Estimating and mitigating cascading failure risk in power systems with smart grid technology

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Commercial partner: IBM Watson Research Center.

2010 DOE Peer Review Meeting
Denver, CO

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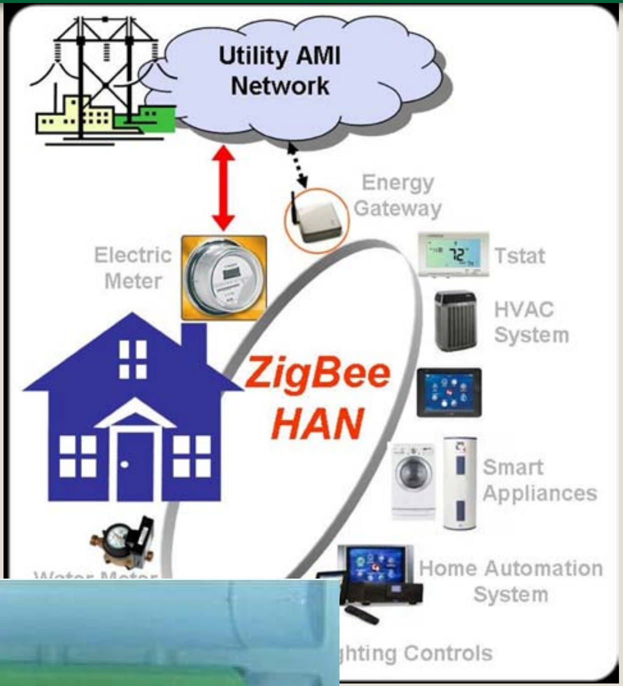
Project Goal #1: Estimate Cascading Failure Risk in Real Time

Develop a method to integrate data from PMUs and ensembles of simulations to measures of risk

Real-time blackout risk meter

Project Goal #2: Develop Methods to Mitigate Emerging Blackout Risk

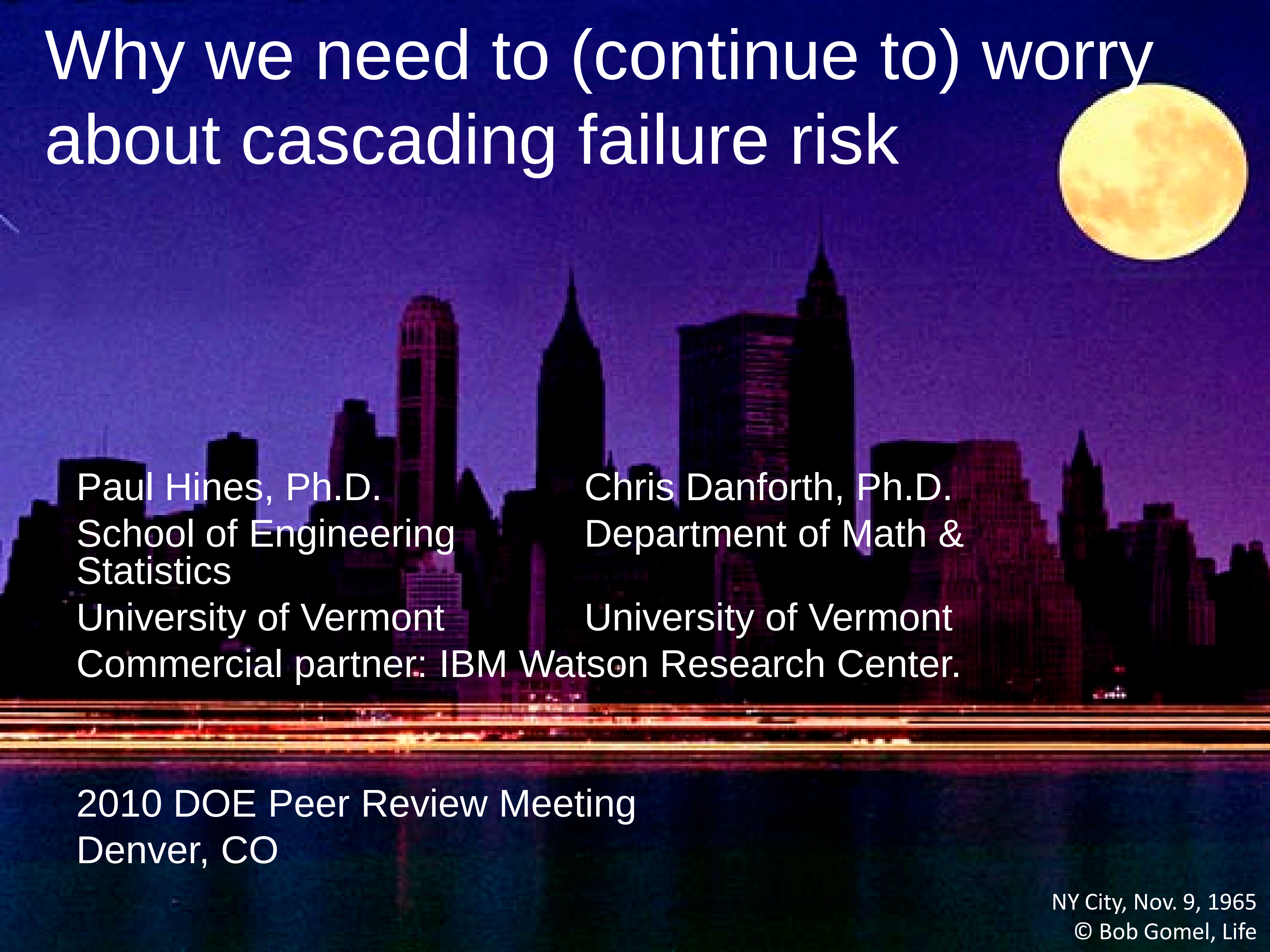
- Develop algorithms to quickly dispatch storage and demand response to mitigate emerging cascading failure risk.



Outline

- Why do we need to worry about cascading failure risk?
- Preliminary results
  - Cascading failures and network structure
  - Critical Slowing Down
- Plan for this project

Why we need to (continue to) worry about cascading failure risk



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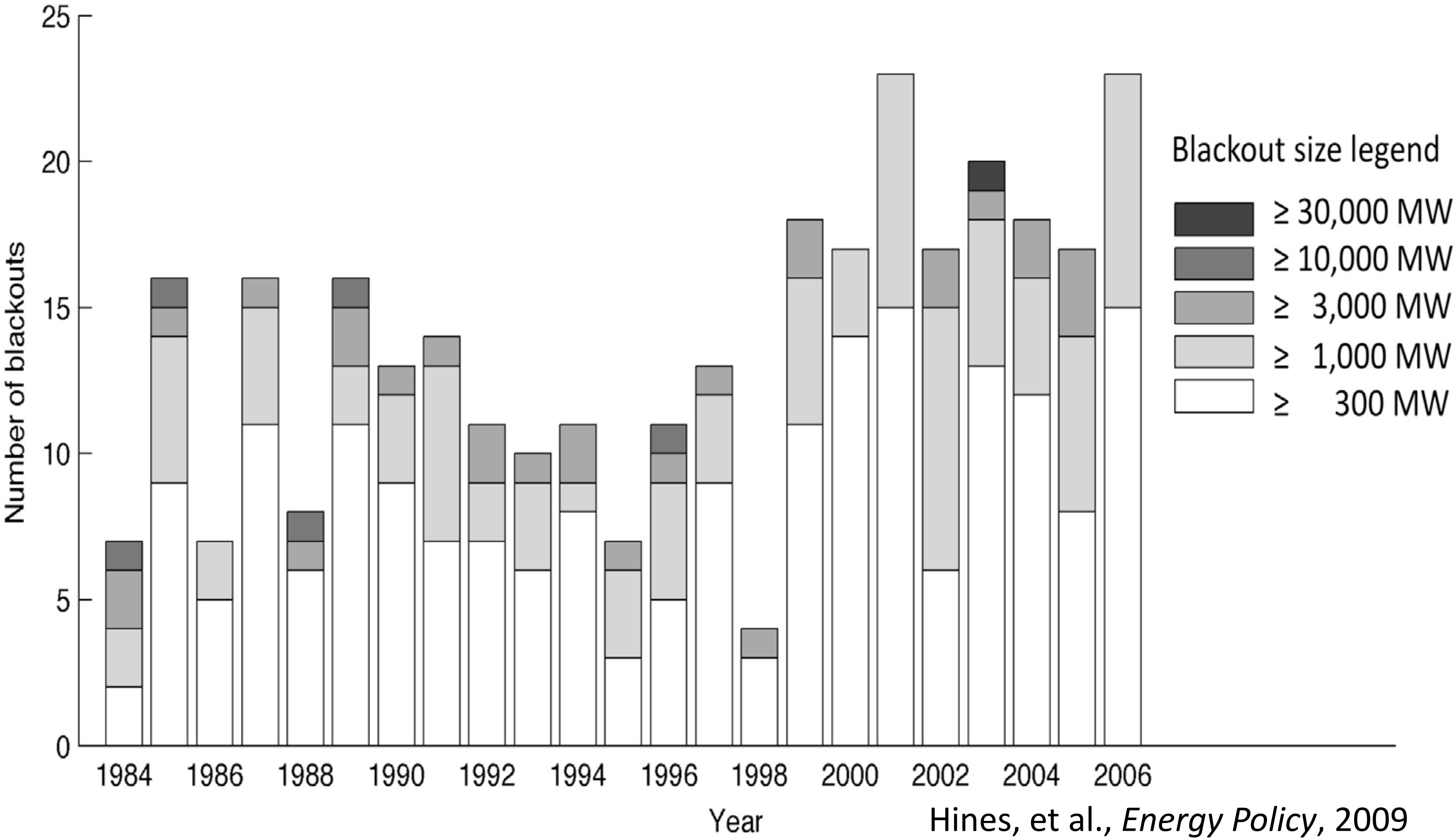
Very large blackouts in N. America

