# Potential indicators of cascading failure risk in power systems


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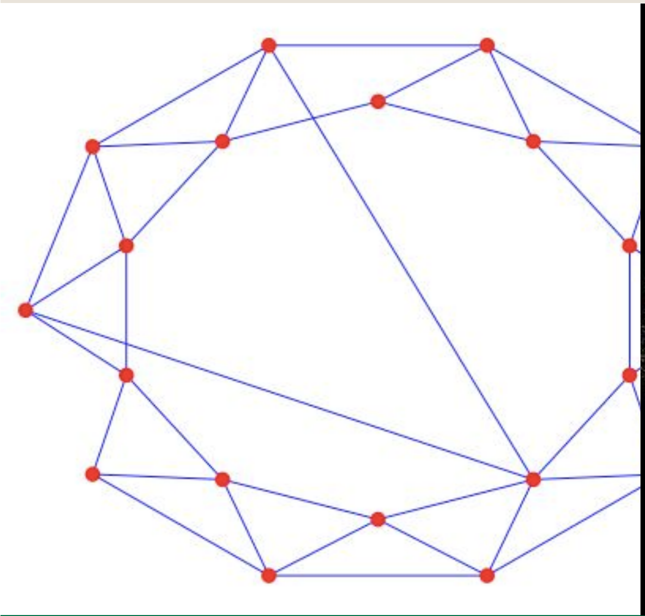
# Outline

- Power grids in the network science literature
  - How are power grid structured?
- Comparing abstract topological models of grid failure with a cascading failure model
  - How do power grids behave?
- Critical slowing down as an indicator of risk???

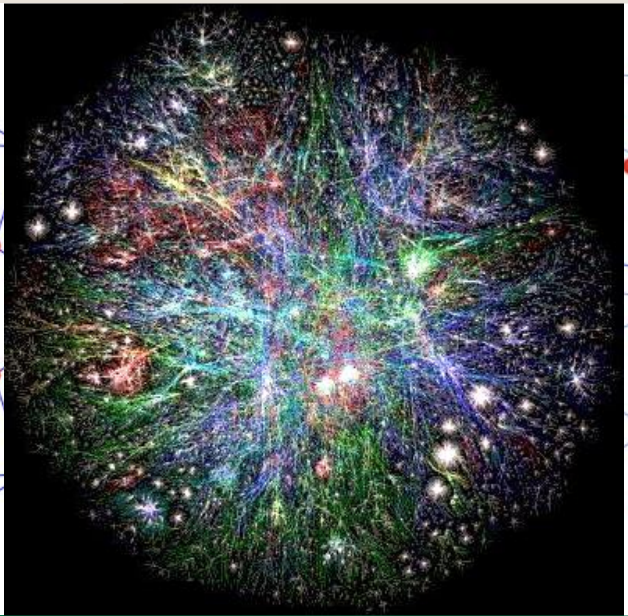
# Question 1: Network Structure

How are power grids structured, and how is this structure similar to or different from other networks?

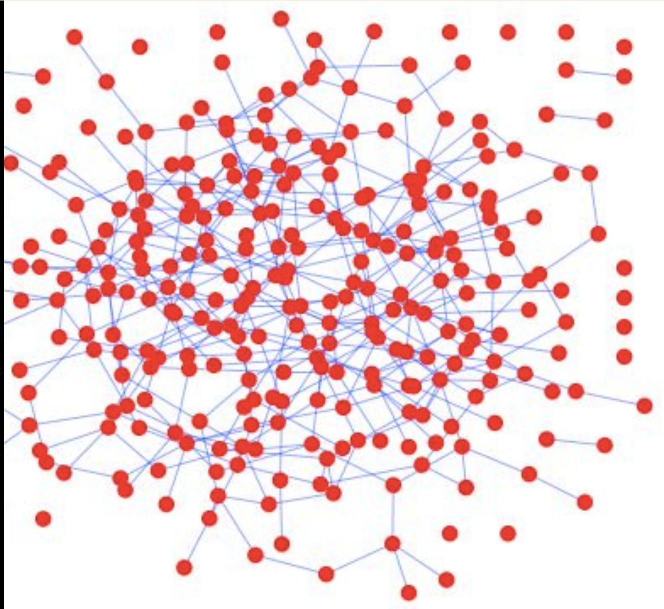
Small World?



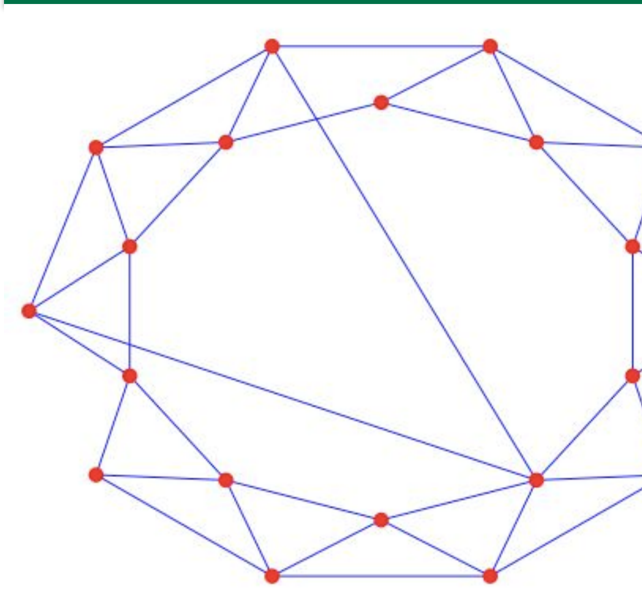
Scale Free?

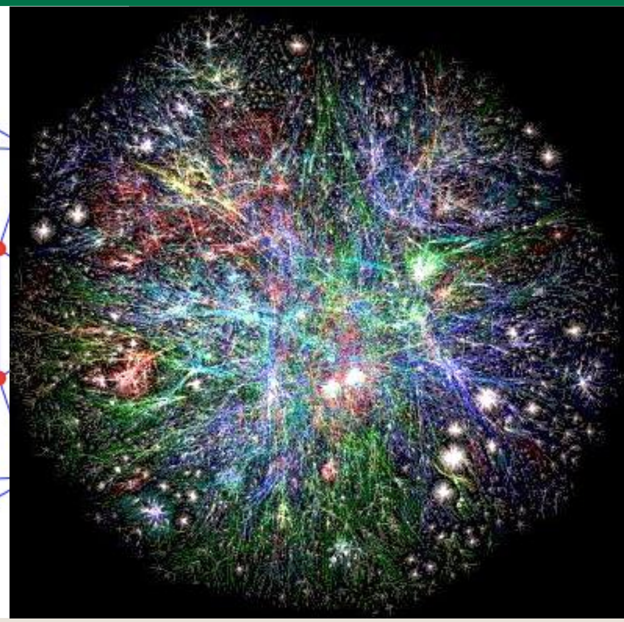


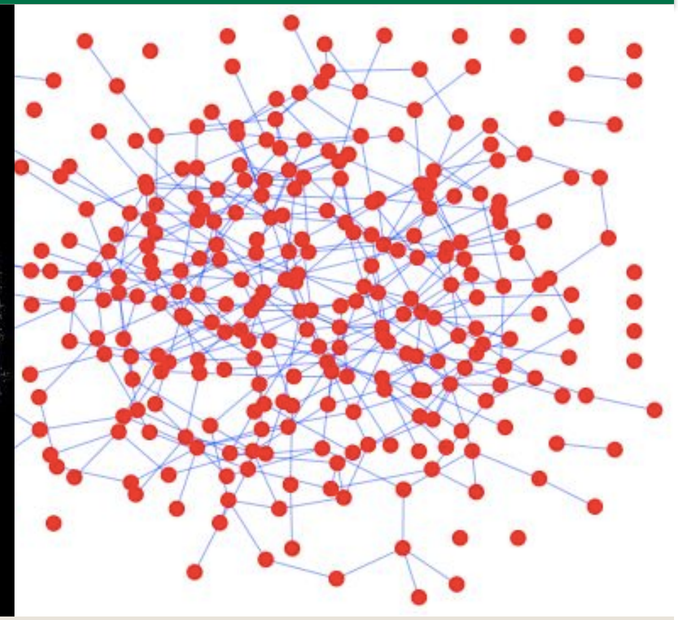
Random?



# Why should we care?







<u>Small-world networks</u>
High clustering, but small diameters.
Tend to synchronize easily (6 degrees of separation)

<u>Scale-free networks</u>
Heterogeneous connectivity (hubs).
Vulnerable to attacks at the hubs, robust to random failure

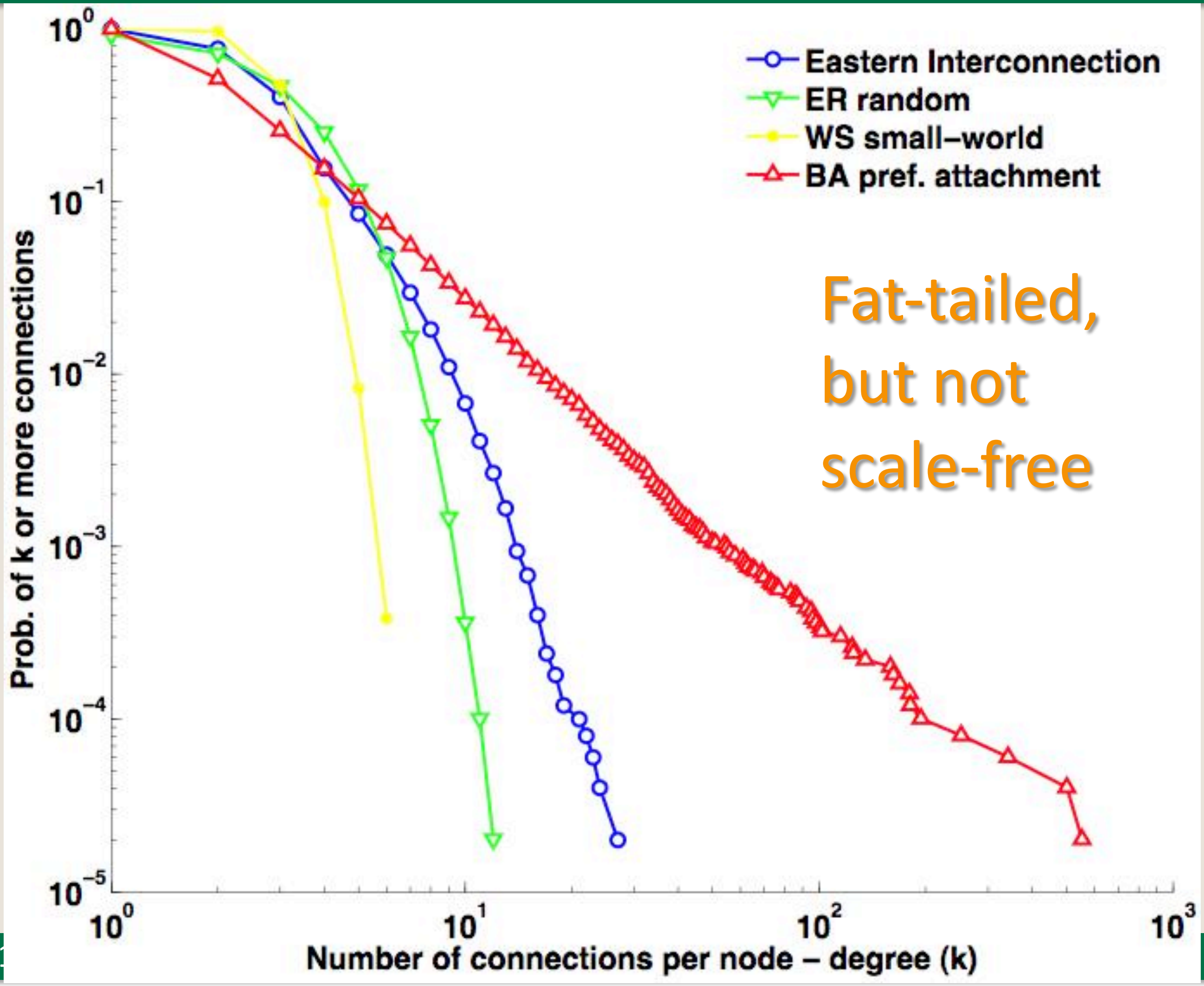
<u>Random graphs</u>
Homogeneous connectivity.
Not particularly vulnerable to attacks or random failure


