

Analyzing and Enhancing Electric Power System Resiliency

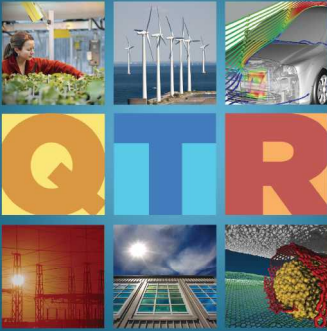
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Electricity Grid Resiliency Framework: Background



QUADRENNIAL TECHNOLOGY REVIEW
AN ASSESSMENT OF ENERGY
TECHNOLOGIES AND RESEARCH
OPPORTUNITIES



September 2015



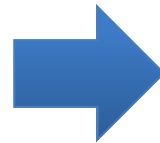
QUADRENNIAL ENERGY REVIEW:
ENERGY TRANSMISSION, STORAGE,
AND DISTRIBUTION INFRASTRUCTURE

April 2015

DOE Quadrennial Energy and Technology Reviews (QER and QTR)

- Initiated by Presidential Policy Directive (PPD) 21

10.5.8 Reliability and Resilience



Watson et al. (2014) lay out a framework for developing resilience metrics and designing a Resilience Analysis Process (RAP).¹¹² While the report focused on the generation, transmission, and distribution of energy (electricity, oil, and natural gas), the framework could be extended to include end-use sectors. A significant effort

QER/QTR effort to develop a resiliency analysis framework for energy systems has led to direct DHS and DOE/EPSCA FY16 funding for follow-on projects

- Mitigation of geomagnetic disturbances for Pennsylvania-Jersey-Maryland (PJM) system operator
- Mitigation of weather and physical attacks for American Electric Power (AEP)

Contrasting Deterministic and Stochastic Optimization

- **Deterministic Mixed-Integer Programming (MIP)**

- The workhorse of (rigorous) Operations Research

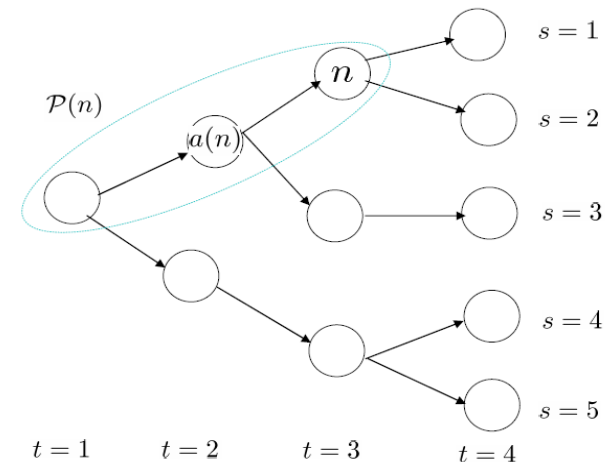
$$\begin{aligned}
 \min \quad & c'x + h'y \\
 \text{s.t.} \quad & Ax + By \leq b \\
 & x \in Z_+^n (x \geq 0, x \text{ integer}) \\
 & y \in R_+^n (y \geq 0)
 \end{aligned}$$

- Approximable for most real-world problems (NP-Hard)

- **Stochastic Mixed-Integer Programming (SMIP)**

- SMIP = MIP + uncertainty + recourse

$$\begin{aligned}
 \min \quad & f(\mathbf{x}) = \mathbf{c}^T \mathbf{x} + \mathbb{E}[Q(\mathbf{x}, \omega)] \\
 \text{s.t.} \quad & A\mathbf{x} \geq \mathbf{b}, \quad \mathbf{x} \in \mathbb{R}_+^{n_1 - p_1} \times \mathbb{Z}_+^{p_1} \\
 & Q(\mathbf{x}, \omega) = \min \mathbf{q}(\omega)^T \mathbf{y} \\
 & \text{s.t.} \quad W\mathbf{y} \geq \mathbf{h}(\omega) - T(\omega)\mathbf{x} \\
 & \mathbf{y} \in \mathbb{R}_+^{n_2 - p_2} \times \mathbb{Z}_+^{p_2}
 \end{aligned}$$



- Still NP-Hard, but far more difficult than MIP in practice

Scenario-Based Decomposition via Progressive Hedging (PH)

Progressive Hedging is proven to quickly identify high-quality incumbent solutions to difficult mixed-integer stochastic programs

0. **Initialization:** Let $\nu \leftarrow 0$ and $w^\nu(\xi) \leftarrow 0, \forall \xi \in \Xi$. Compute for each $\xi \in \Xi$

$$(x^{\nu+1}(\xi), y^{\nu+1}(\xi)) \in \arg \min_{(x(\xi), y(\xi)) \in X(\xi)} c^\top x(\xi) + g(\xi)^\top y(\xi).$$

1. **Iteration Counter Increment:** $\nu \leftarrow \nu + 1$.

2. **Aggregation:** Compute $\hat{x}^\nu \leftarrow \sum_{\xi \in \Xi} p_\xi x^\nu(\xi)$.

3. **Price Update:** $w^\nu(\xi) \leftarrow w^{\nu-1}(\xi) + \rho(x^\nu(\xi) - \hat{x}^\nu), \forall \xi \in \Xi$.

4. **Decomposition:** Compute for each scenario $\xi \in \Xi$

$$(x^{\nu+1}(\xi), y^{\nu+1}(\xi)) \in \arg \min_{(x(\xi), y(\xi)) \in X(\xi)} c(\xi)^\top x(\xi) + g(\xi)^\top y(\xi) + w^\nu(\xi)^\top x(\xi) + \frac{\rho}{2} \|x(\xi) - \hat{x}^\nu\|.$$

We have a price-based penalty term and a proximal term added to the objective of each scenario subproblem.

5. **Termination:** If all the 1st-stage scenario solutions $x^{\nu+1}(\xi)$ agree, then stop. Otherwise, return to Step 1.