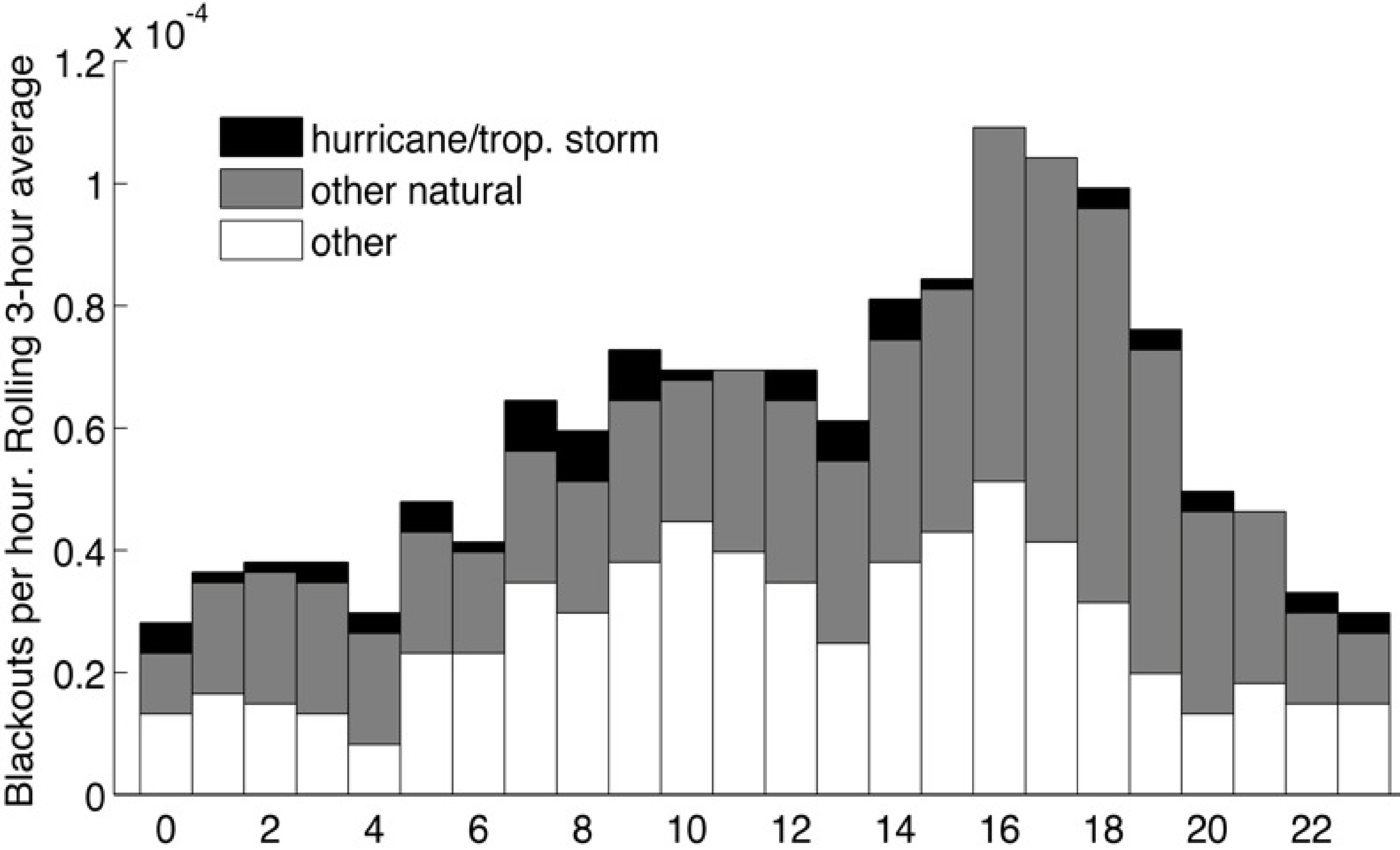
Date	Location	MW	Customers	Type
14-Aug-2003	Eastern US, Canada	57,669	15,330,850	Cascading failure
13-Mar-1989	Quebec, New York	19,400	5,828,453	Solar flare, cascade
18-Apr-1988	Eastern US, Canada	18,500	2,800,000	Ice storm
10-Aug-1996	Western US	12,500	7,500,000	Cascading failure
18-Sep-2003	Southeastern US	10,067	2,590,000	Hurricane Isabel
23-Oct-2005	Southeastern US	10,000	3,200,000	Hurricane Wilma
27-Sep-1985	Southeastern US	9,956	2,991,139	Hurricane Gloria
29-Aug-2005	Southeastern US	9,652	1,091,057	Hurricane Katrina
Jan-1998	Northeast US/Canada	9,000	1,400,000	Ice storm
29-Feb-1984	Western US	7,901	3,159,559	Cascading failure
4-Dec-2002	Southeastern US	7,200	1,140,000	Ice/wind/rain storm
10-Oct-1993	Western US	7,130	2,142,107	Transmission failure, cascade
14-Dec-2002	Western US	6,990	2,100,000	Winter storm
4-Sep-2004	Southeastern US	6,018	1,807,881	Hurricane Frances
25-Sep-2004	Southeastern US	6,000	1,700,000	Hurricane Jeanne
14-Sep-1999	Eastern US	5,525	1,660,000	Hurricane Floyd

