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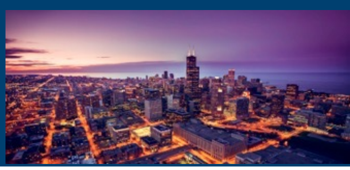
Sandia National Laboratories

Sandia and UT Collaboration: Power System Resilience Investment Projects



Manuel Garcia

Sandia Team: Brian Pierre, Bryan Arguello, Manuel Garcia, Nathan Stewart, Ben Emery, Dan Krofcheck.

University of Texas Partners: Erhan Kutanoglu, Surya Santoso, Brent Austgen, Joshua Yip, Baris Bilir.

This work was supported by the Energy Storage Program at the U.S. Department of Energy Office of Electricity Delivery and Energy Reliability managed by Dr. Imre Gyuk.

This work was supported by the Laboratory Directed Research and Development program at Sandia National Laboratories.

Power System Resilience Investment Projects

“Critical Nodes” Project

- Title: Critical Node Identification, Vulnerability Modeling, and Topology Optimization for the Electric Grid
- Funding source: Laboratory Directed Research and Development (LDRD)
  - Resilient Energy Mission Campaign (2021-2027)
  - Other investment areas outside of energy systems
- Currently in year 2 of 3
- Two goals:
  - Identifying critical (or vulnerable) nodes
  - Investment decision making methodology

“Energy Storage Restoration” Project

- Title: Improving Grid Resilience with Optimal Restoration Utilizing Energy Storage
- Funding source: Energy Storage Program
  - Lead by Dr. Babu Chalamala
  - Funded through DOE OE (Dr. Imre Gyuk)
- Currently in year 2 of 3
- Black-Start restoration using Mobile Energy Storage

"Critical Nodes" Project

<u>Goal</u>: Develop Sandia capabilities to **identify** electric grid **critical nodes** and their vulnerability levels to various threats and to develop a decision-making methodology to **improve resilience**.

- Identifying critical nodes
  - Interdiction analysis (determining worst N-k attacks)
    - Down select possible N-k attacks (combinatorial explosion in k)
  - Cascading outage analysis
    - Temporal clustering to determine component outages resulting in full collapse
- Decision making methodology
  - Three-stage scenario-based stochastic investment optimization

Three-Stage Resilience Optimization Problem

1st Stage (Investment)
Decides investments x.
Minimizes Conditional Value at Risk (CVaR).

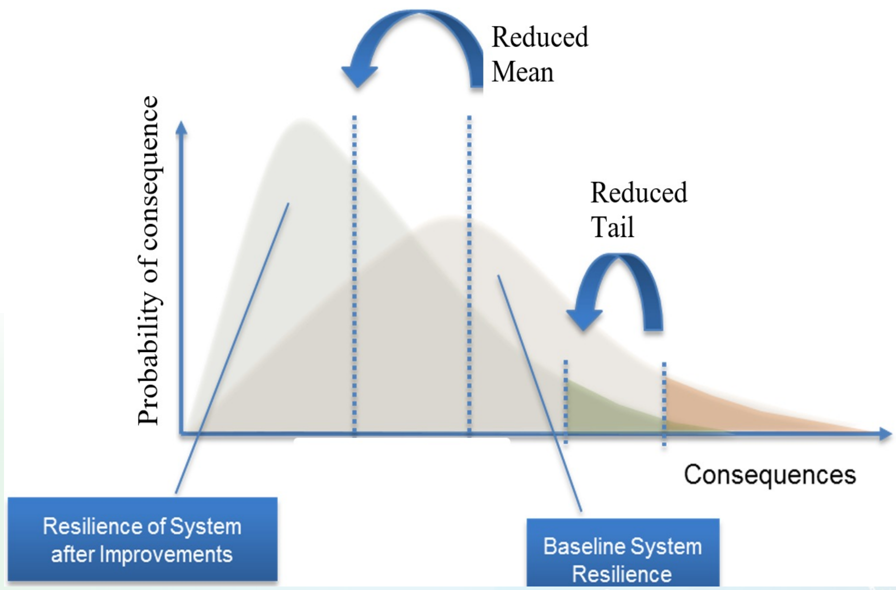
$$\min_{x \in \mathcal{X}} CVaR_f^{\epsilon}\left[\tilde{\ell}(x,f)\right]$$