Advantages:

- Parallelizable
 - Asynchronous
- Even workload distribution
 - No master problem bloat
- No assumptions on variable structure
 - Discrete variables in any stage

BUT: Lack of lower bounding techniques has mitigated impact in practice

Lower Bounding for PH: Highlights

Proposition 1: The price system $w(\xi)$ defines **implicit** lower bounds

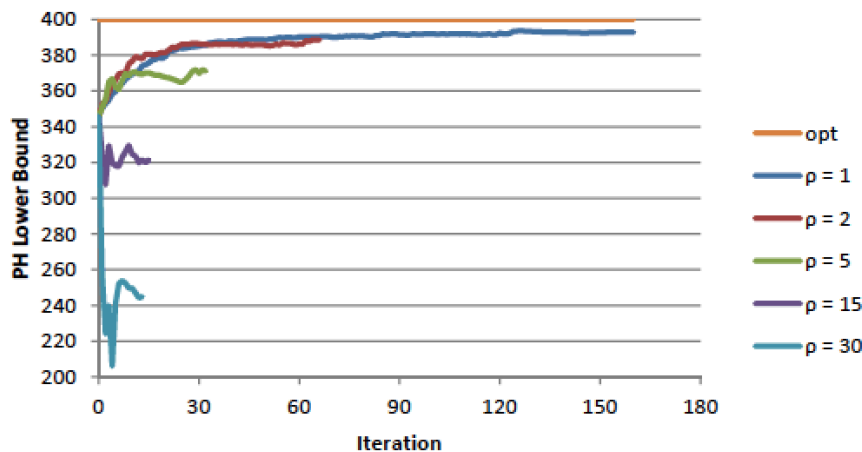
Let z^* be the optimal objective function value of the stochastic program. Let $w(\xi) \in \mathbb{R}^n$ be such that $\sum_{\xi \in \Xi} p_\xi w(\xi) = 0$ (component-wise). Let

$$D_\xi(w(\xi)) := \min_{(x(\xi), y(\xi)) \in X(\xi)} \left(c^\top x(\xi) + g(\xi)^\top y(\xi) + w(\xi)^\top x(\xi) \right).$$

Then $D(w) := \sum_{\xi \in \Xi} p_\xi D_\xi(w(\xi)) \leq z^*$.

- PH weights satisfy $\sum_{\xi \in \Xi} p_\xi w^\nu(\xi) = 0$ for every ν .
- Every so often, use the current weights to compute $D(w)$.

Bound quality is a function of PH ρ parameter



PH can now be viewed as a primal-dual algorithm for stochastic mixed-integer programming

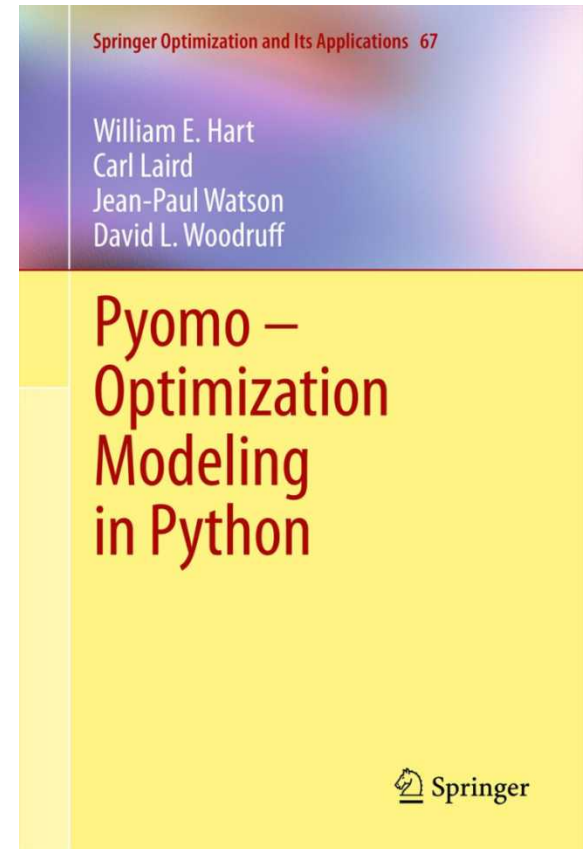
Application – Stochastic Unit Commitment: <1% gaps in minutes of run time

Our Optimization Environment: Pyomo

- **Project homepage**

- <http://software.sandia.gov/pyomo>

- **“The Book”**



- **Mathematical Programming Computation papers**

- **Pyomo: Modeling and Solving Mathematical Programs in Python (Vol. 3, No. 3, 2011)**
- **PySP: Modeling and Solving Stochastic Programs in Python (Vol. 4, No. 2, 2012)**

Defining Resilience



Presidential Policy Directive (PPD) 21

1. “[preserve] infrastructure that are vital to the public confidence and the Nation's safety, prosperity, and well-being.”
2. “[prevent] debilitating impact on the national security, economic stability, public health and safety, or any combination thereof”
3. “...analyze threats to, vulnerabilities of, and potential consequences from all hazards on critical infrastructures”.

-PPD-21: Critical Infrastructure Security and Resilience

“without some numerical basis for assessing resilience, it would be impossible to monitor changes or show that community resilience has improved. At present, no consistent basis for such measurement exists...”