Blackouts over time



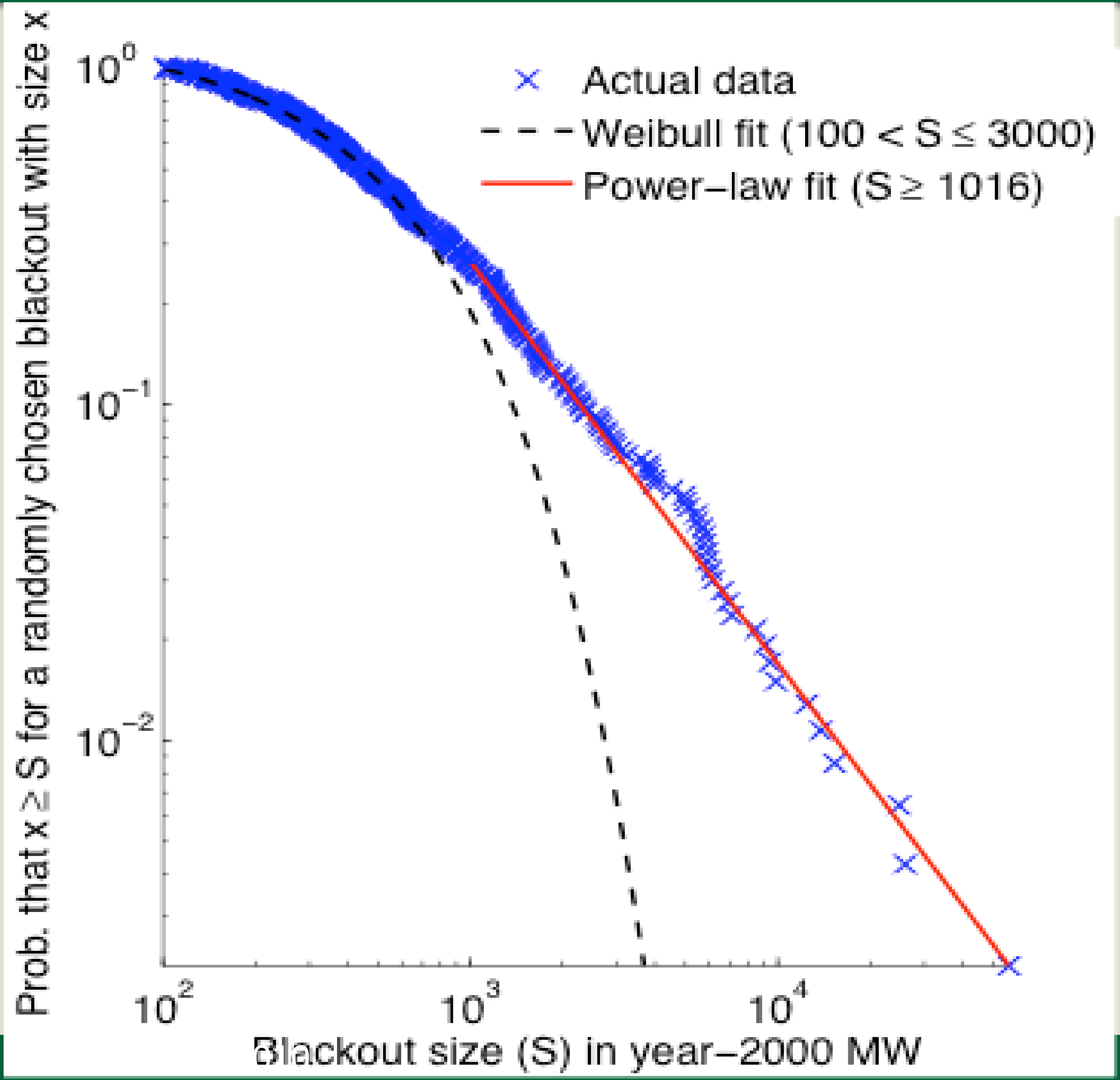
Hines, et al., *Energy Policy*, 2009

Blackouts by time of day



Hines, et al., *Energy Policy*, 2009

Power-laws



Size of the 100 year blackout:

1/3 of US peak demand

Therefore we need to spend considerable effort reducing risk associated with blackouts that are larger than what we have seen from empirical data

(not so with Weibull failures)

How should we model cascading failure in power grids?

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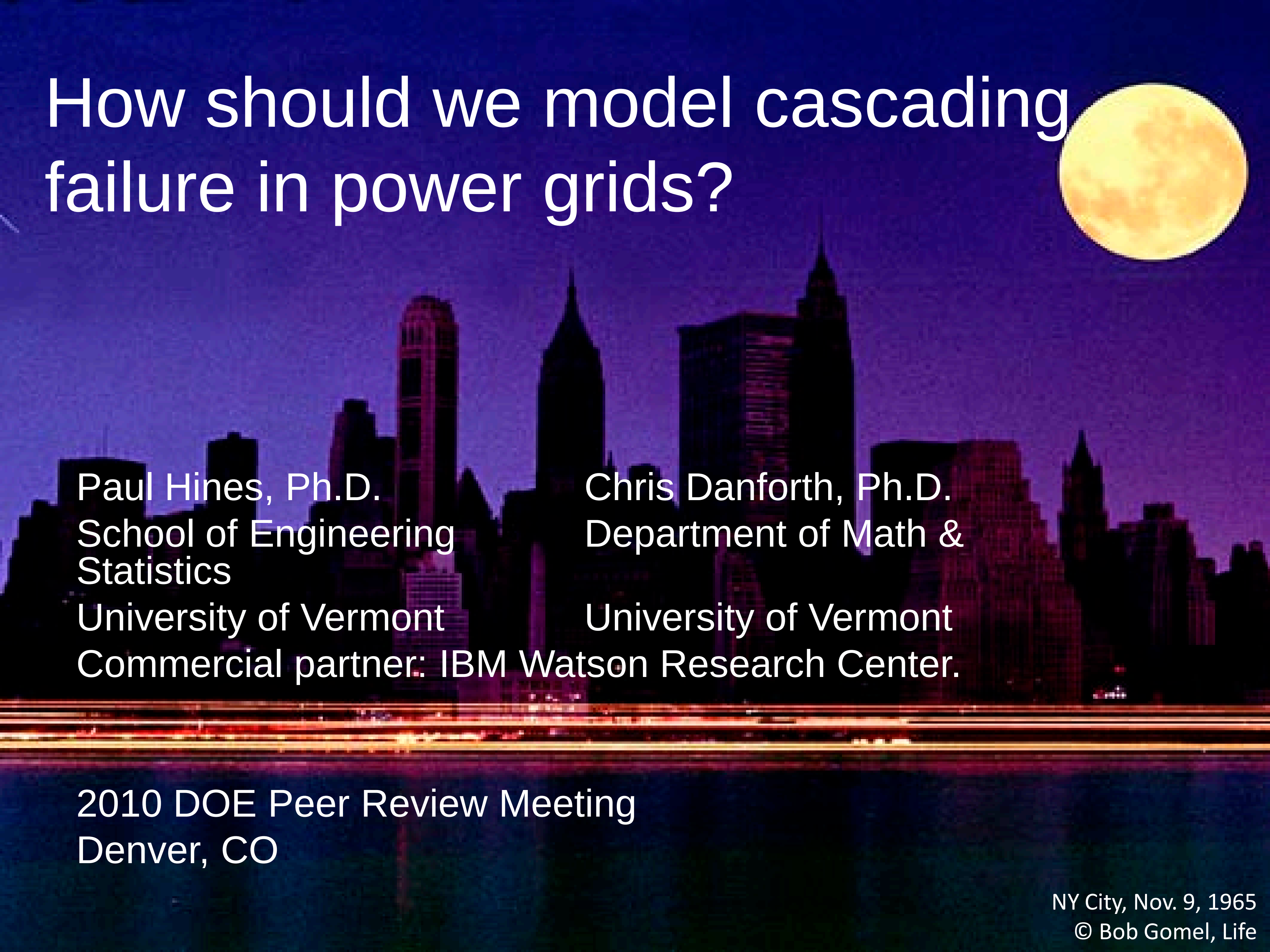

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Question: What models provide useful information about grid vulnerability?

The New York Times

Asia Pacific

WORLD U.S.

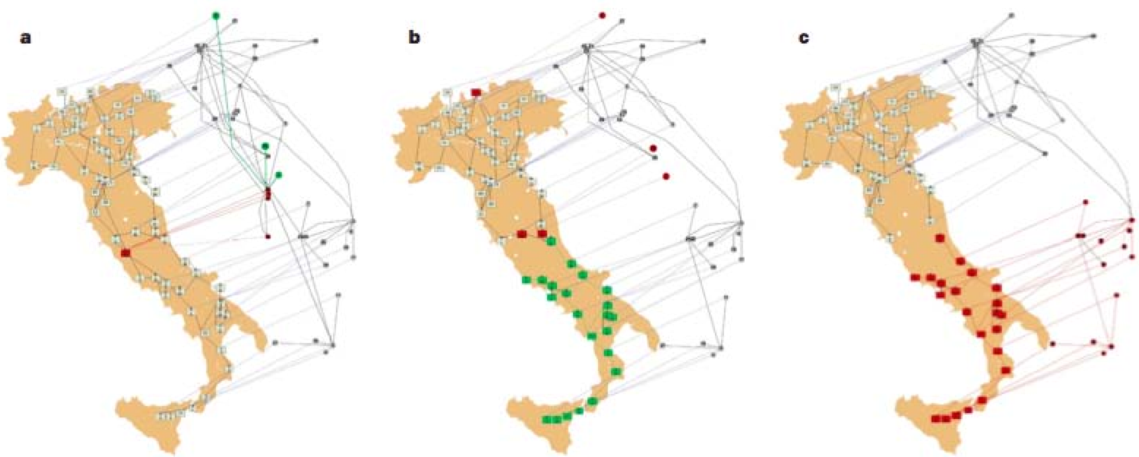
Academic Paper in China Sets Off Alarms in U.S.