(Ref. Albert & Barabasi, 2002)

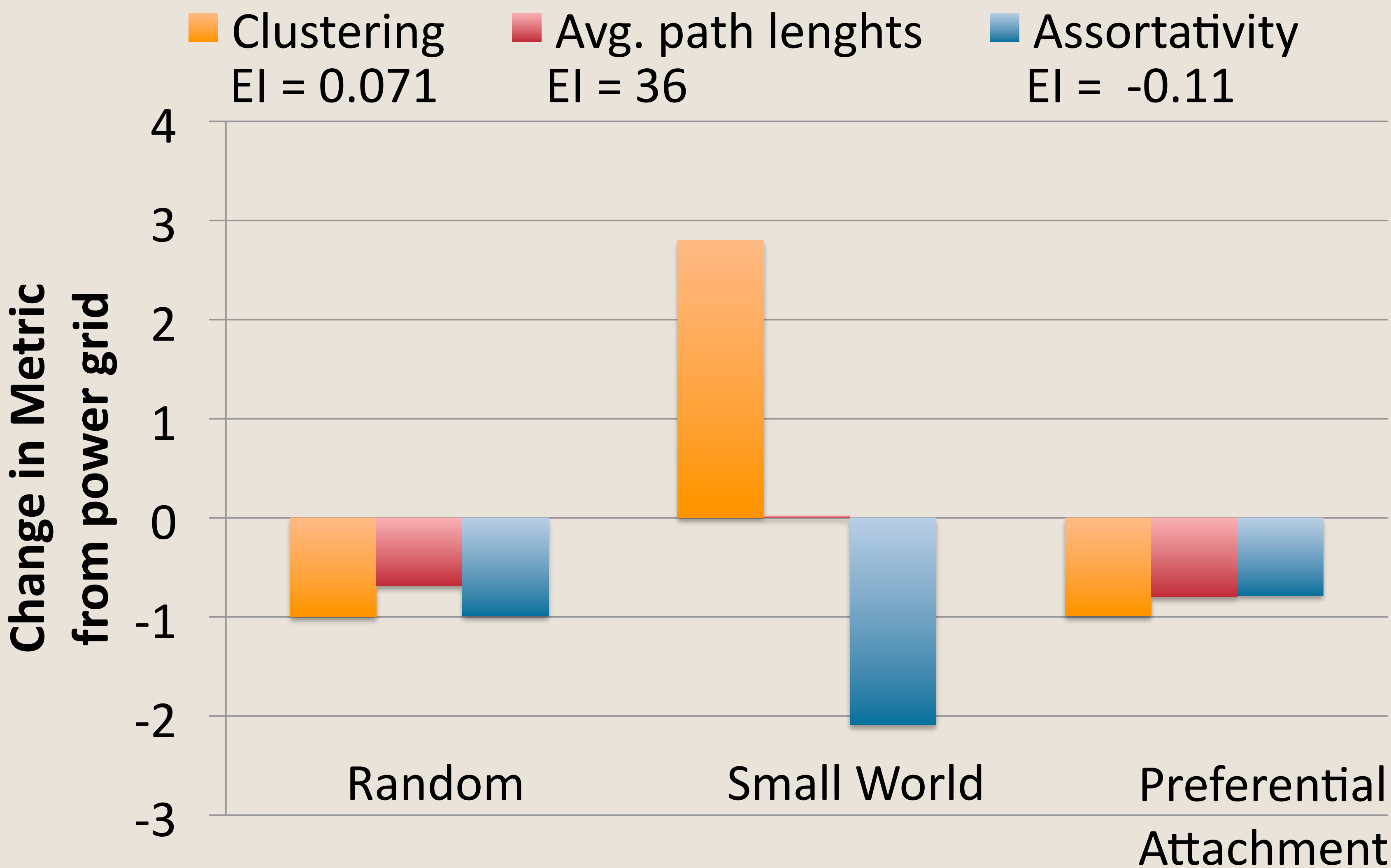
# Existing studies of power grid structure

| Authors | Power grid data | Findings |
|---|---|---|
| Watts and Strogatz (1998) | Western US | Power grids are small-world |
| Amaral et al. (2000) | Southern California | Exponential degree |
| Albert et al. (2004) | North America | Exponential degree, scale-free behavior |
| Crucitti et al. (2004) | Italy | Power-law degree |
| Chassin and Possee (2005) | US East and West | Power-law degree |
| Holmgren et al. (2006) | Nordic, Western US | Power grids fail in ways similar to scale-free nets |
| Blumsack et al. (2007) | IEEE 118 | Wheatstone motifs |
| Wang, et al. (2008) | Various | Synthetic power grids |
| Bompard et al. (2009) | Italy | "Net-ability" |

# Degree distribution results



# Topology metrics results

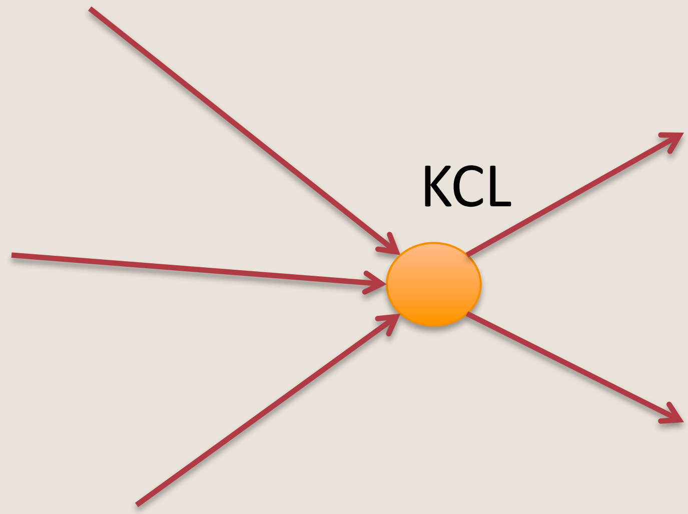


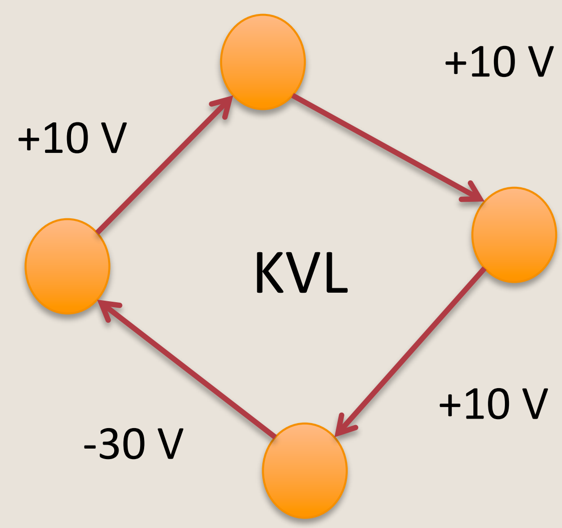
# Therefore… ???

- Since the power network is not scale-free,
  - perhaps we don't really need to worry too much about directed attacks.
- Since the power network is not small-world
  - perhaps we don't really need to worry too much about bad things spreading quickly.

# However

- Power flows in power grids by Kirchhoff's and Ohm's laws, not by topology.
- Small failures can cascade to become large failures
- What models provide useful insights about resilience?



# Question: What models provide useful information about grid vulnerability?

The New York Times

**Asia Pacific**

WORLD U.S.

AFRICA AME

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


Du Bin for The New York Times

A Chinese student, Wang Jianwei, above, and his professor, wrote an academic paper on the vulnerability of the American power grid to a computer attack. Scientists said the paper was merely a technical exercise.