-Disaster Resilience: A National Imperative, National Academy of Sciences

Resilience versus Reliability

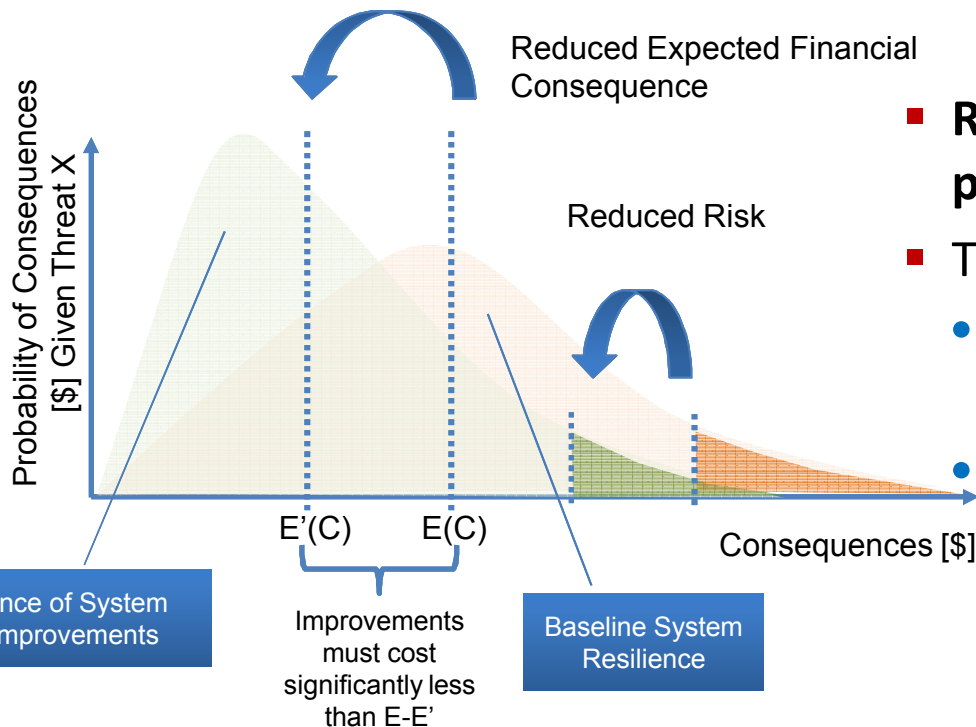
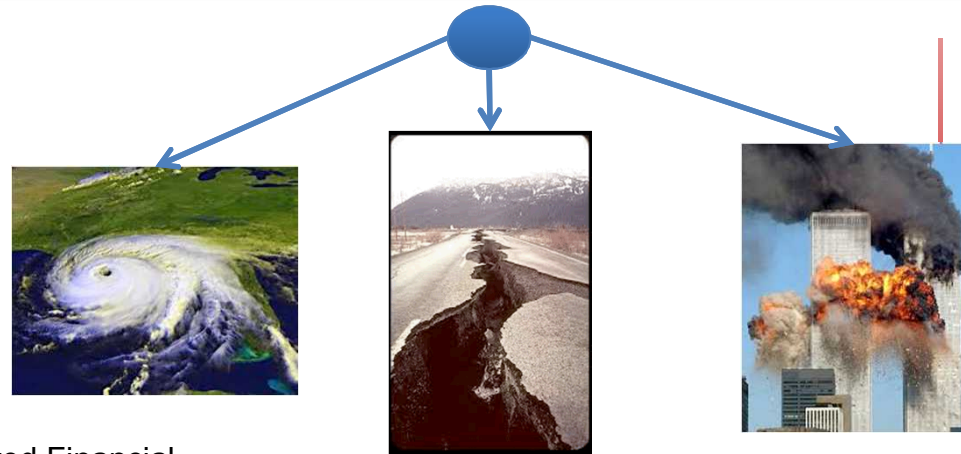
Differentiating reliability and resilience is important

- Reliability is compulsory
- Reliability is related to rate recovery
- Adoption of resilience metrics will be easier if reliability definitions remain as-is

Reliability	Resilience
High Probability, Low Consequence (SAIDI/SAIFI exclude storm data)	Low Probability, High Consequence
Not risk-based	Risk-based, and considers: Threat System vulnerability Consequence
Operationally, you are reliable, or you are not. Confidence is unspecified.	Resilience is a continuum, confidence is specified.
Focus is on the measuring impact to the system.	Focus is on measuring impact to society.

Resilience Quantification Framework (QER)

- Sandia developed a framework for rigorous quantification of energy system resilience
- This framework enables decision making to obtain demonstrable resilience improvements



- Resulting resilience metrics are probabilistic
- The framework is flexible:
 - Can handle different types of threats
 - Provides information for different types of decision makers

Scenario Analysis: Identify Threat Types

A infrastructure is designed to be resilient to a specific set of possible disruptions

Definition of possible disruptions can proceed via construction of a **scenario tree**

Alternatives exist, but they are more nuanced in terms of definition

We begin with
high-level
threat
definitions



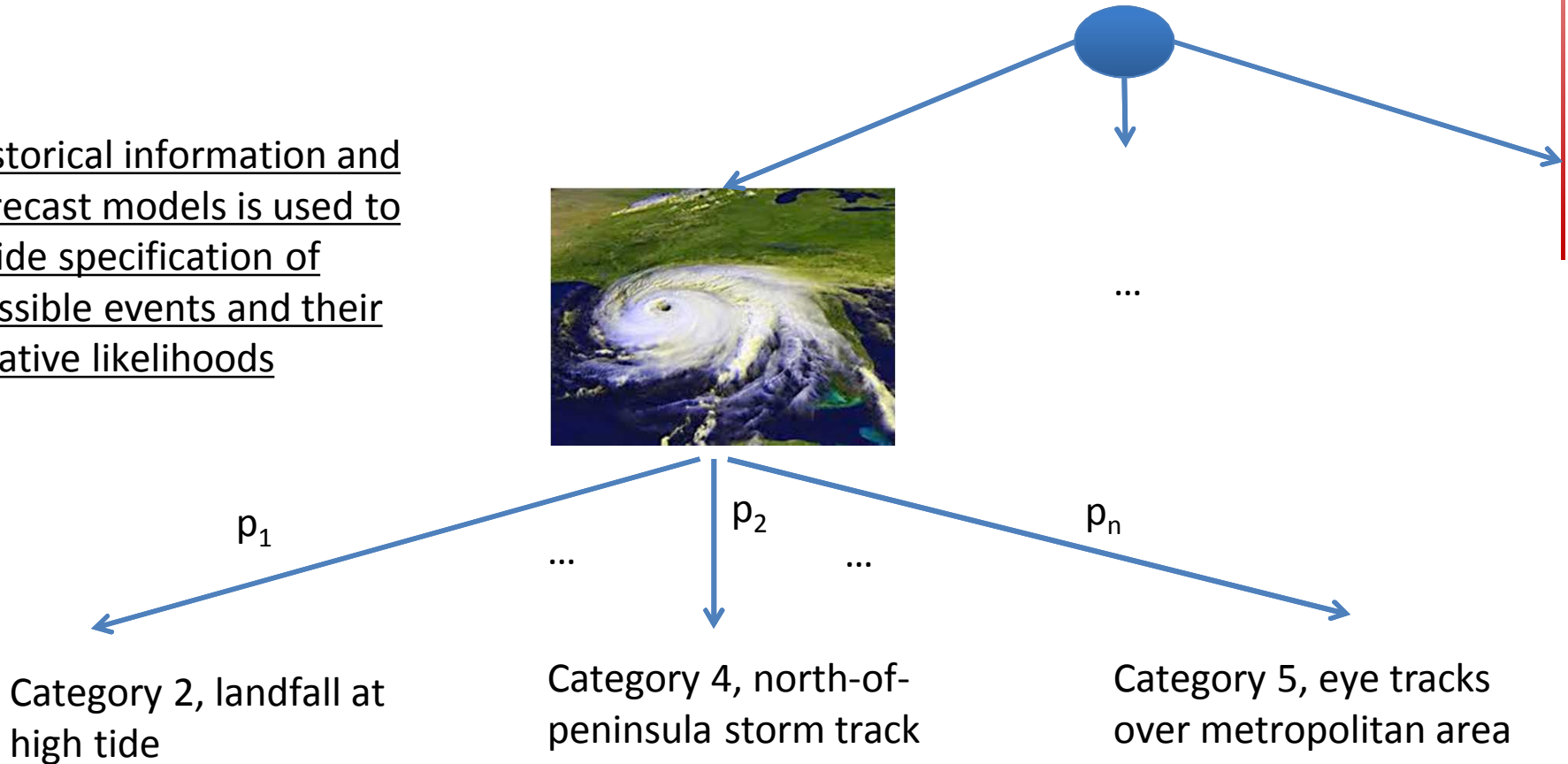
Probabilities are uniform (all-hazard), or skewed to reflect different emphases