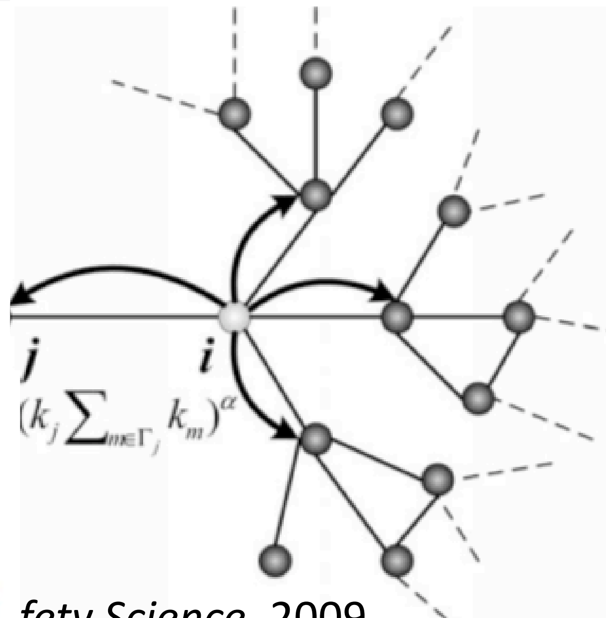
Vol 464 | 15 April 2010 | doi:10.1038/nature08932 nature

LETTERS

Catastrophic cascade of failures in interdependent networks

Sergey V. Buldyrev[1,2], Roni Parshani[3], Gerald Paul[2], H. Eugene Stanley[2] & Shlomo Havlin[3]





fety Science, 2009

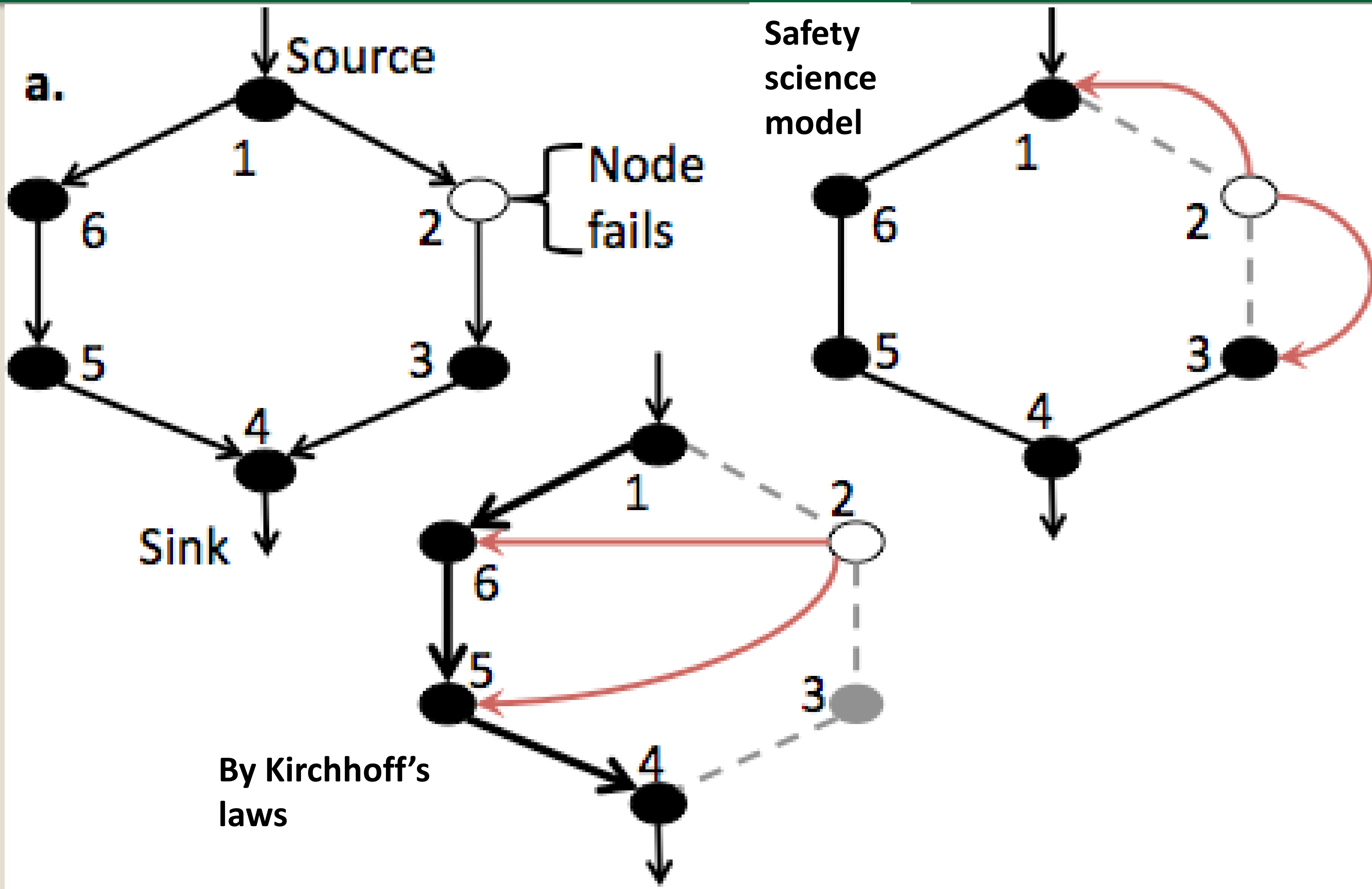
es the load redistribution triggered by an node-based nd the load on it is redistributed to the neighboring . Among these neighboring nodes, the one with the higher shared load from the broken node.

a technical exercise.