By JOHN MARKOFF and DAVID BARBOZA
Published: March 20, 2010

# Wang & Rong, *Safety Science*, 2009

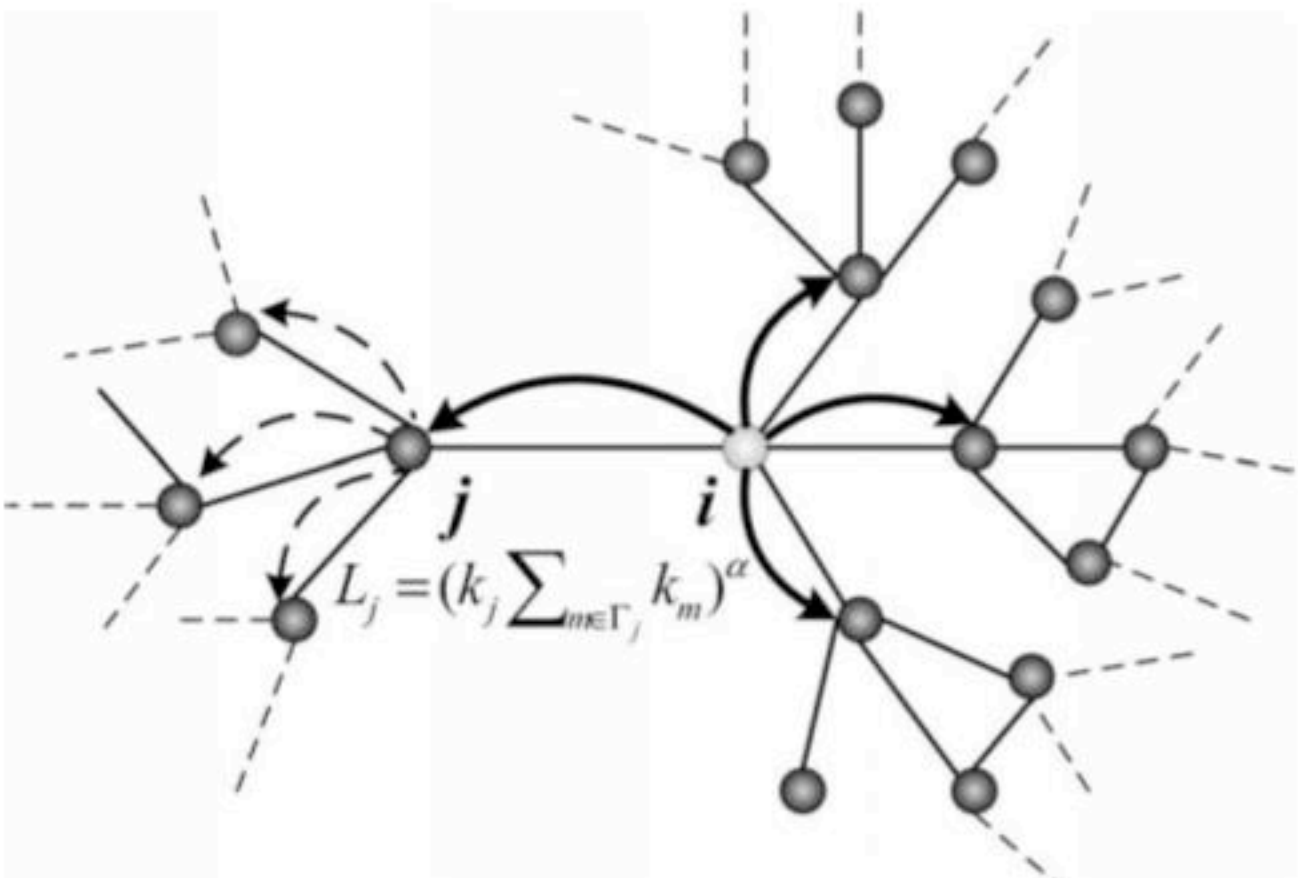
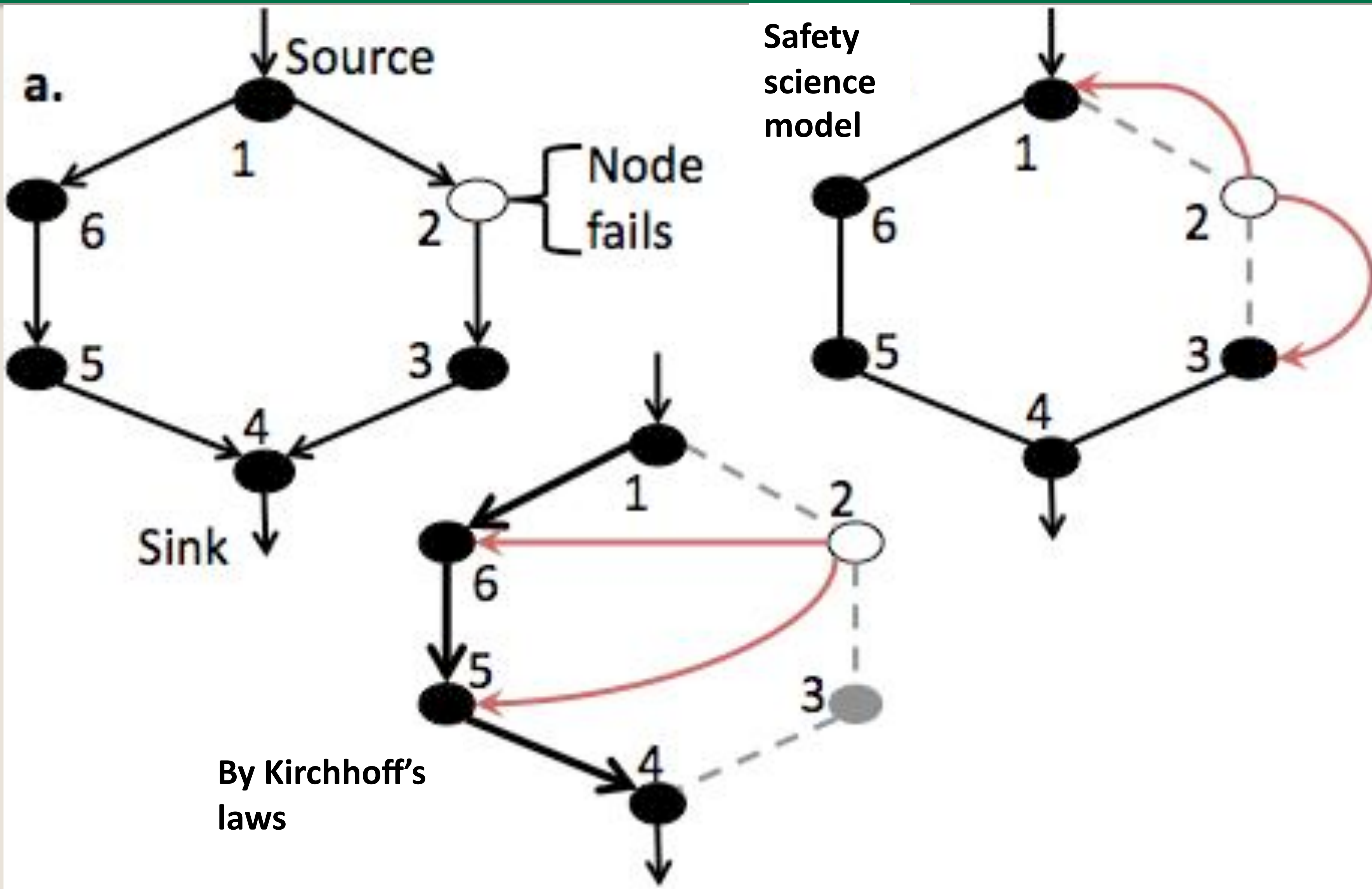



**Fig. 2.** The scheme illustrates the load redistribution triggered by an node-based attack. Node *i* is removed and the load on it is redistributed to the neighboring nodes connecting to node *i*. Among these neighboring nodes, the one with the higher load will receive the higher shared load from the broken node.

<u>Conclusion</u>

Power grids are particularly vulnerable to attacks at low-load (traffic) nodes

# But cascades in power grids are different…

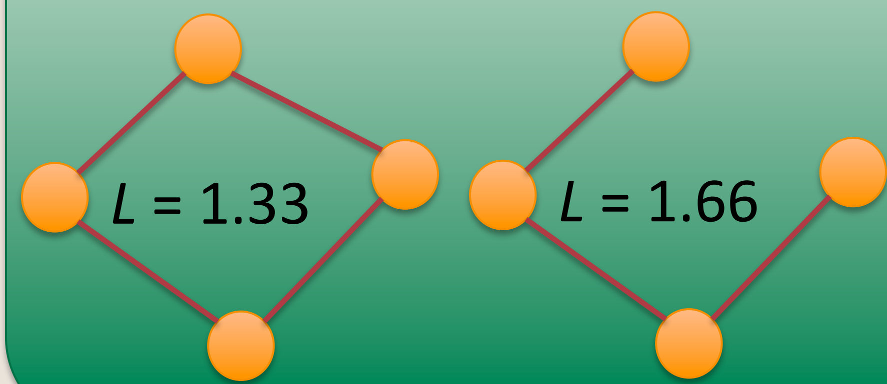


# An Experiment: Test the resistance of the Eastern Interconnect to random failure/directed attack

- Five (bus) attack/failure vectors:
  - Random failure
  - Degree attack
  - Min "traffic" attack
  - Max "traffic" attack
  - "Betweenness" attack
- Three measures of impact:
  - "Characteristic Path Length" after the disturbance
  - "Connectivity Loss" after the disturbance
  - Blackout size from a model of cascading overloads

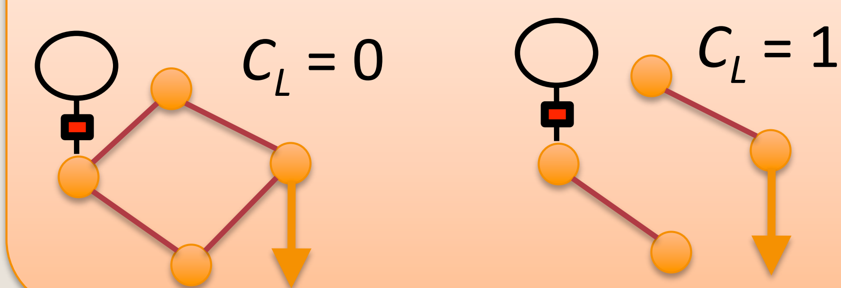
# Measures of Impact

Characteristic Path Length

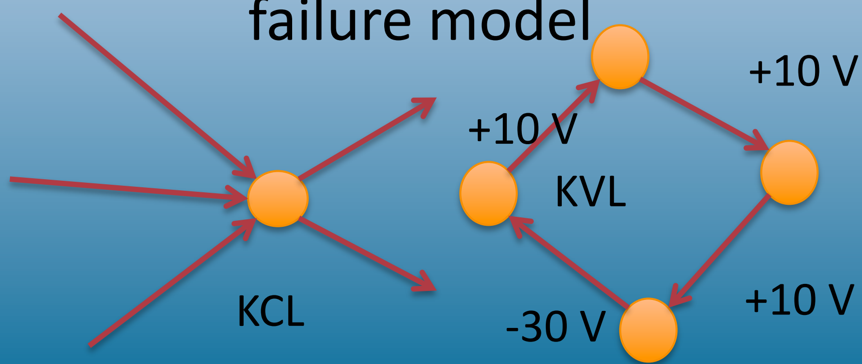



Albert et al. (2001): $L$ increases rapidly with directed attacks in scale-free graphs, but not in random graphs

Connectivity Loss




Blackout size from a cascading failure model




Albert et al. (2004): $C_L$ increases rapidly as hub nodes are removed from a power grid

# Blackout model

- Use DC power flow
- Relays
  - Trip time based on the integral of the overload
- After separation into subgrids:
  - Generators can ramp up/down <10% to rebalance supply and demand in islands
  - When there is still too much supply, trip smallest generator
  - When there is still too much demand, shed load

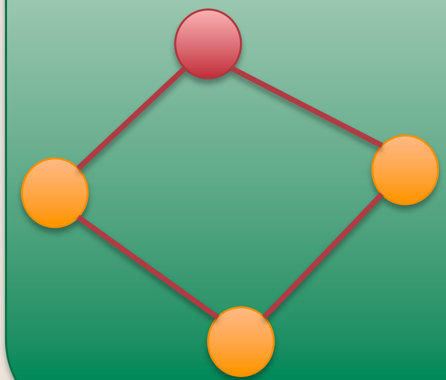
$$P_i = \Re(S_i) = |V_i| \sum_{j=1}^{n} (g_{ij}|V_j|\cos(\theta_i - \theta_j) + b_{ij}|V_j|\sin(\theta_i - \theta_j))$$

$$Q_i = \Im(S_i) = |V_i| \sum_{j=1}^{n} (g_{ij}|V_j|\sin(\theta_i - \theta_j) - b_{ij}|V_j|\cos(\theta_i - \theta_j)) \ .$$

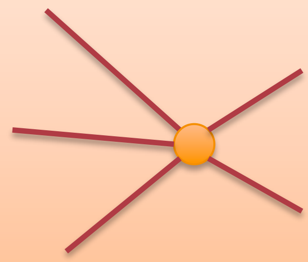
$$P_i = \sum_{j=1}^{n} (\theta_i - \theta_j)/X_{ij}$$

# Attack/Failure Vectors

Random failure

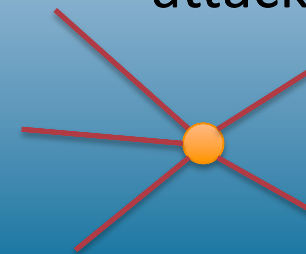


Degree-based attack



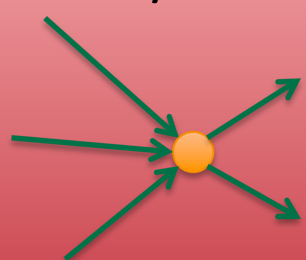
Albert et al (2000)

Betweenness attack



Albert et al (2004)