High-level scenario identification is expected to be an output from an iterative and interactive stakeholder-driven process

Scenario Analysis: Characterize Individual Threat

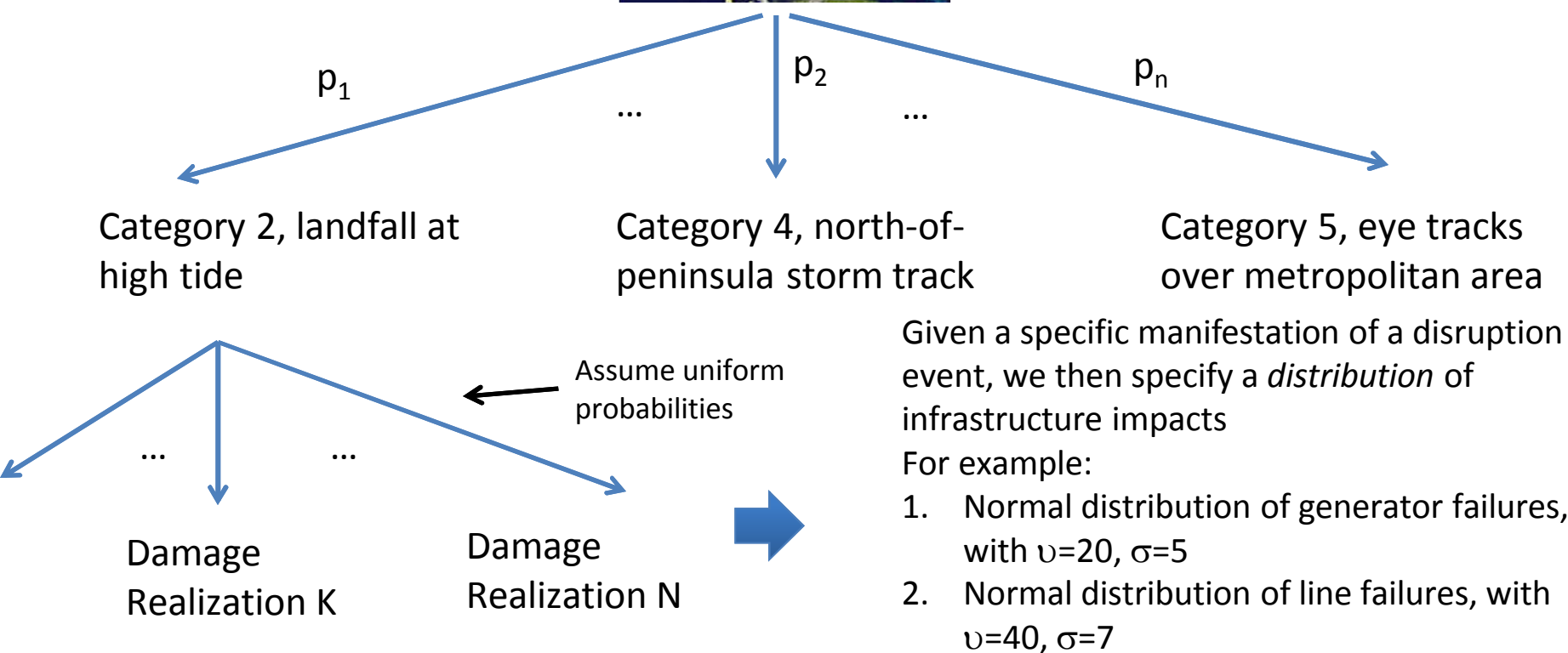
Given high-level threat characterization, the next step is to further refine the description of the specific threats

Historical information and forecast models is used to guide specification of possible events and their relative likelihoods