By JOHN MARKOFF and DAVID BARBOZA

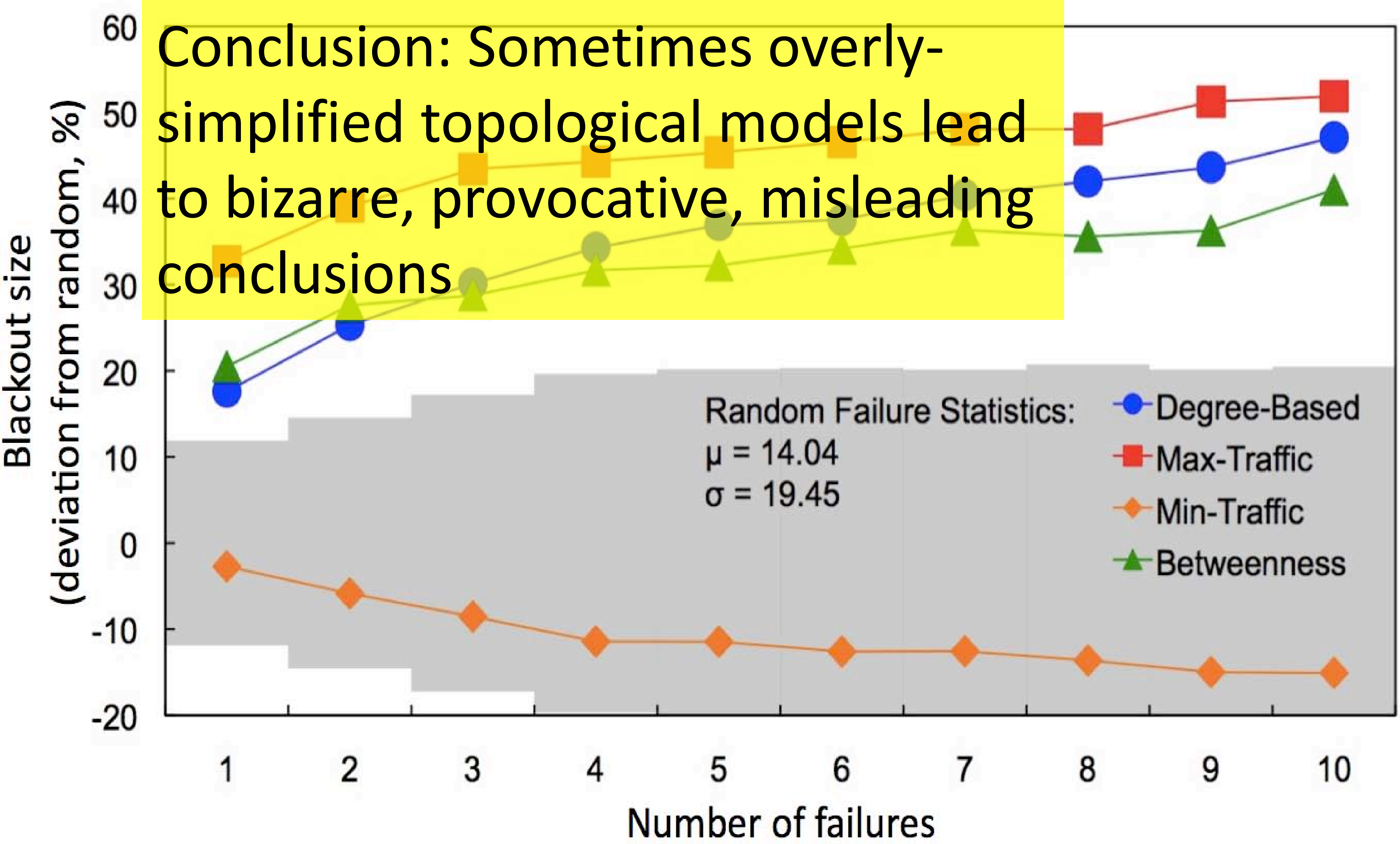
Published: March 20, 2010

But cascades in power grids are different...

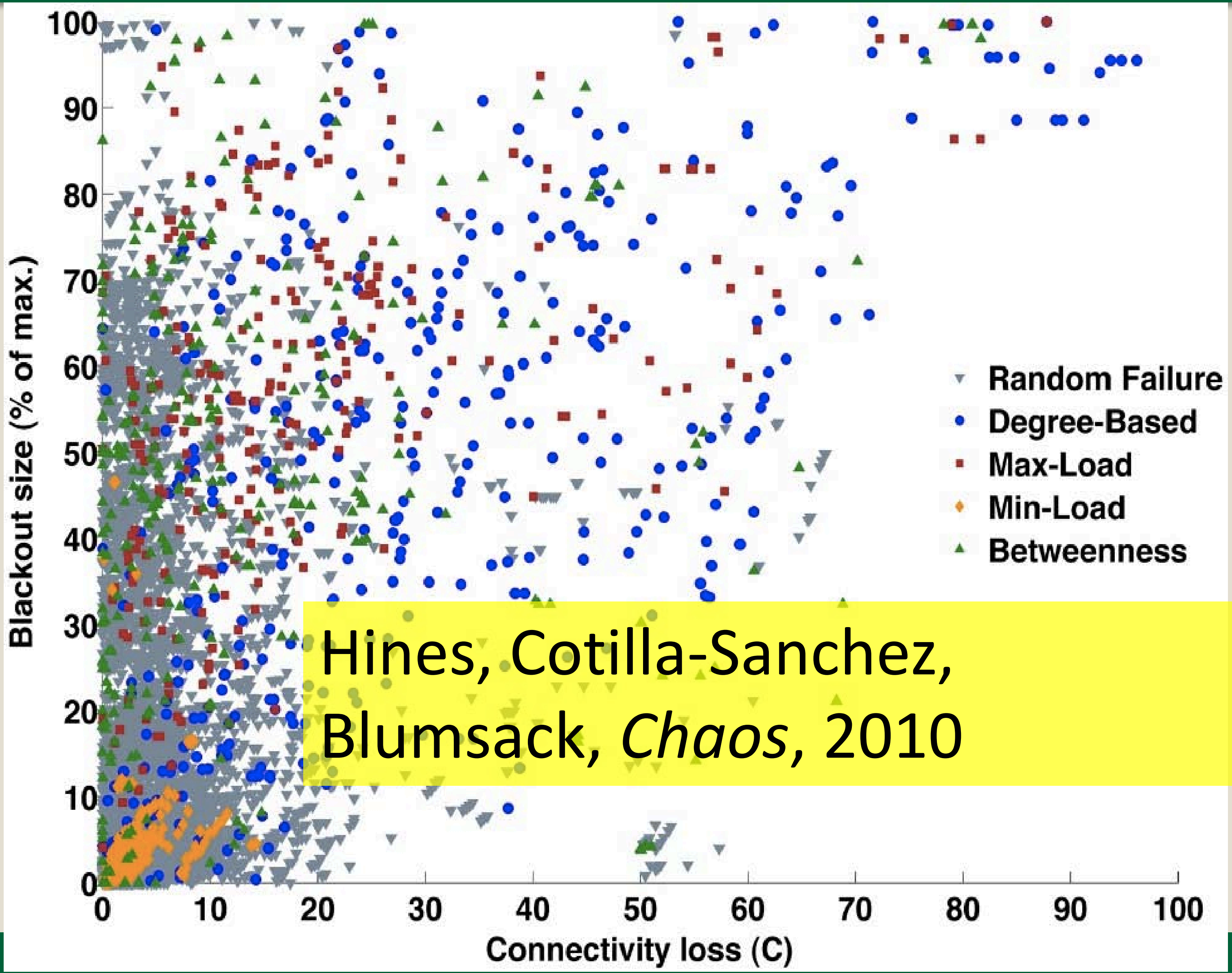


Results for 40 areas in the Eastern Interconnect

Conclusion: Sometimes overly-simplified topological models lead to bizarre, provocative, misleading conclusions