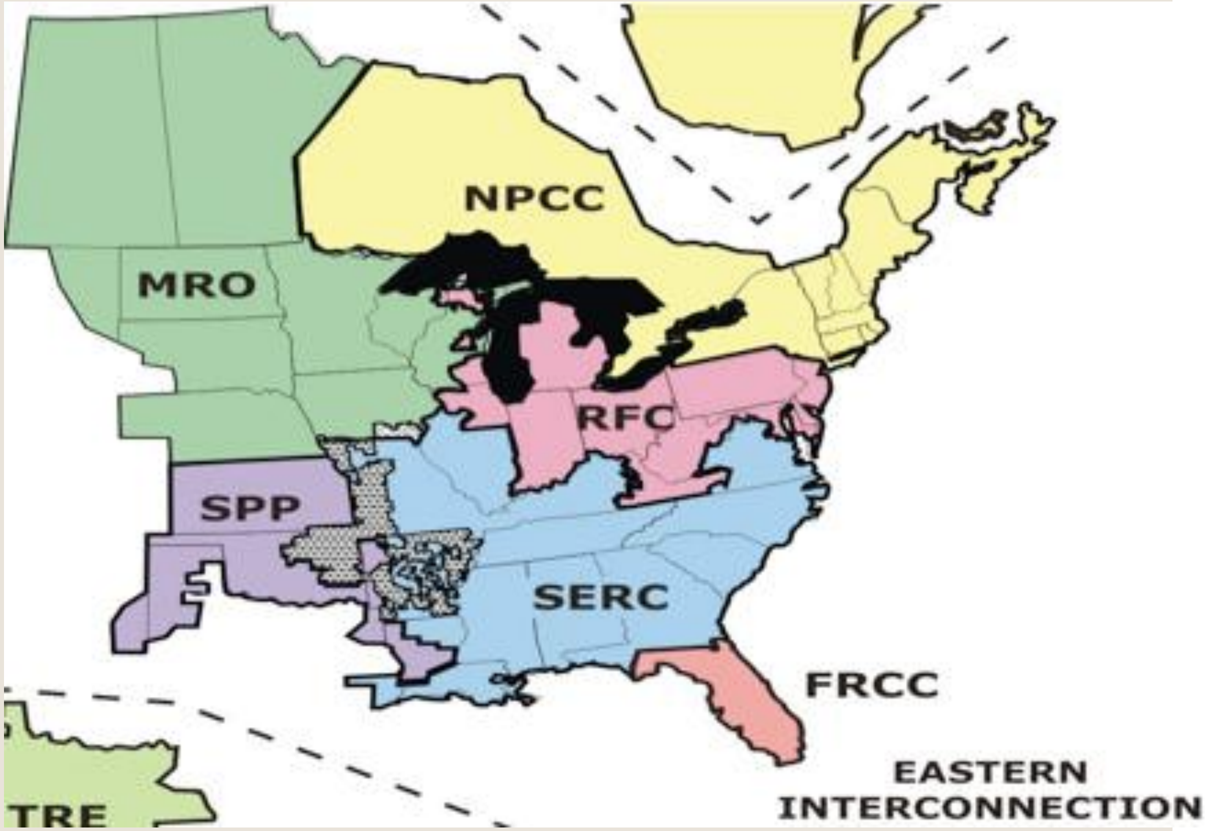
Min/max load/traffic



Wang & Rong (2009):
Min-traffic leads
to large failures

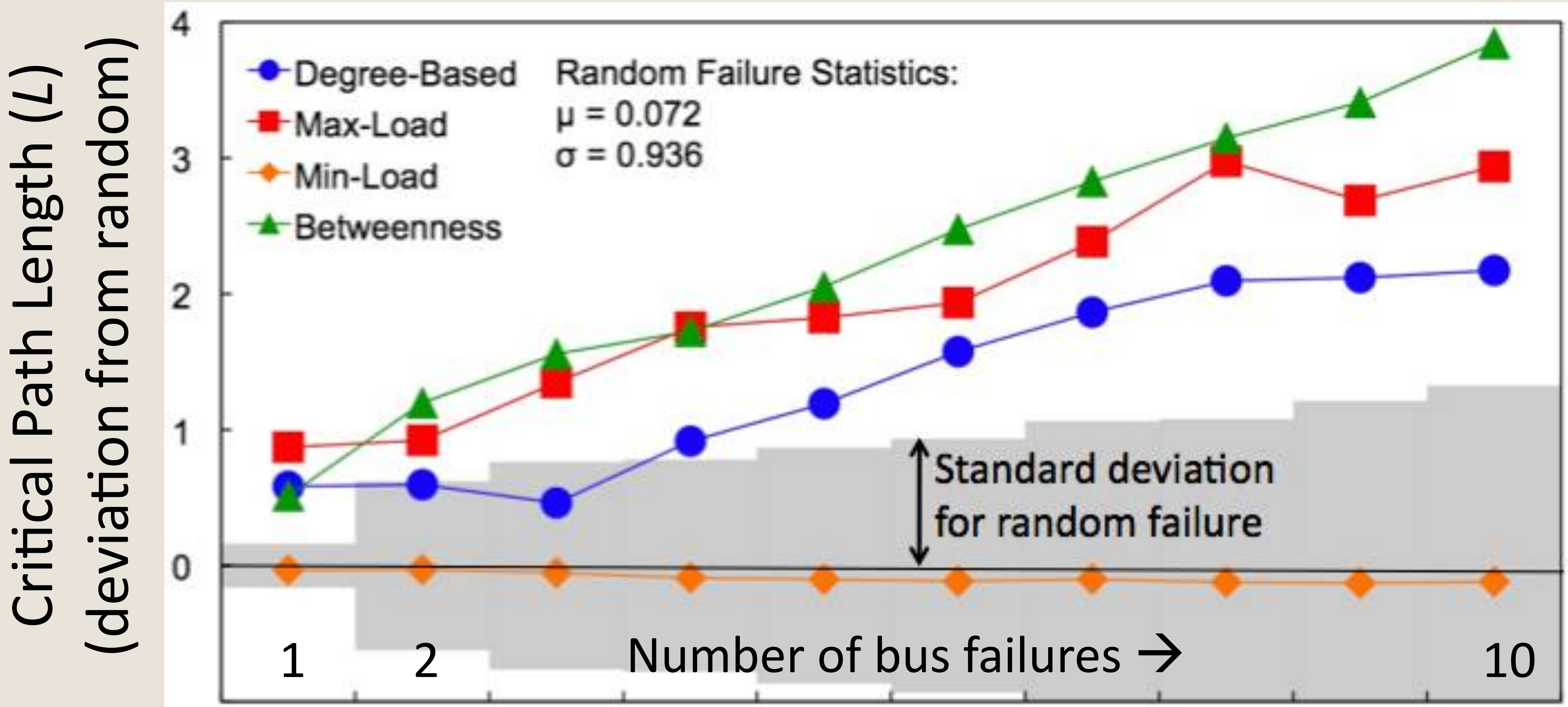
# Data

- 40 control areas from the Eastern Interconnect (2012 planning case)
- 336-1473 buses
- 29,261 of 49,907 buses total
- Study each area separately and look for trends



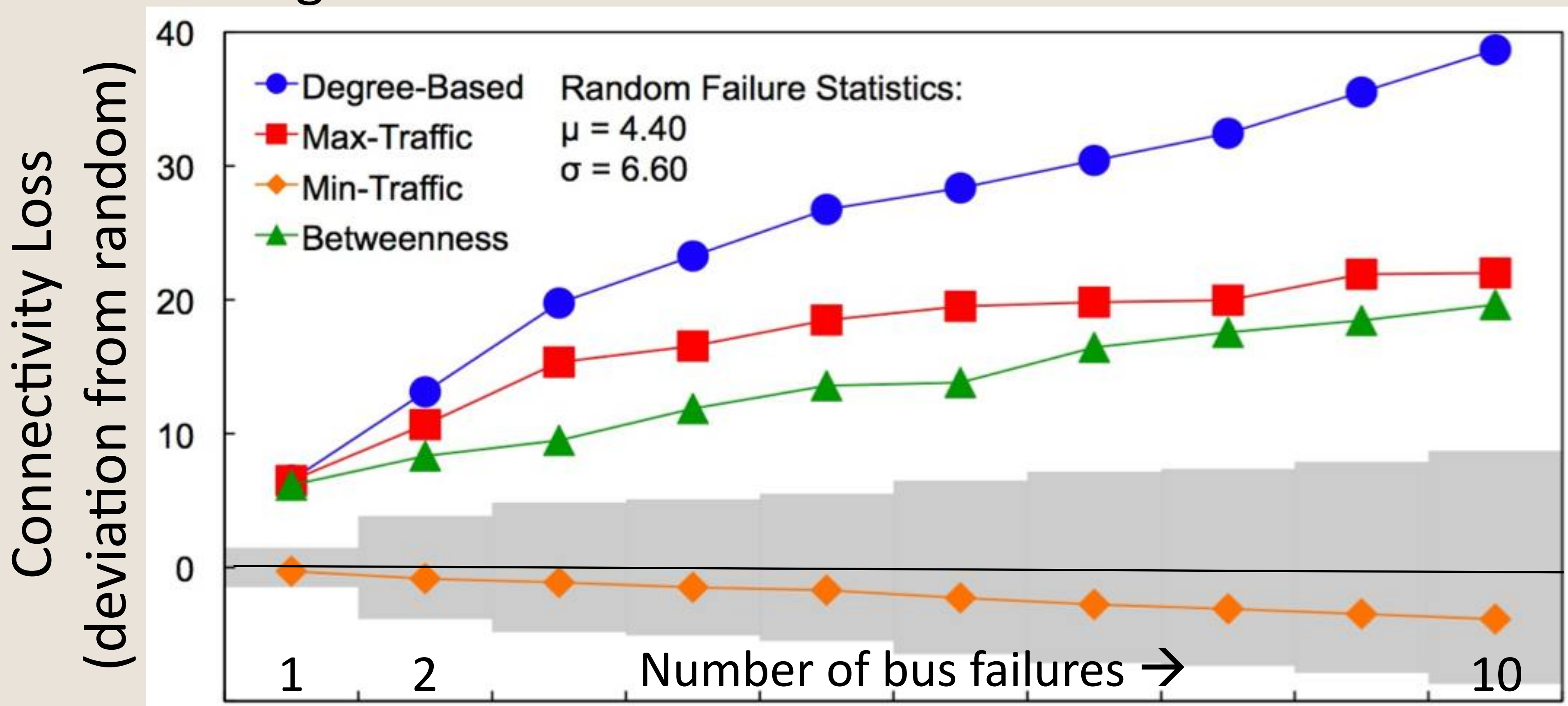
# Results: Critical Path Length

High betweenness attacks are the most "successful" Min-traffic is least. Directed attacks ~2 sigma larger than random



