade County have high correlation of outages with both wind gust and temperature, while in Cook County ,wind gust alone has a notable impact.

Future Work

- Develop algorithms to extract outage events from individual outages data using spatiotemporal information
- Understand weather variables relationship and dependencies
- Implement multi regression techniques to capture full weather-outage relationship

[1] Center for Climate and Energy Solutions (C2ES). (2025) Extreme weather and climate change. [Online]. Available: https://www.c2es.org/content/extreme-weather-and-climate-change/ [2] 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. [3] C. Brelsford, S. Tennille, A. Myers, S. Chinthavali, V. Tansakul, M. Den-man, M. Coletti, J. Grant, S. Lee, K. Allen et al., "A dataset of recorded electricity outages by United States county 2014–2022," Scientific Data, vol. 11, no. 1, p. 271, 2024. [4] "Climate data online: Dataset discovery," 2024. [Online]. Available:https://www.ncdc.noaa.gov/cdo-web/datasets/ [5] M. Abdelmalak, J. Cox, S. Ericson, E. Hotchkiss, and M. Benidris, "Quantitative resilience-based assessment framework using EAGLE-I power outage data," IEEE Access, vol. 11, pp. 7682–7697, 2023. [6] N. K. Carrington, I. Dobson, and Z. Wang, "Extracting resilience metrics from distribution utility data using outage and restore process statistics, "IEEE Transactions on Power Systems, vol. 36, no. 6, pp. 5814–5823,2021.