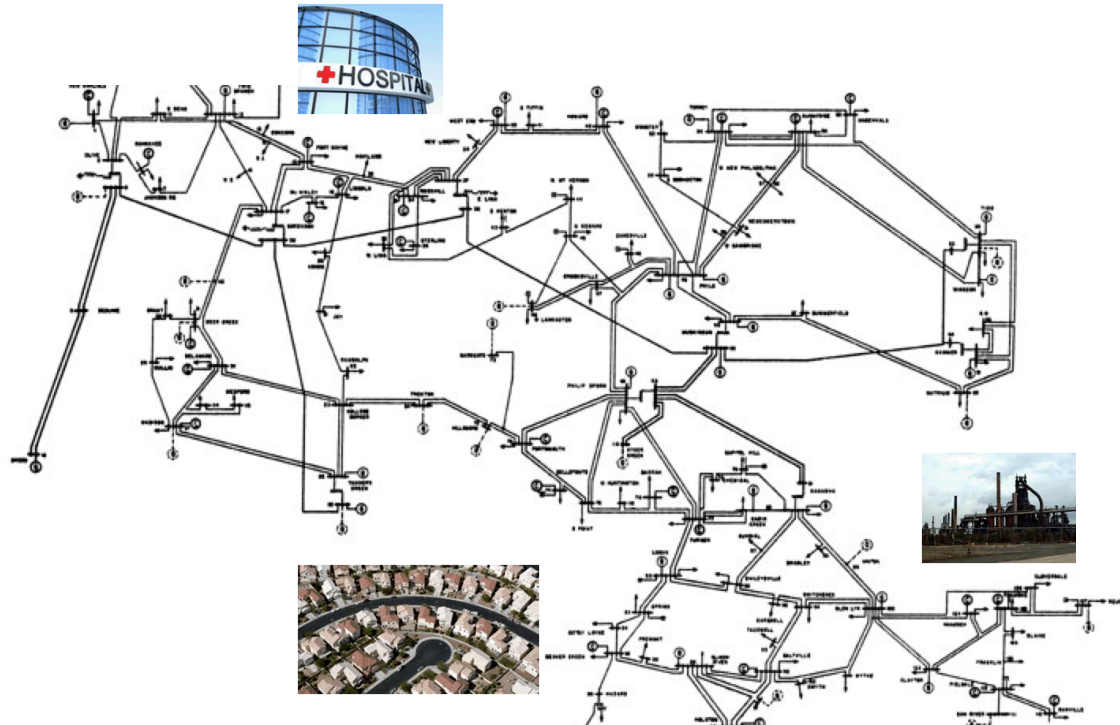


Scenario Analysis: Disrupting the System

The final step is to translate disruption events into system impacts



Resiliency Analysis Requires an Operations Model



Modified IEEE 118 Bus Test Case System
<http://motor.ece.iit.edu/data/ltscuc>

Operations model is used to quantify system impact, and is expressed as delivery failure

Stochastic Optimization and Resilience

- Models uncertainty about the future explicitly, using scenarios
 - Requirement captured in our resiliency framework
- In both operations and planning contexts
 - Minimize expected loss of load across all scenarios
 - Two-stage decision model
 - ◆ Stage 1: Here-and-now decisions, prior to disruption event
 - ◆ Stage 2: Reactive or “recourse” decisions, following the disruption event
- The decision space

Stage 1 Decisions	Stage 2 Decisions
Generator set points	Generators to re-dispatch
Transmission switching	Transmission switching
Lines to bury	N/A

Use Case: Assessing Baseline Resiliency

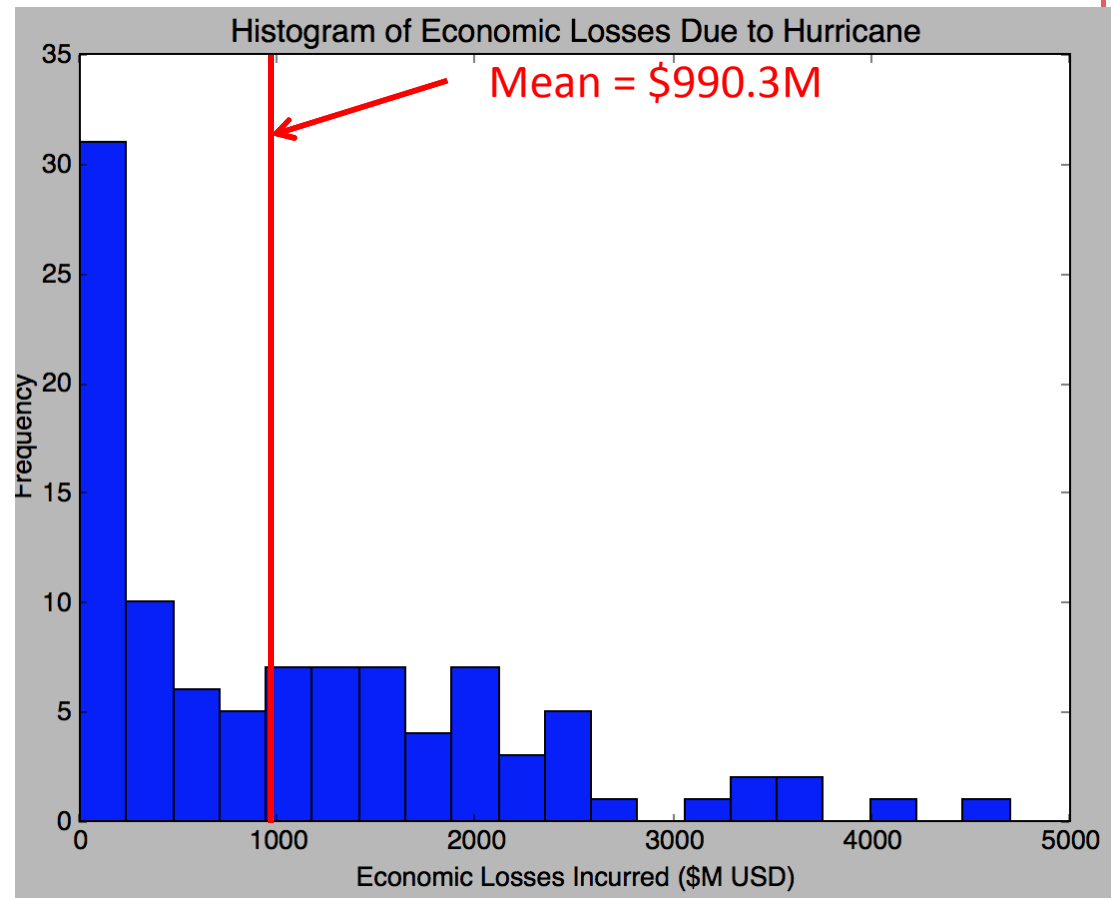
Assessing the economic losses incurred by a hypothetical hurricane event on the IEEE 118 bus test system