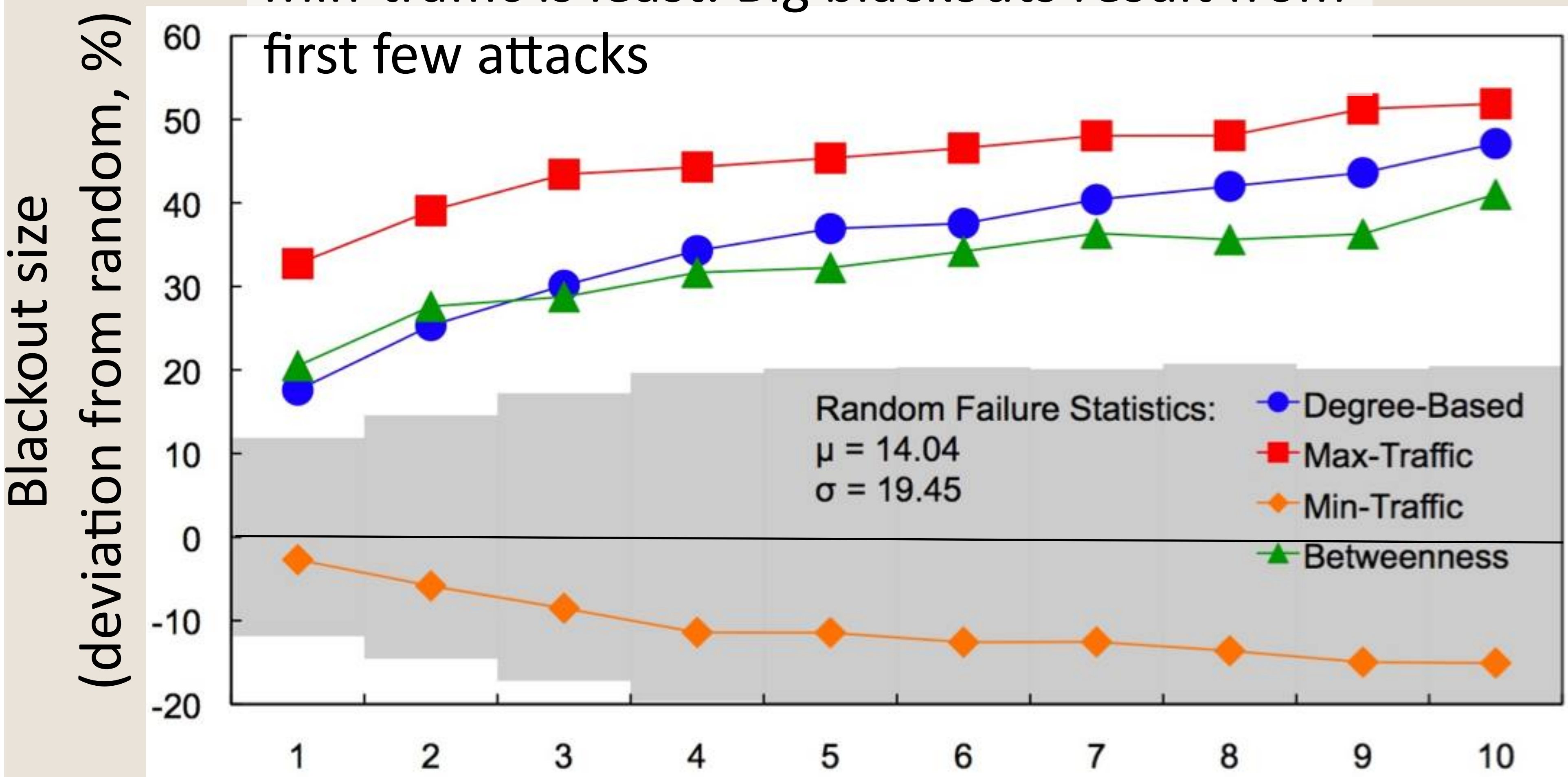
# Results: Connectivity Loss

Degree-based attacks are much more "successful" Min-traffic is least. Directed attacks ~3 sigma larger than random

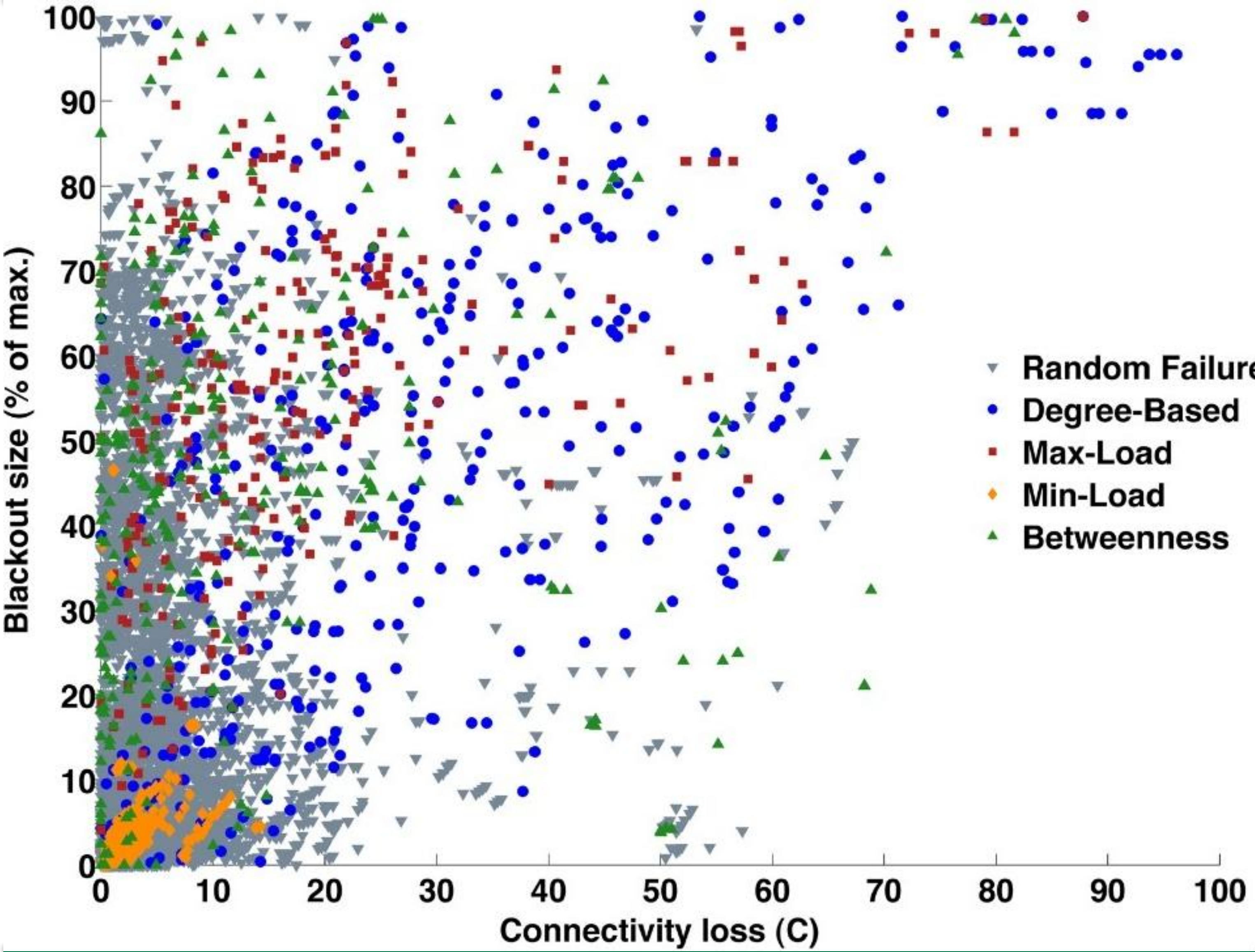


# Results: Blackout Size

Max-traffic attacks are most "successful"
Min-traffic is least. Big blackouts result from first few attacks



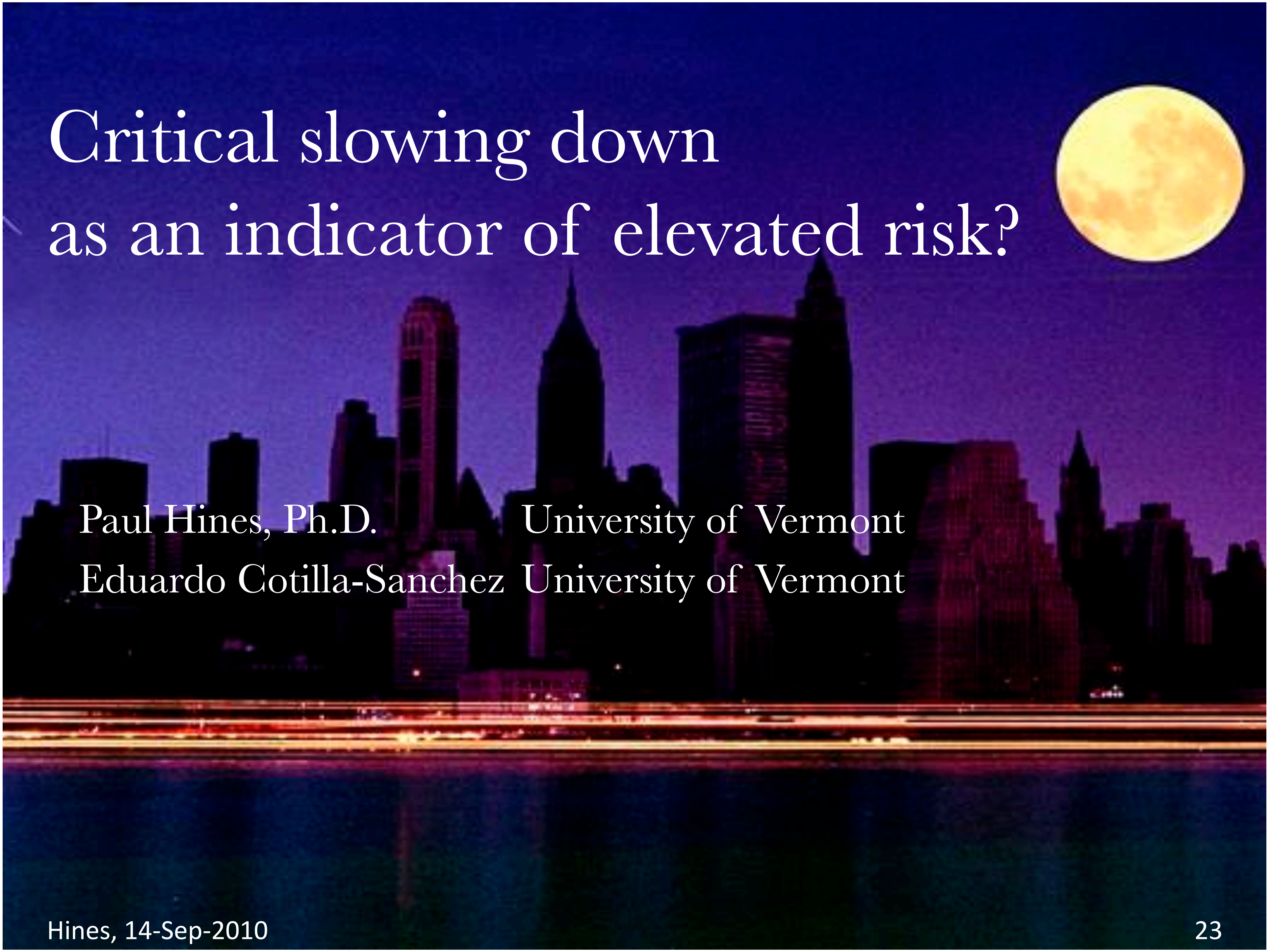
# Blackout size vs. Connectivity Loss




While the trends are similar the correlation for individual disturbances is low

# Implications

- The low-traffic nodes are not the most vulnerable.
  - Some topological models are grossly misleading
- All of the topological models tested suggest that directed attacks are notably more successful than random ones
  - But different models provide different implications. Topological methods appear to be useful only for identifying general trends
- Protecting high-traffic nodes (transformers) seems like a good idea



# Critical slowing down as an indicator of elevated risk?

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# Measuring risk in real time

- We need methods to detect problems as they emerge: even the ones that we cannot imagine

Real-time blackout risk meter

# Alternatives for dynamic stability assessment

- Use traditional stability methods.
  - Eigenvalue analysis, Lyapunov methods.
    - Effective when the state of the system is know well and system size is manageable
- PMU's. PMU data can be used to measure the state more accurately.
  - But, is it possible to see indicators of risk, directly in the raw time-series data?