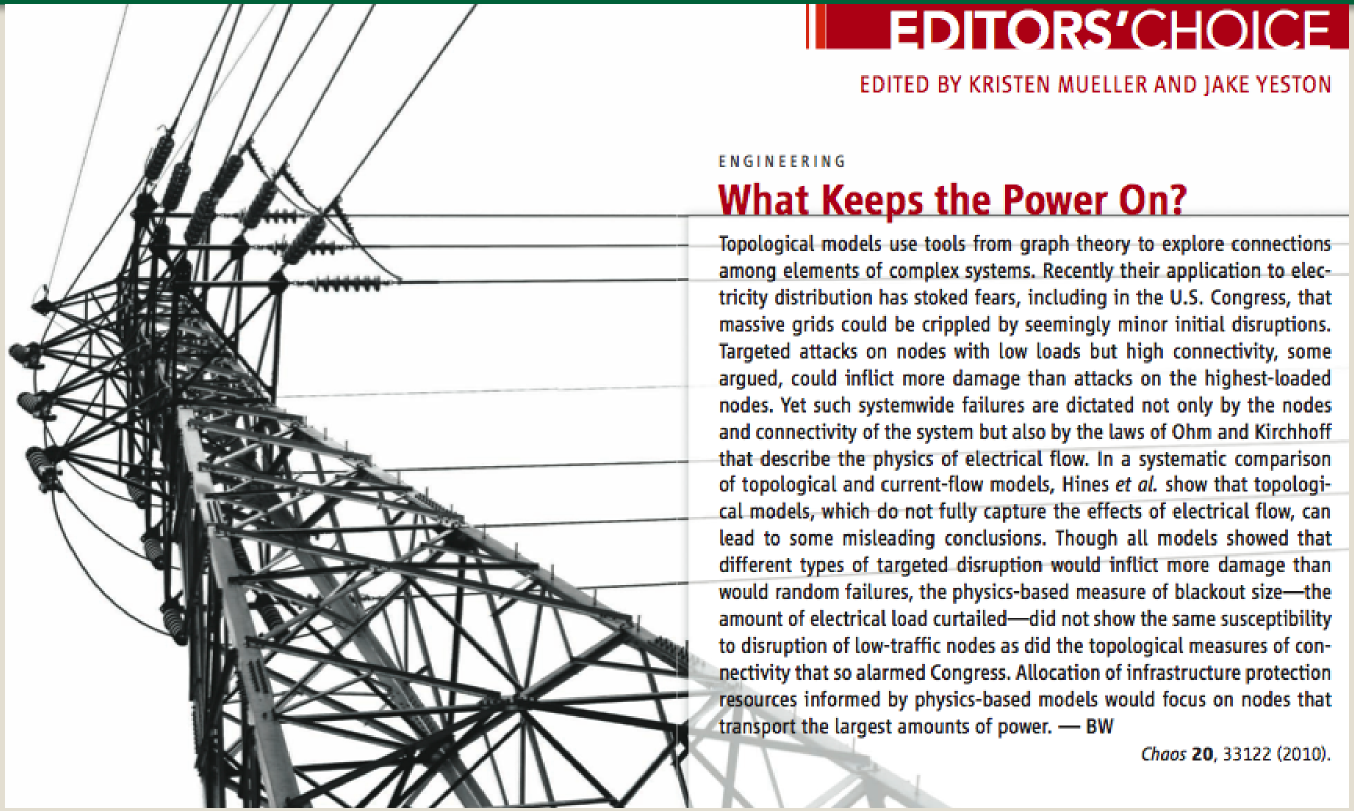


Even measures that work in the averages, fail to predict the impact of individual disturbances



Hines, Cotilla-Sanchez, Blumsack, *Chaos*, 2010

For some reason everyone is interested in the grid these days…



EDITORS'CHOICE

EDITED BY KRISTEN MUELLER AND JAKE YESTON

ENGINEERING

What Keeps the Power On?

Topological models use tools from graph theory to explore connections among elements of complex systems. Recently their application to electricity distribution has stoked fears, including in the U.S. Congress, that massive grids could be crippled by seemingly minor initial disruptions. Targeted attacks on nodes with low loads but high connectivity, some argued, could inflict more damage than attacks on the highest-loaded nodes. Yet such systemwide failures are dictated not only by the nodes and connectivity of the system but also by the laws of Ohm and Kirchhoff that describe the physics of electrical flow. In a systematic comparison of topological and current-flow models, Hines *et al.* show that topological models, which do not fully capture the effects of electrical flow, can lead to some misleading conclusions. Though all models showed that different types of targeted disruption would inflict more damage than would random failures, the physics-based measure of blackout size—the amount of electrical load curtailed—did not show the same susceptibility to disruption of low-traffic nodes as did the topological measures of connectivity that so alarmed Congress. Allocation of infrastructure protection resources informed by physics-based models would focus on nodes that transport the largest amounts of power. — BW

Chaos **20**, 33122 (2010).

- Bottom line: vulnerability is hard to predict. The greatest vulnerabilities are generally where the power flow is greatest.

Critical slowing down as an indicator of risk in power grids

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Context

Vol 461|3 September 2009|doi:10.1038/nature08227 nature

REVIEWS

Early-warning signals for critical transitions

Marten Scheffer[1], Jordi Bascompte[2], William A. Brock[3], Victor Brovkin[5], Stephen R. Carpenter[4], Vasilis Dakos[1], Hermann Held[6], Egbert H. van Nes[1], Max Rietkerk[7] & George Sugihara[8]

Complex dynamical systems, ranging from ecosystems to financial markets and the climate, can have tipping points at which a sudden shift to a contrasting dynamical regime may occur. Although predicting such critical points before they are reached is extremely difficult, work in different scientific fields is now suggesting the existence of generic early-warning signals that may indicate for a wide class of systems if a critical threshold is approaching.

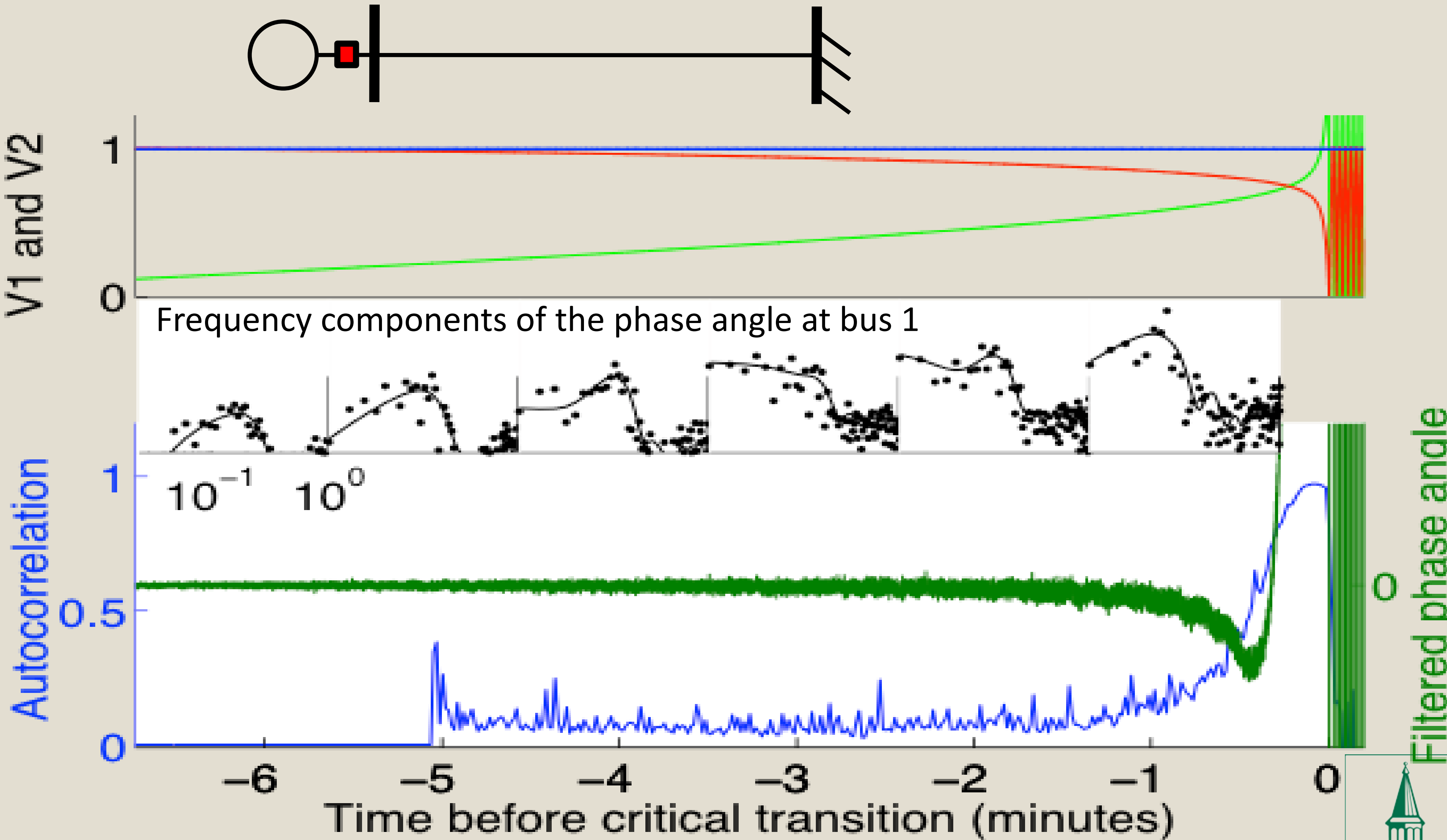
As systems approach “collapse” they shows signs of critical slowing down.

Could this be useful for power grids?

- Operators will soon have terrabytes of time-series PMU data available.
- Are there statistical patterns in PMU data that indicate proximity to collapse?