2nd Stage (Preemptive Action)
Decides pre-emptive action z.
Minimizes expected value.

$$\tilde{\ell}(x,f) = \min_{z \in \mathcal{Z}(x)} \mathbb{E}_{e|f}\left[\hat{\ell}(z,x,e)\right]$$

3rd Stage (Restoration)
Decides restoration variables y.
Minimizes deterministic value.

$$\hat{\ell}(z,x,e) = \min_{y \in \mathcal{Y}(x,z,e)} \ell(y,e)$$



Two-Stage Preemptive Action Optimization

In partnership with University of Texas, Brent Austgen

2nd Stage (Pre-Emptive Action)

Decides pre-emptive action z.
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3rd Stage (Restoration)

Decides restoration variables y.
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$$\hat{\ell}(z,e) = \min_{y \in \mathcal{Y}(z,e)} \ell(y,e)$$

- Given a warning an event may occur, how to optimally prepare your system for that event, and optimally recover from the event.
- Example 1: given a 24-hour warning a hurricane will strike a specific city, how to optimally dispatch limited flood walls around substations, to minimize load shed.
- Example 2: given a 24-hour warning a winter storm will occur, how to redispatch your generators to minimize load shed.

[1] Brent Austgen, John Hasenbein and Erhan Kutanoglu, "Impacts of Approximate Power Flow Models on Optimal Flood Mitigation in a Stochastic Program", Proceedings IISE Annual Conference and Expo, 22-25 May 2021

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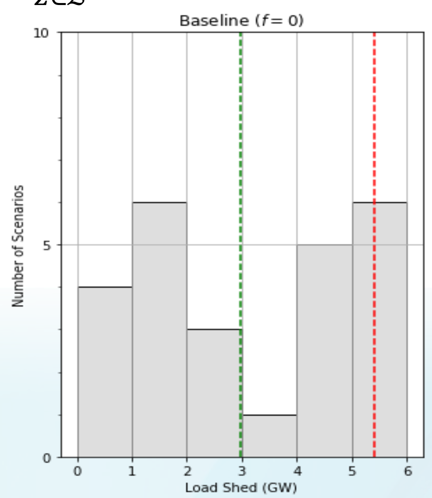
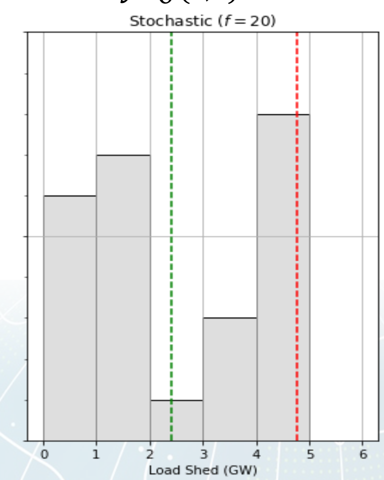


Not Pre-positioning flood barriers in advance of a hurricane



Pre-positioning flood barriers in advance of a hurricane

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[1] Brent Austgen, John Hasenbein and Erhan Kutanoglu, "Impacts of Approximate Power Flow Models on Optimal Flood Mitigation in a Stochastic Program", Proceedings IISE Annual Conference and Expo, 22-25 May 2021

Investments Targeting Winter Storms: Application to Uri

1st Stage (Investment)
Decides investments x.
Minimizes Conditional Value at Risk (CVaR).

$$\min_{x\in\mathcal{X}} CVaR_f^{\epsilon}\left[\hat{\ell}(x,f)\right]$$

3rd Stage (Restoration)
Decides restoration variables y.
Minimizes deterministic value.

$$\hat{\ell}(z,x,e) = \min_{y\in\mathcal{Y}(x,z,e)} \ell(y,e)$$

Scenario Generation

- A mixed random variable represents the fraction of available generation.
- Empirically constructed probability distributions from Winter Storm Uri data.
- Categorized generators with respect to fuel type and region.
- Introduced a random storm severity variable (not shown here).