# Context

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

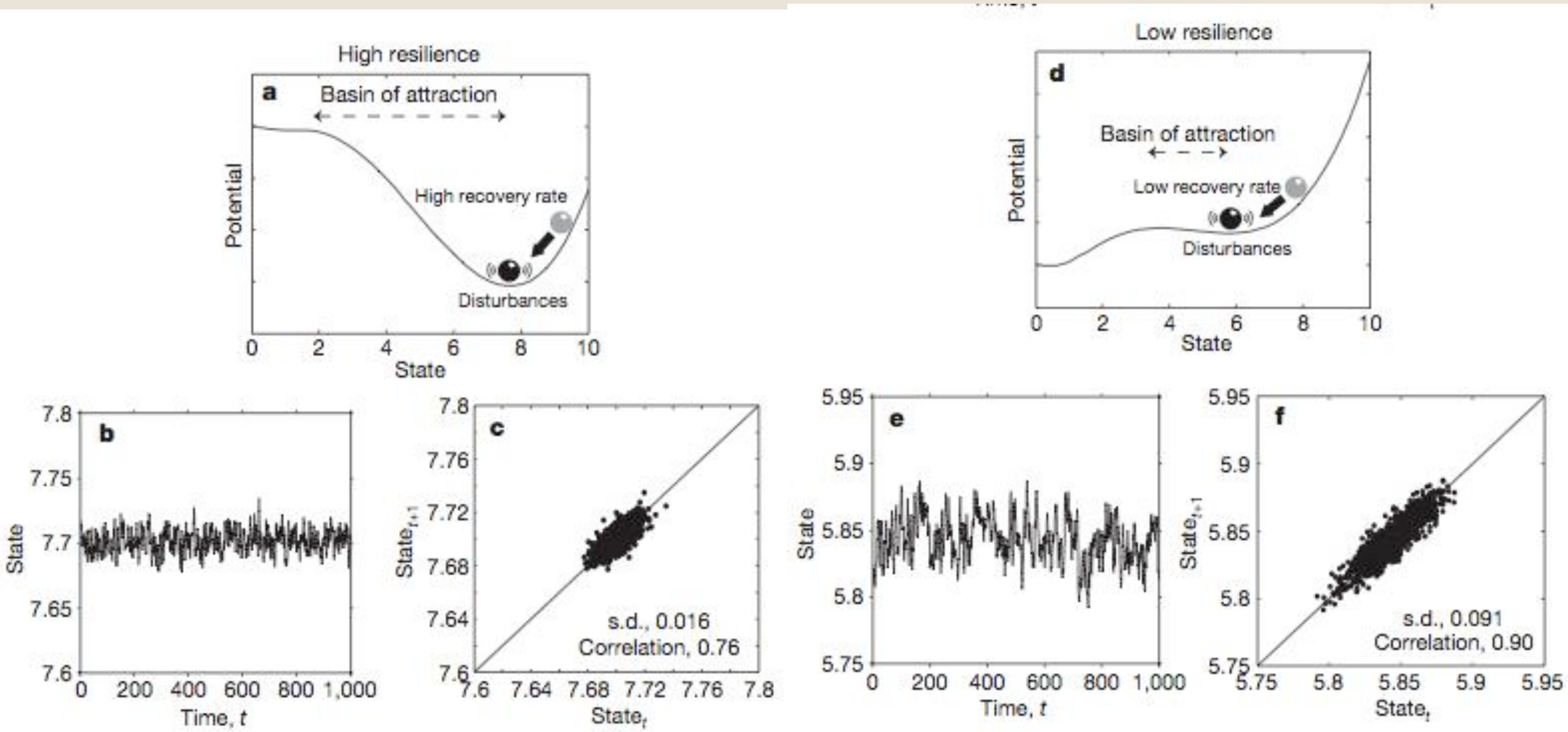
REVIEWS

## 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.

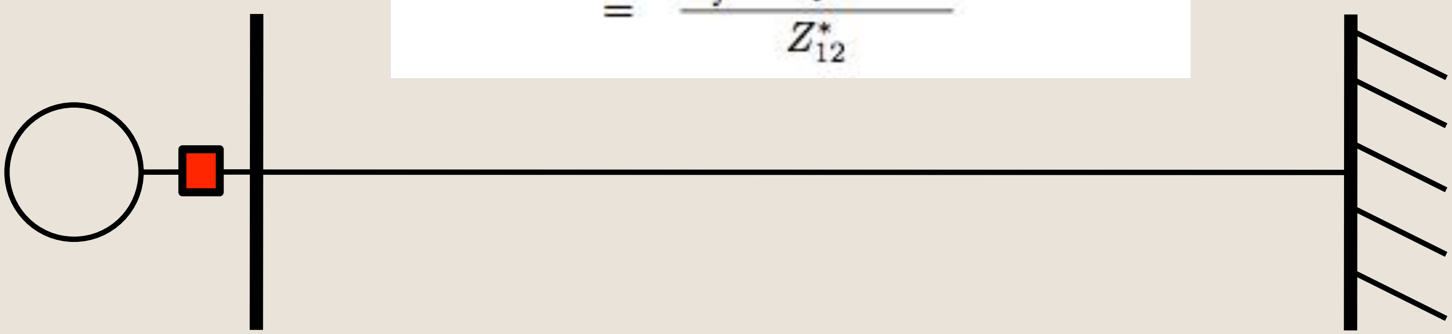


High resilience
a
Basin of attraction
High recovery rate
Disturbances
Potential
State
Low resilience
d
Basin of attraction
Low recovery rate
Disturbances
Potential
State
b
State
Time, t
c
s.d., 0.016
Correlation, 0.76
State$_{t+1}$
State$_t$
e
State
Time, t
f
s.d., 0.091
Correlation, 0.90
State$_{t+1}$
State$_t$

# 1-machine, infinite bus model

$$\begin{aligned} P_e(\delta(t)) &= \Re(V_1(t)I(t)^*) = \Re(E_f e^{j\delta} I^*) \\ E_f e^{j\delta} I^* &= E_f e^{j\delta} \frac{(E_f e^{j\delta} - V_2)^*}{Z_{12}^*} \\ &= \frac{E_f^2 - E_f V_2 e^{-j\delta}}{Z_{12}^*} \end{aligned}$$

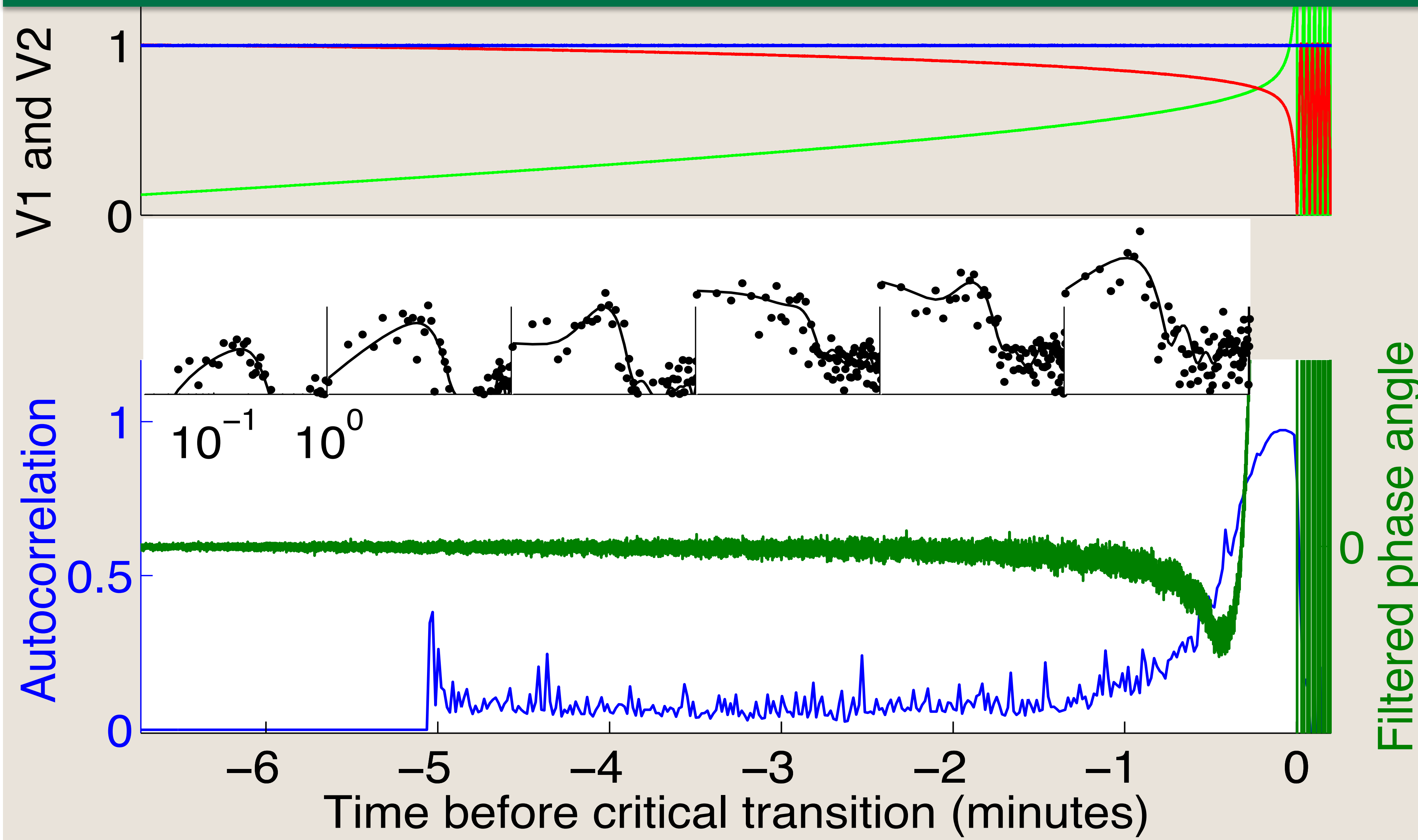
Infinite bus,
but noisy voltage



$$P_m(t) = P_e(\delta(t)) + D\omega(t) + M\dot{\omega}(t)$$

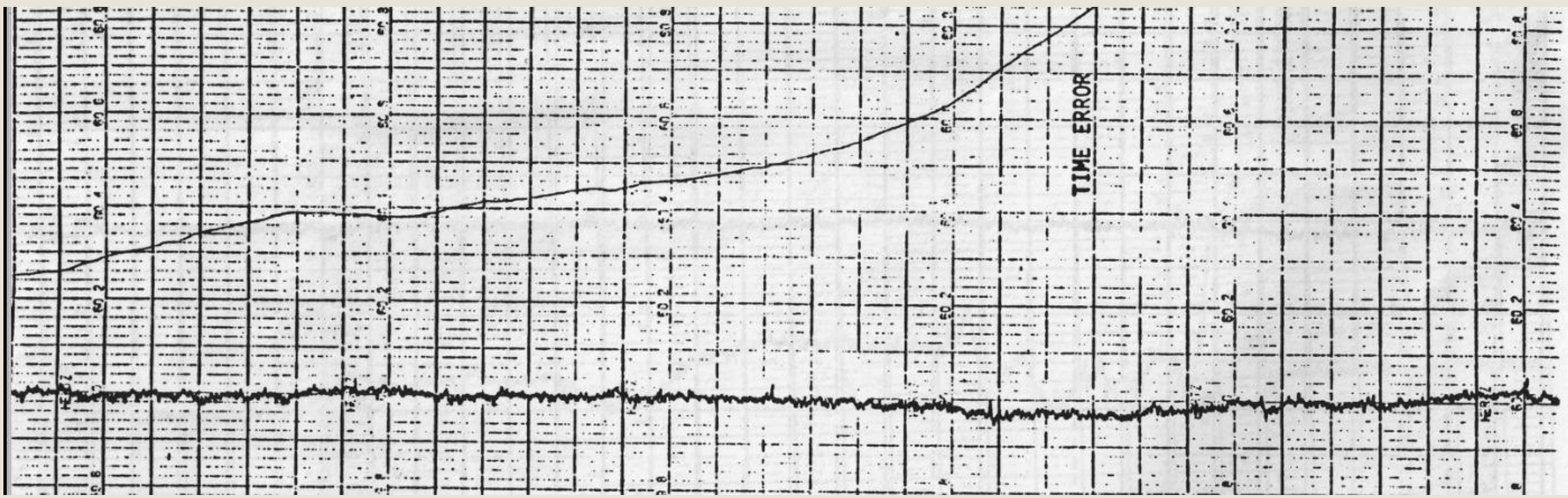
$$P_{\max} = \frac{|E_f||V_2|}{X_{12} + X_s}$$