Methodology

1. Sample 100 scenarios specifying potential damage from a hurricane
2. For each scenario, compute a minimal-cost dispatch and associated loss of load
3. For each scenario, compute the cumulative economic losses incurred

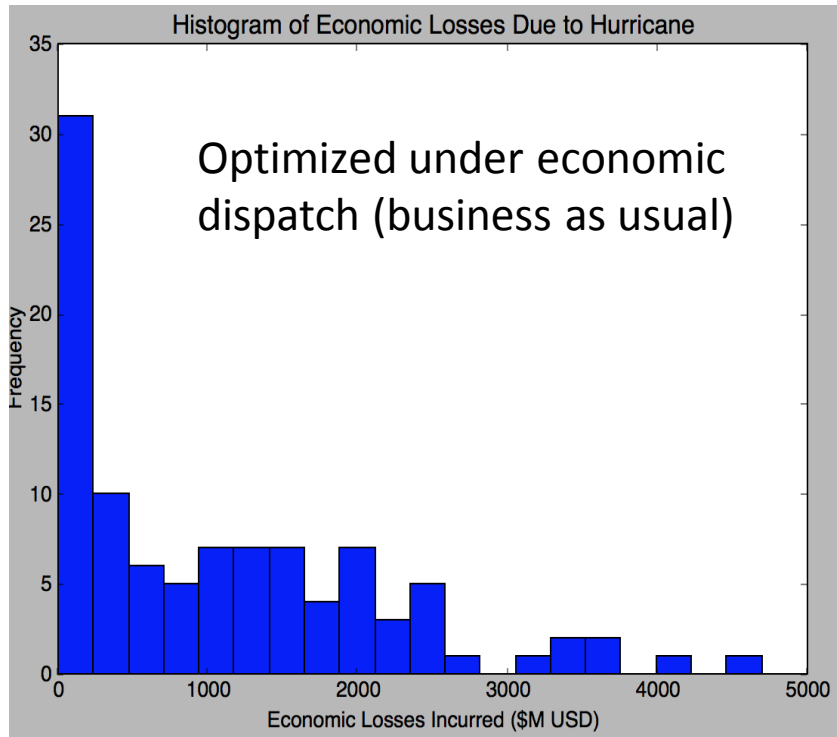
Assumptions

1. No recovery possible for first 48 hours
2. Independent scenario analysis

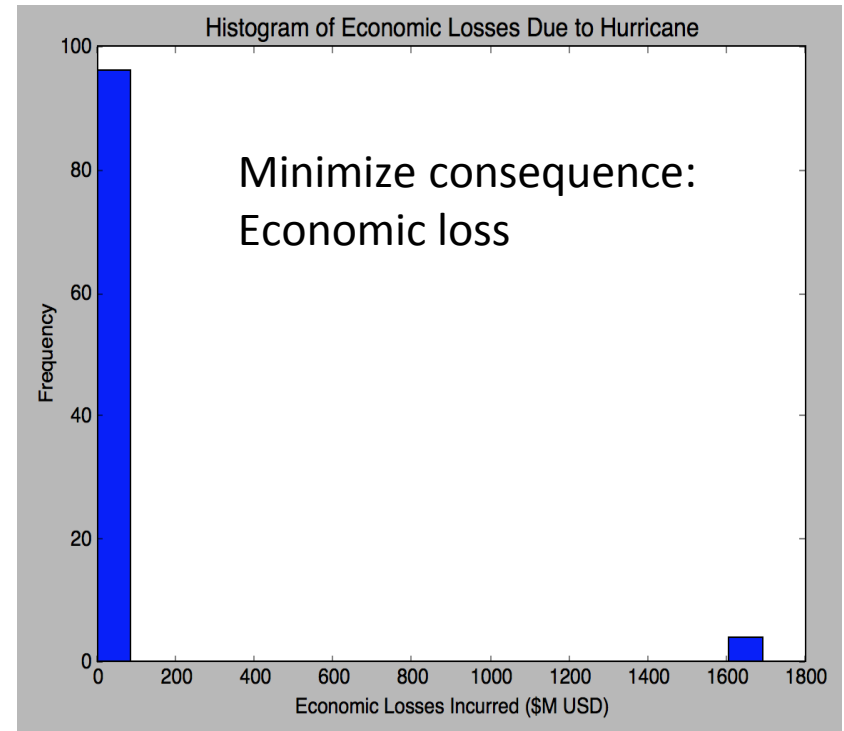


Shifting from Economic to Consequence-Driven Dispatch

Operating in a resilience-focused, as opposed to standard economic- and reliability-focused, manner can lead to dramatic reductions in consequence



VS

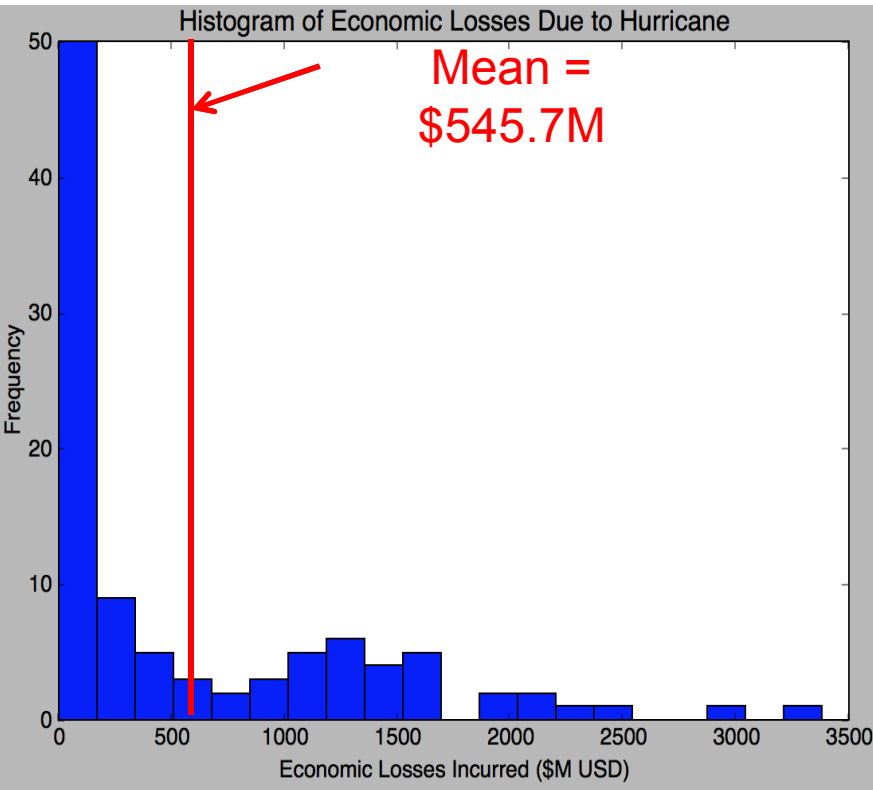


In our IEEE 118 bus resiliency example, it is possible to mitigate nearly all economic consequences of the posited hurricane