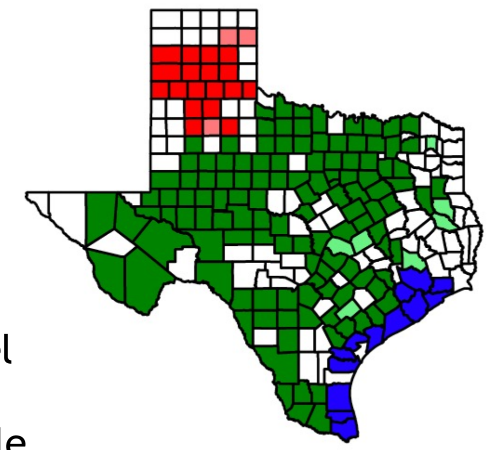

Figure: Texas counties categorized as panhandle (red), coastal (blue), or neither (green)

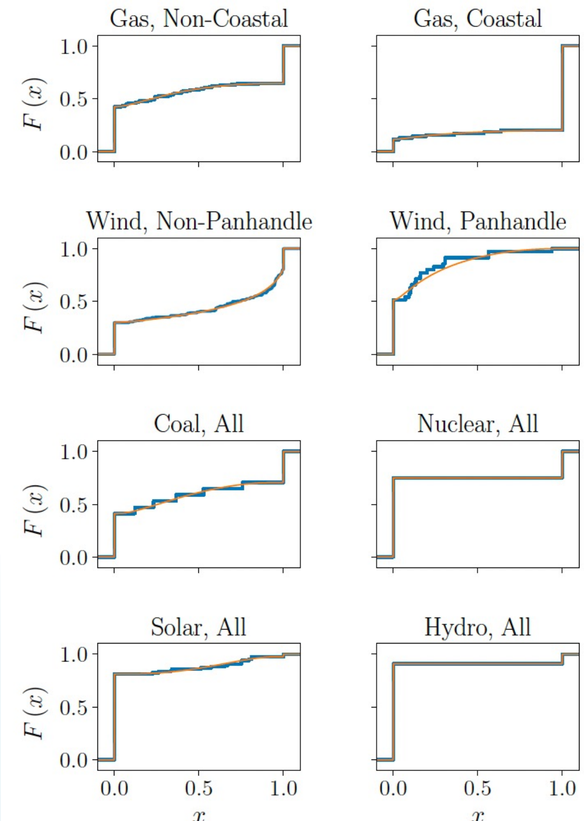

Figure: Cumulative Distribution Function for outage fraction of each generator type

[2] Brent Austgen, Manuel Garcia, Brian Pierre, John Hasenbein and Erhan Kutanoglu, "Winter Storm Scenario Generation for Power Grids Based on Historical Generator Outages" Proceedings of the IEEE PES T&D Conference and Exposition, New Orleans, LA, April 25-28, 2022

Winterization Investment Results

Numerical Results

- Optimized over 3554 scenerios
- Validated results using 5000 out-of-sample scenarios
- Increasing budget significantly reduced load loss
- Adjusting CVaR to focus more on the tail results in more investment in “Gas Coastal” generator type. (The most outted generator type in Uri)