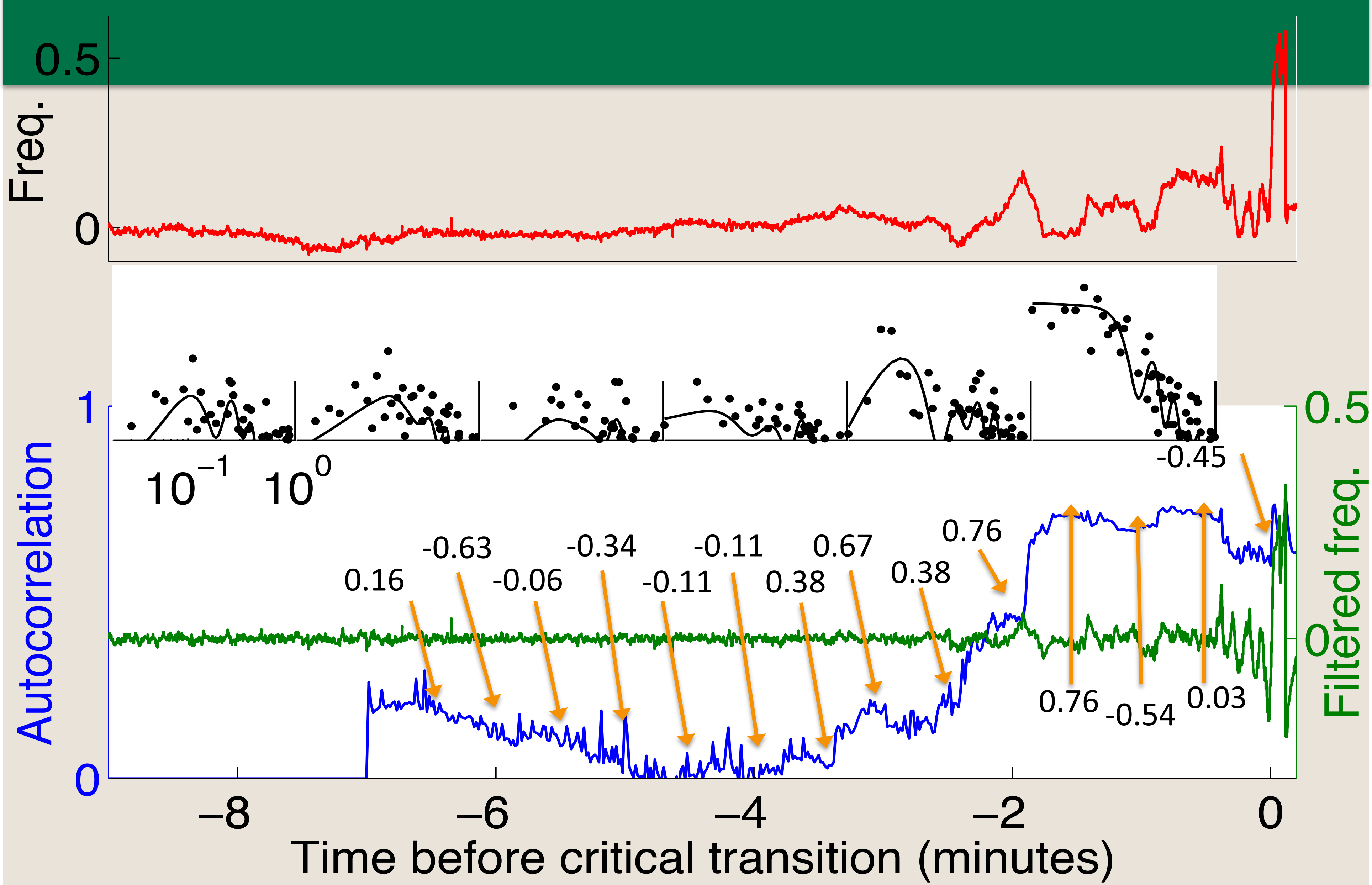
# Two-bus results



# 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.

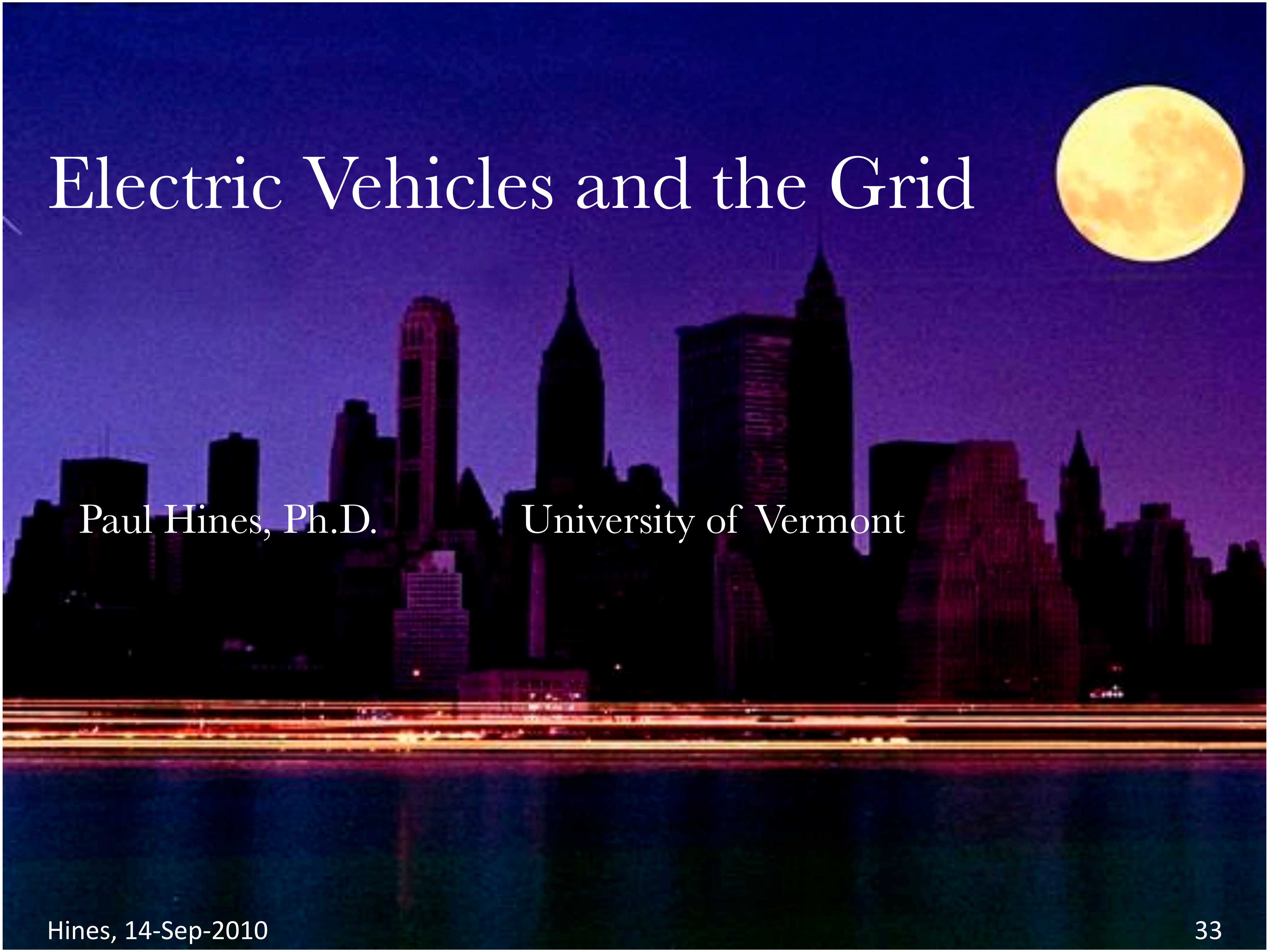




0.5
Freq.
0
1
Autocorrelation
0
0.5
0
Filtered freq.
$10^{-1}$
$10^{0}$
-0.45
0.76
0.67
-0.11
-0.34
-0.63
0.16
-0.06
-0.11
0.38
0.38
0.76
-0.54
0.03
–8
–6
–4
–2
0
Time before critical transition (minutes)

# Conclusions

- Changes in autocorrelations and cross correlations in PMU data could indicate proximity to critical points.
- Additional research is needed to determine the utility of this approach (false positives, false negatives, etc.)
- Theoretical work on small models?