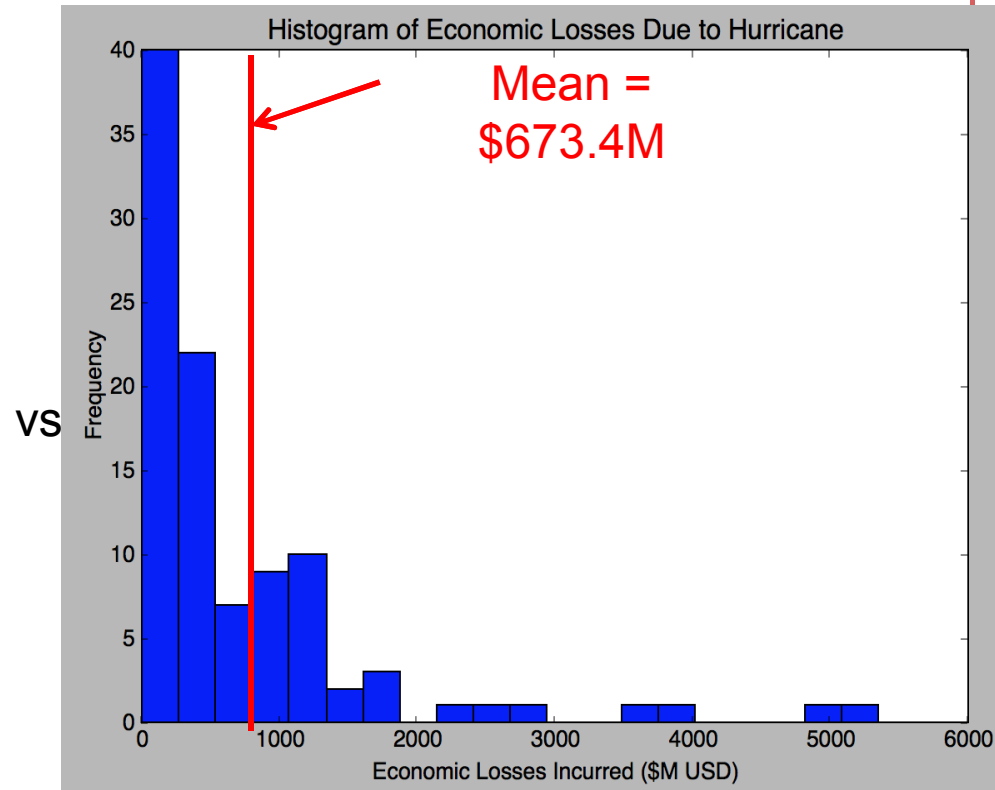
Analysis of Investment Alternatives

Two alternatives improve baseline – but one by more than the other

With generator flood walls

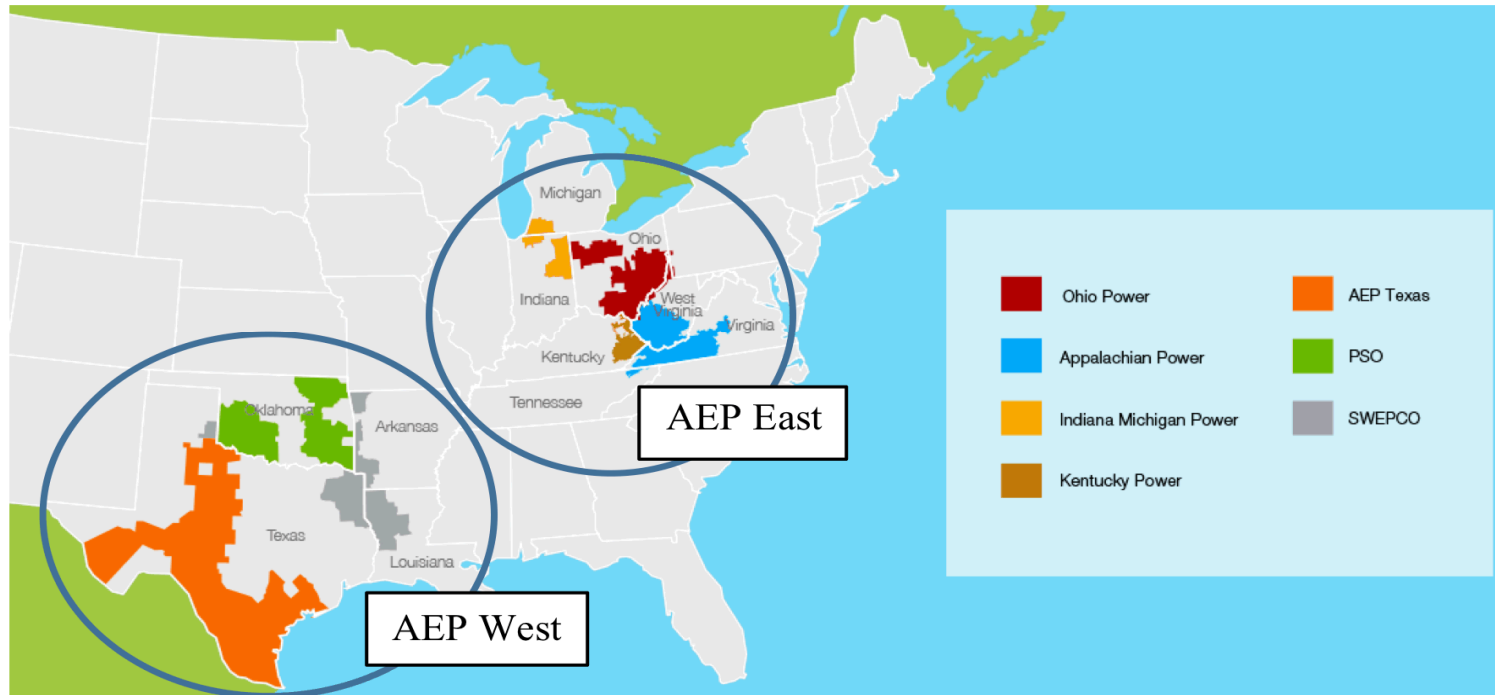


With line burying



Result: Line burying admits some higher-consequence events, with approximately the same mean impacts