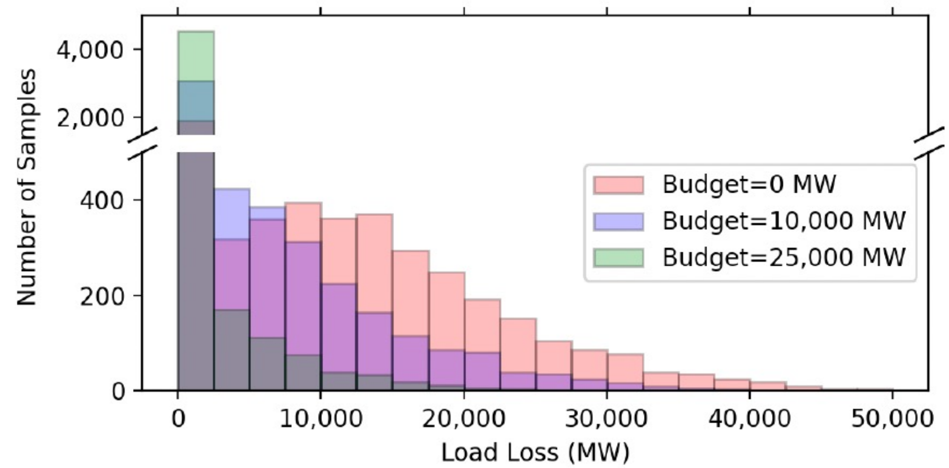

Figure: Histogram of load loss with different budgets using validation scenarios

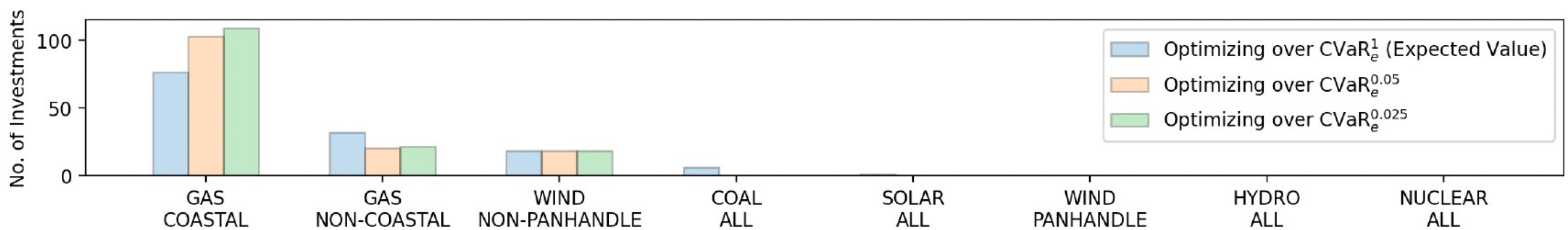

Figure: Number of investments by generator type for different values of ϵ

[3] Manuel Garcia, Brent Austgen, Brian Pierre, John Hasenbein and Erhan Kutanoglu, “Risk-Averse Investment Optimization for Power System Resilience to Winter Storms” Proceedings of the IEEE PES T&D Conference and Exposition, New Orleans, LA, April 25-28, 2022

"Energy Storage Restoration" Project

<u>Goal</u>: Develop optimization models to improve grid resilience by utilizing large-scale energy storage throughout a multi-time period restoration process.

- Black-Start Restoration with Mobile Energy Storage
  - Process of restoring grid after a complete blackout
  - Mobile energy storage can assist in the process
- Three-Stage Decision Making
  - Investment in mobile energy storage connection points in the grid
  - Preemptive action to place mobile energy storage before an event occurs
  - Dispatching mobile energy storage during the restoration process

Black-Start Restoration Assisted by Mobile Energy Storage

Black-Start Restoration Process

- Restore grid after complete black-out.
- Most generators require electric power to start-up (Cranking power).
- Few generators can start-up on their own.
- Grid components become energized, propagating from the generators, and eventually coalescing.

Mobile Energy Storage Assistance

- Energy storage can provide cranking power.
- Mobile energy storage can be pre-positioned or deployed after an event occurs.

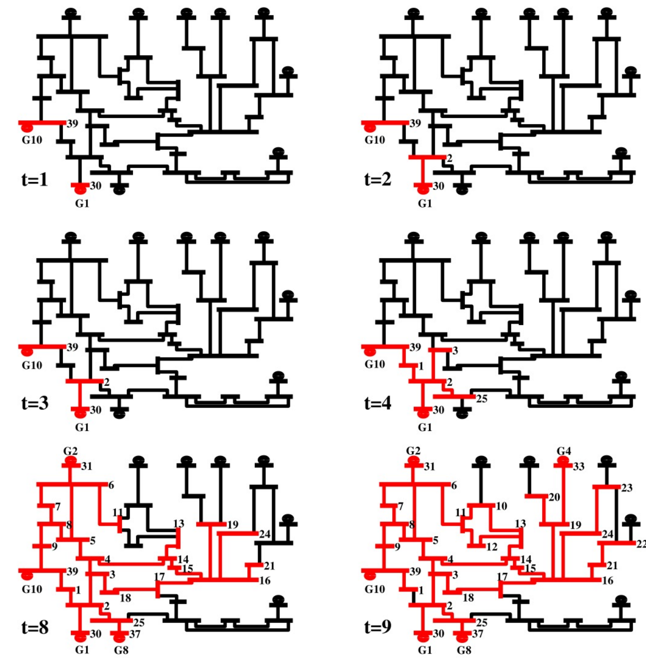

Figure: Illustrating how energized components propagate during the restoration process. Red components are energized. Time increases as you move down and to the right.