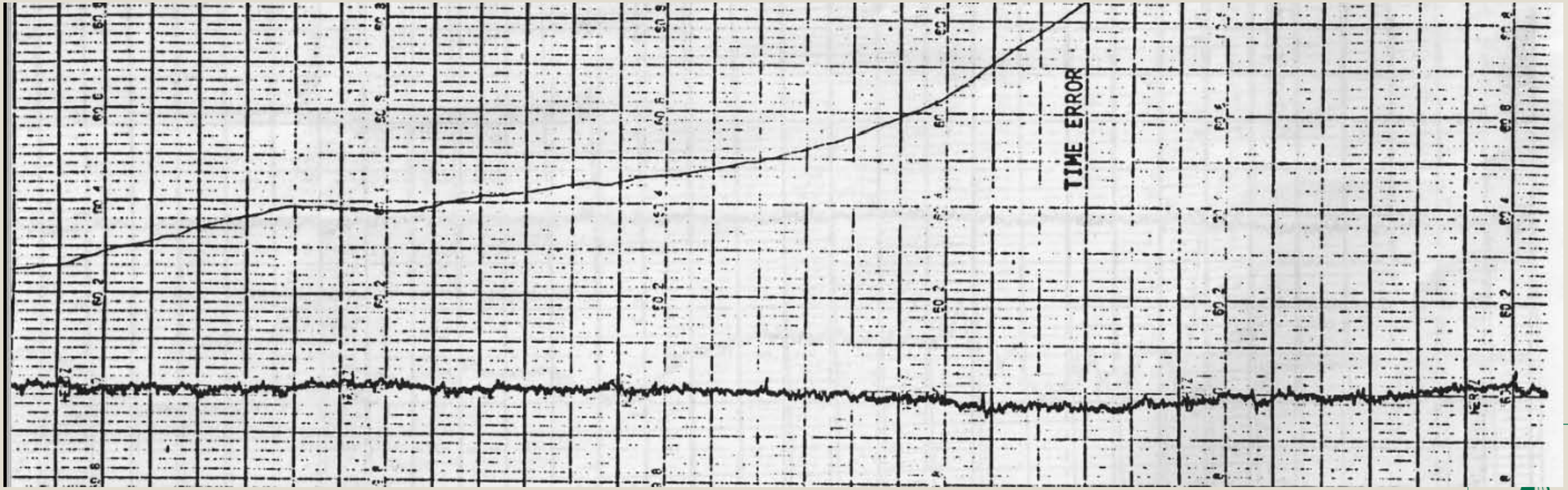
Real-time blackout risk meter

1-machine, infinite bus model results

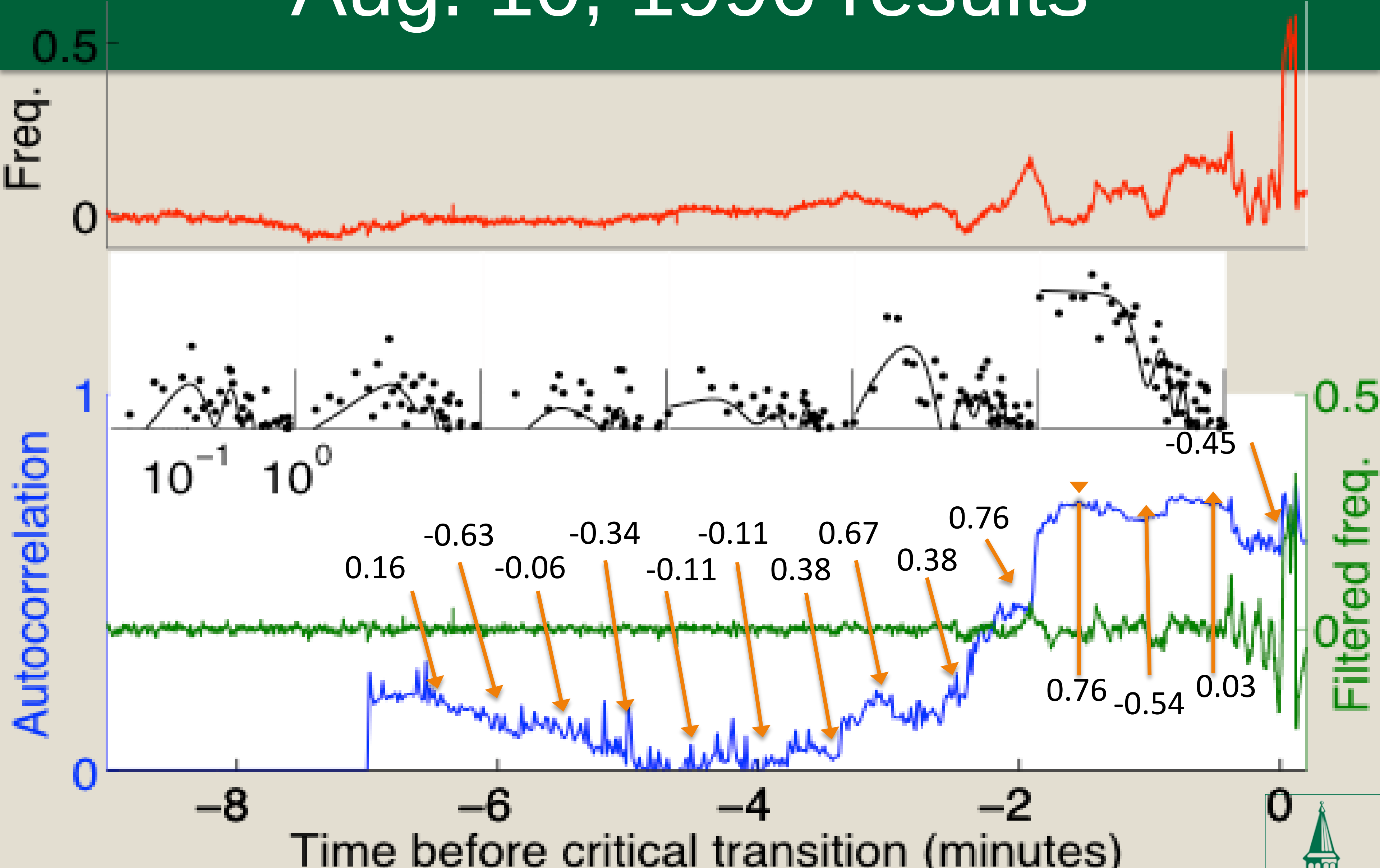


What about the WSCC on August 10, 1996?

- Lines sagged into trees, triggering a cascading failure
- 7.5 million customers lost power. 7 states + Canada.



Aug. 10, 1996 results



Conclusions

- Changes in autocorrelations and cross correlations in PMU data may indicate proximity to critical points, like voltage collapse.
- As a component of this project we will develop metrics that can be used by operators to identify proximity to cascading failure risk.