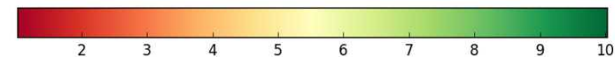
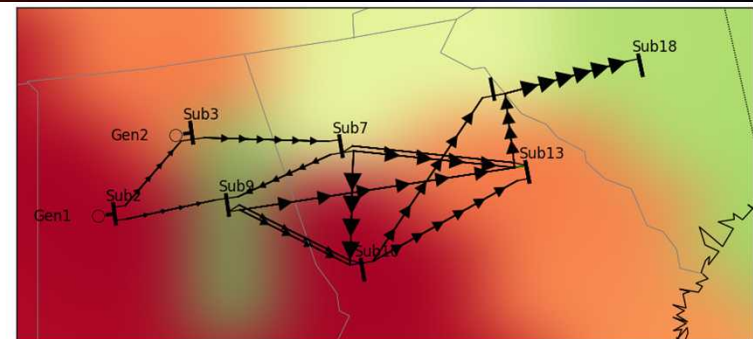
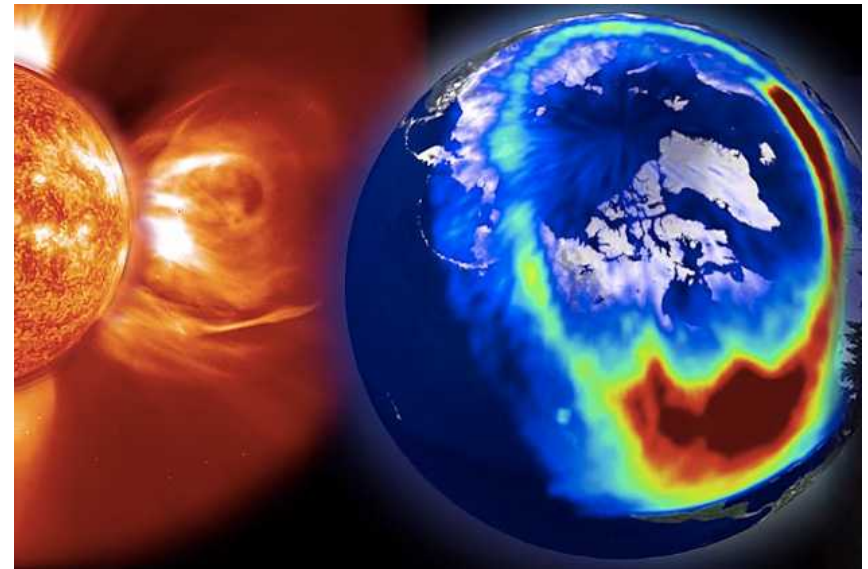
American Electric Power (AEP): Threats and Data Sources



- **AEP East: Extreme weather (e.g., snow and ice storms)**
 - Historical outage data, with attribution (from 1990 to present)
- **AEP West: Physical security threats (e.g., copper thieves)**
 - Interview data with AEP subject matter experts

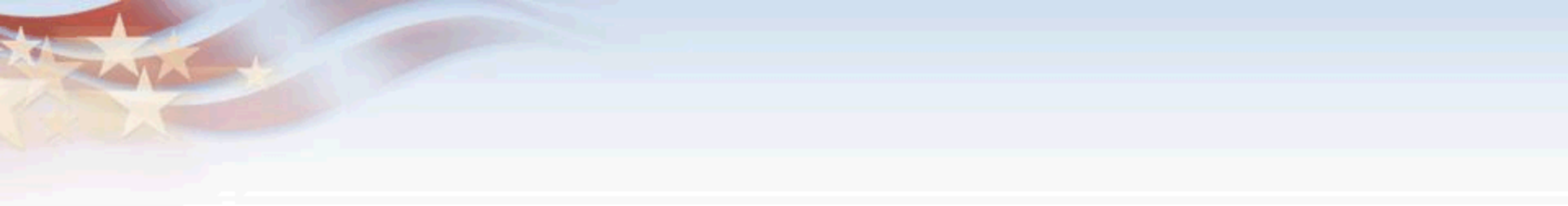
Resilience to Geomagnetic Disturbances

- The goal is to increase grid resilience to voltage collapse caused by GMDs.
- Requires non-linear (AC) power flow model, leading to non-linear and mixed-integer non-linear programs.
- Control actions considered are reactive power support devices installation during planning (years/months ahead), and generator dispatch orders during operations (day-ahead/real-time).
- A key deliverable is an resilient operating plan for PJM.



Research Impact and Follow-On Efforts

- **Initial AEP and PJM analysis results are available (but sensitive)**
 - Complete preliminary analyses in July 2016, final iteration November 2016
- **Exemplar of positive joint Sandia VP-1000 and VP-6000 collaboration**
 - Solution of problem requires S&T capabilities and advances
 - Solution of problem requires significant domain expertise and modeling
 - Impacting real end-users, studies executed using real data
- **This effort has led to a second-round Grand Challenge LDRD (FY16)**
 - Optimization-Based Interdiction for Cyber-Physical Systems
- **Project has had significant impact on S&T base**
 - Identified gaps in stochastic non-linear and mixed-integer non-linear solvers
 - Being addressed by DOE/SC and DOE GMLC funding



QUESTIONS