[3] Joshua Yip, Manuel Garcia, Brian Pierre, Erhan Kutanoglu, and Surya Santoso, “Optimal Black-Start Restoration Assisted by Mobile Energy Storage” Proceedings of the IEEE PES General Meeting, Denver, CO, July 17-21, 2022

Black-Start Restoration Assisted by Mobile Energy Storage

Experiments

- Model provided in reference.
- IEEE 14 bus test case divided into three regions.
- Simulate black-start restoration for cases where each individual region experiences outages.

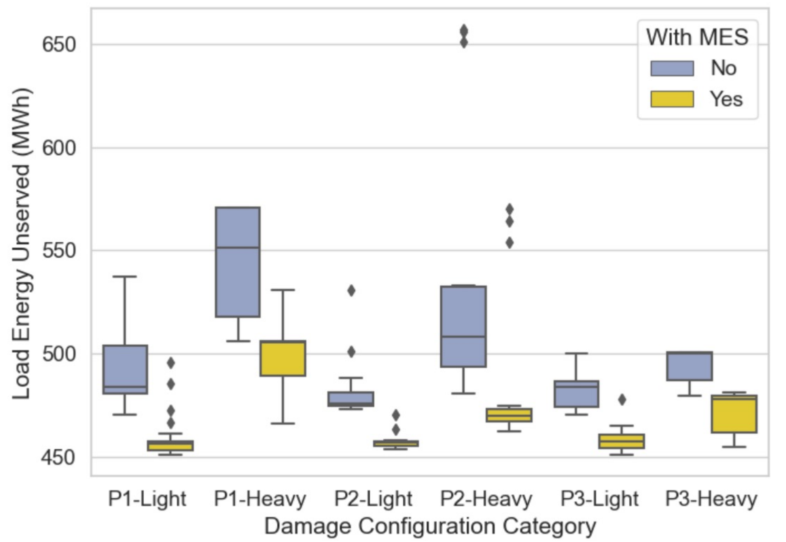

Figure: Box and whiskers plot of the load energy unserved for outages occurring in different zones. Light and heavy outages scenarios are considered.

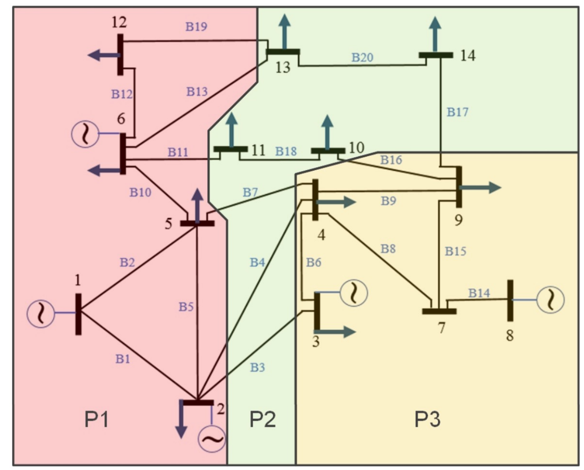

Figure: One-line diagram for IEEE 14 bus test case split into three regions that experience separate outage scenarios.

Results

- Significant decrease in average load energy unserved.
- Variance of the outcome is smaller (Less outliers).

[3] Joshua Yip, Manuel Garcia, Brian Pierre, Erhan Kutanoglu, and Surya Santoso, “Optimal Black-Start Restoration Assisted by Mobile Energy Storage” Proceedings of the IEEE PES General Meeting, Denver, CO, July 17-21, 2022

Thank you to all UT and Sandia colleagues

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- Energy Storage Program at the U.S. Department of Energy Office of Electricity Delivery and Energy Reliability managed by Dr. Imre Gyuk
- Laboratory Directed Research and Development (LDRD) program at Sandia National Laboratories


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