Work Plan

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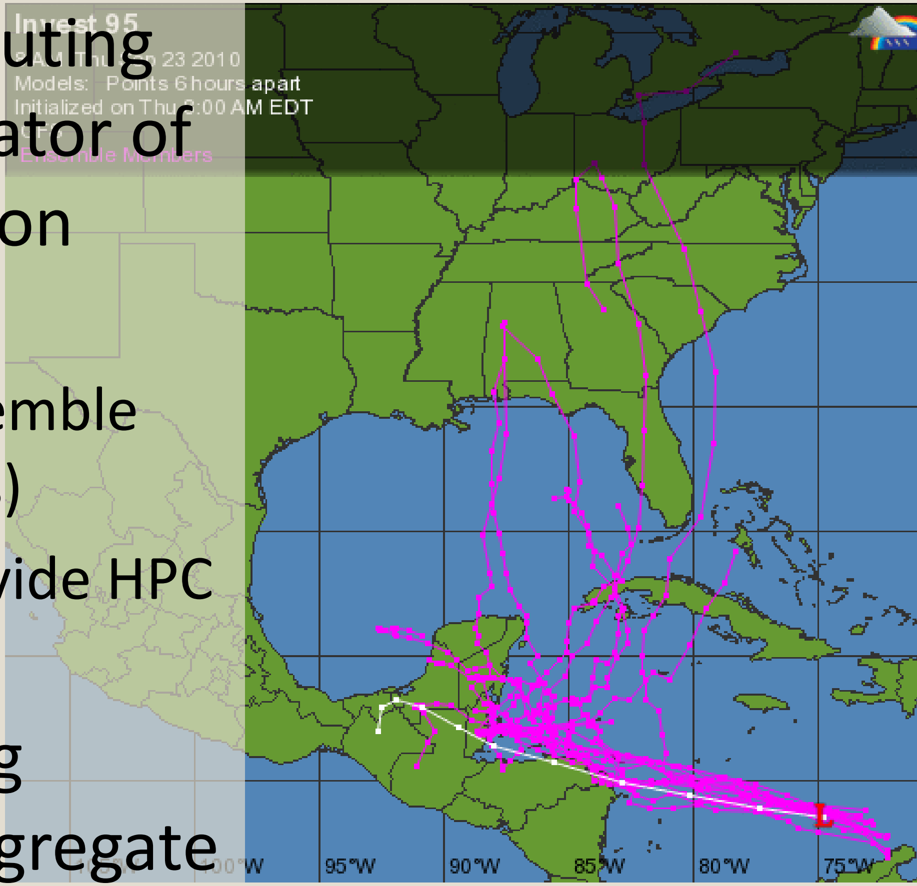
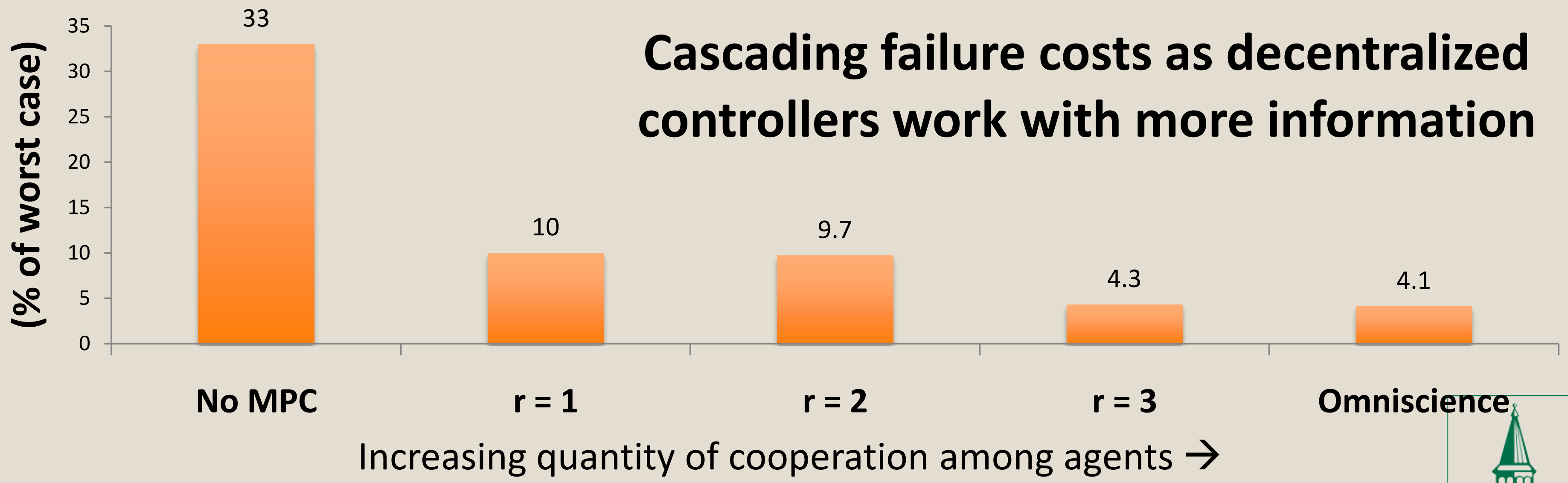
1. Estimating cascading failure risk

- Use high-performance computing to develop a real-time estimator of cascading failure risk, based on ensembles of simulations
  - Led by Co-PI C. Danforth (Ensemble Prediction for Chaotic systems)
  - IBM Watson research will provide HPC expertise.
- Correlate CSD with Cascading Failure risk to produce an aggregate estimator of risk.

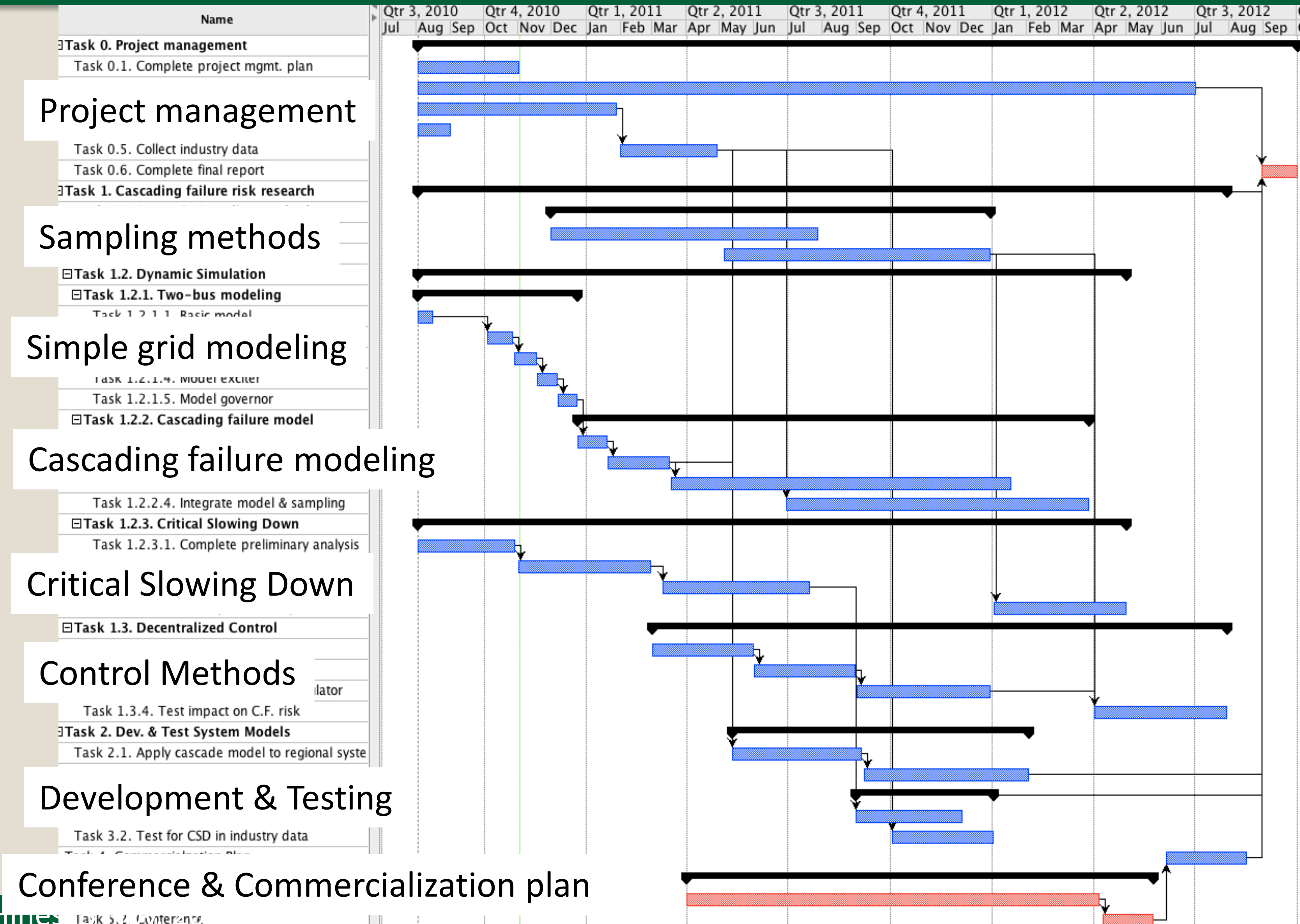


2. Mitigating Risk

- Develop algorithms based on Decentralized Model Predictive Control for the emergency dispatch of storage and demand response for Cascading Failure risk mitigation.



Prelim. work plan. Currently in Q1 of 8.



Team Roles

- Hines (PI): Power Systems, Cascading Failures, Smart Grid, Control Methods
  - Technical lead
- Danforth (Co-PI): Mathematics, Numerical Methods, Ensemble Prediction
- IBM Watson (cost-share): High-performance computing, Smart Grid industry, commercialization

Questions?

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