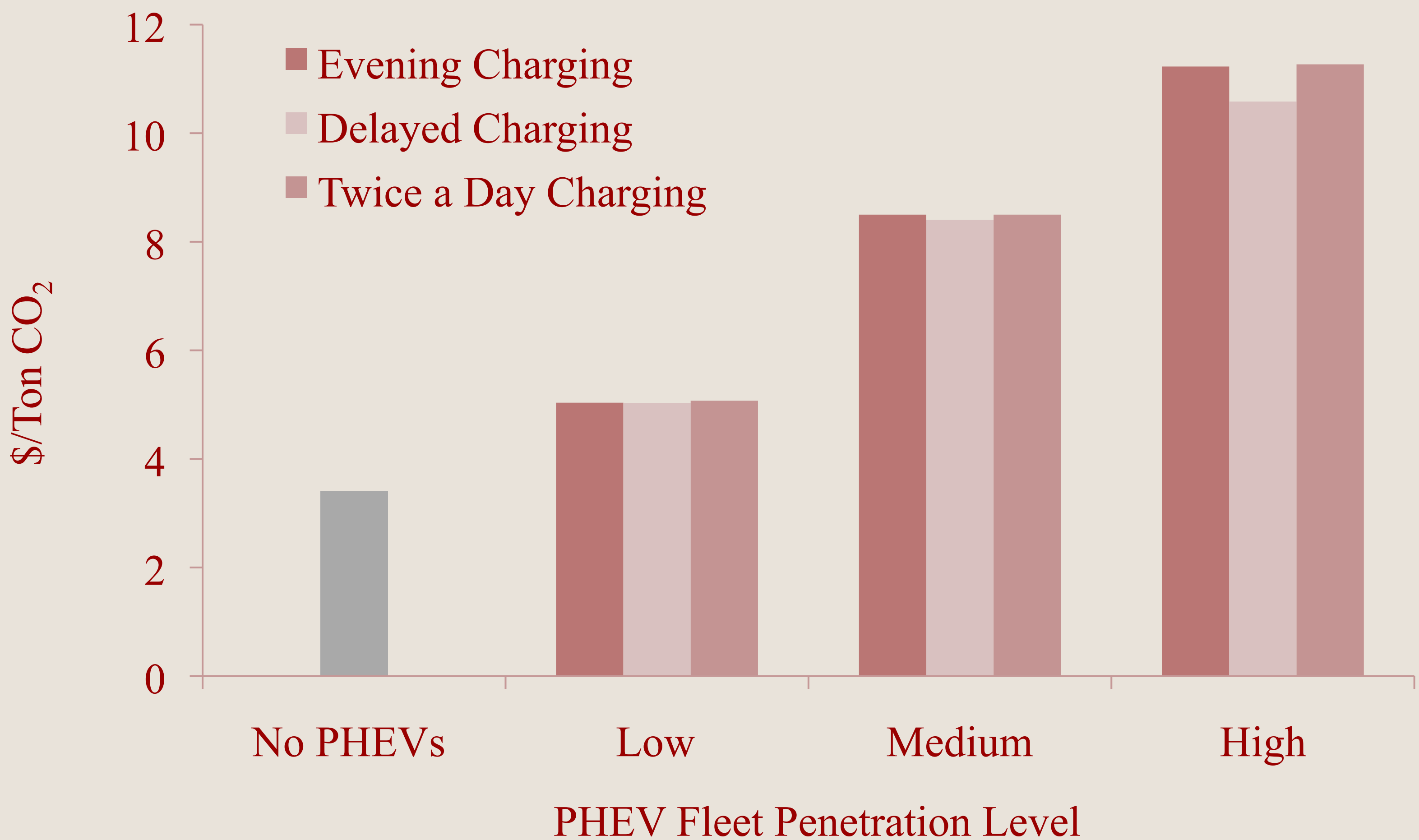
# Electric Vehicles and the Grid

Paul Hines, Ph.D. University of Vermont

# Electric vehicles

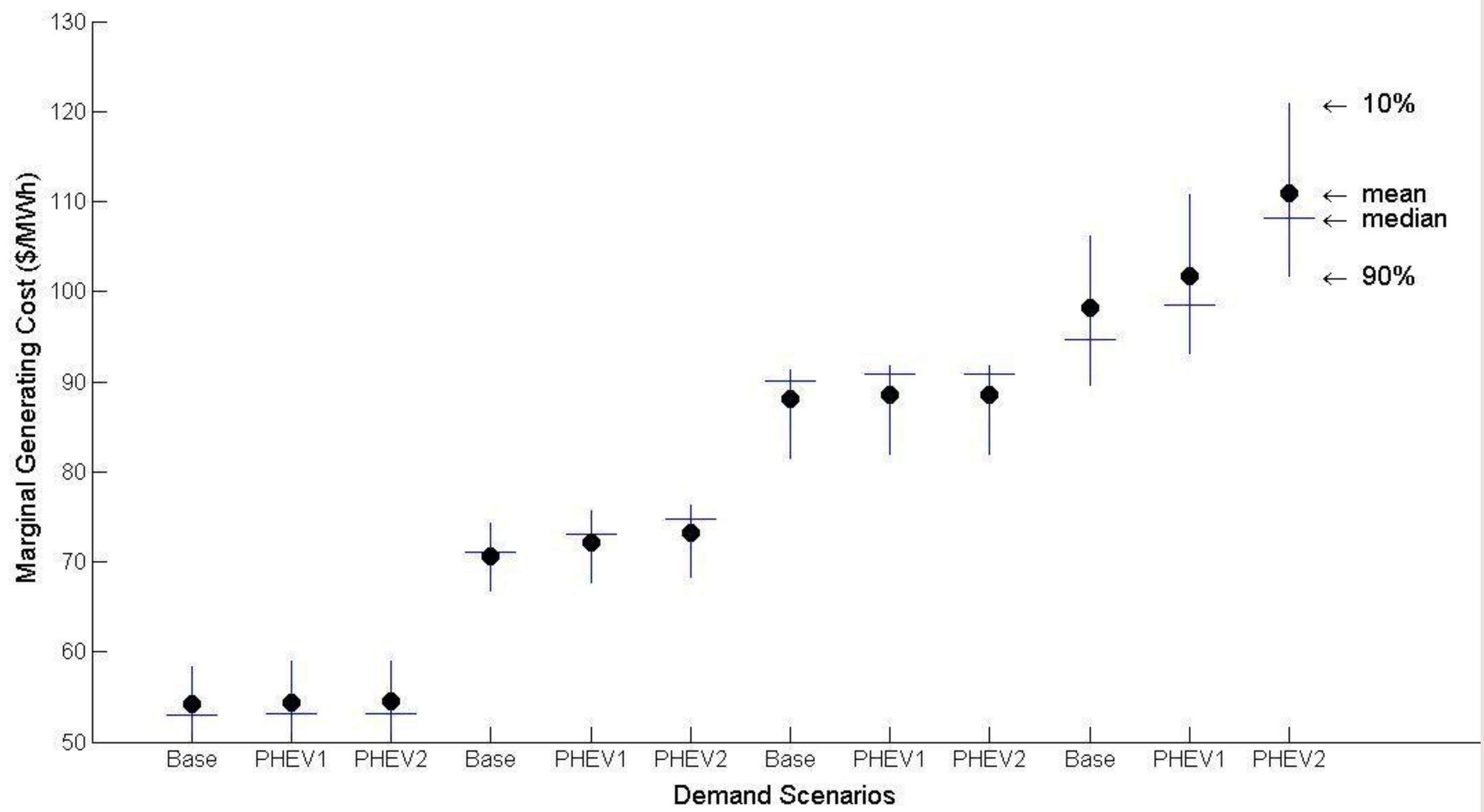
- What happens when we mix electric vehicles and cap-and-trade systems?
- Create an optimization model to minimize hourly dispatch cost over a year subject to $CO_2$ cap

# CO2 allowance costs

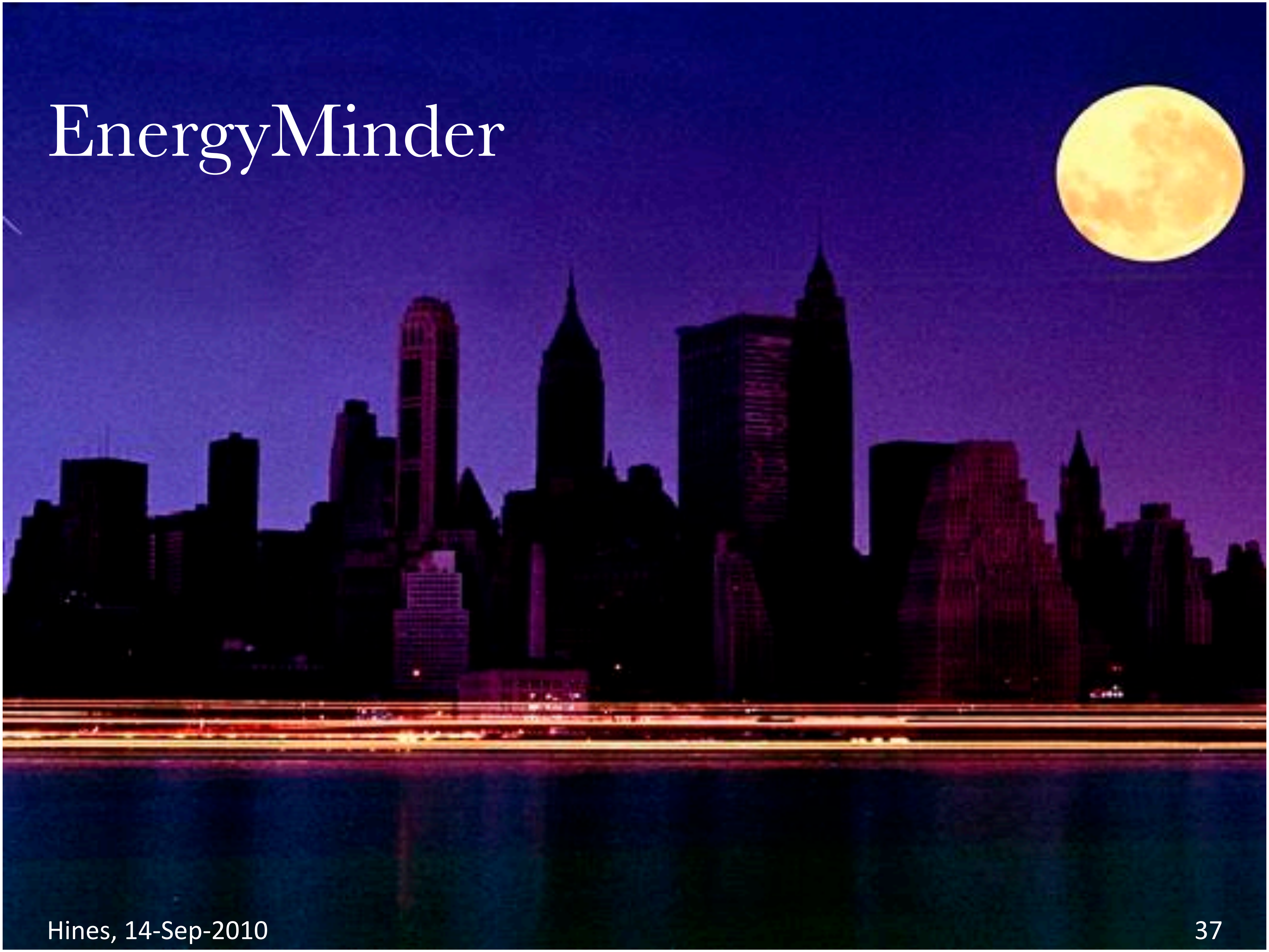



Forthcoming: J. Dowds et al., Transportation Research Record, 2010

# With power plant construction



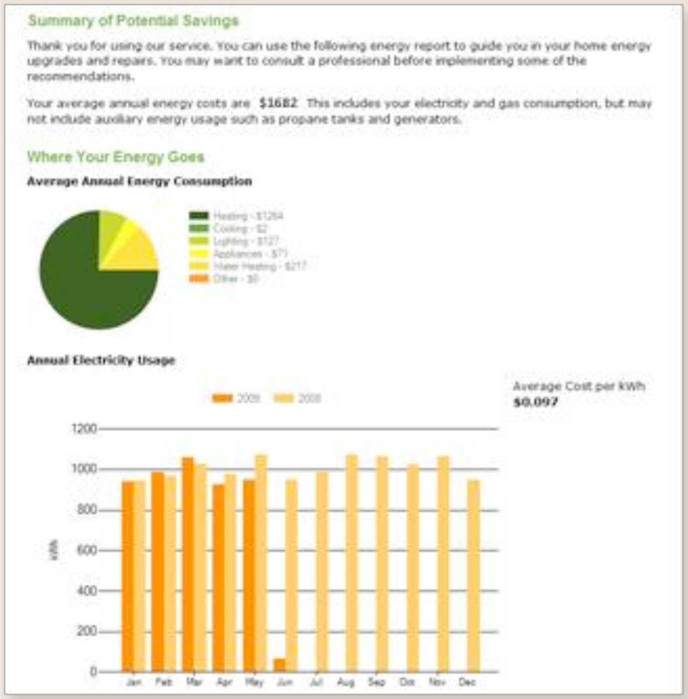
# EnergyMinder

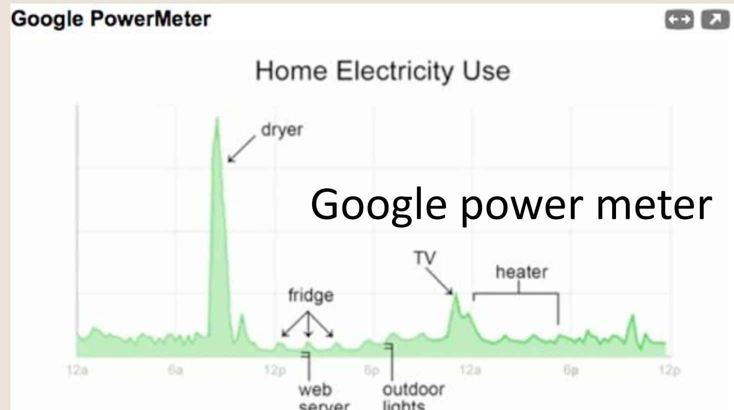


# Visual Feedback for Energy Eff.

- Commercial growth

Microsoft Hohm




Google power meter


Davis Center

# Academic studies

**Dormitory residents reduce electricity consumption when exposed to real-time visual feedback and incentives**

John E. Petersen, Vladislav Shunturov, Kathryn Janda, Gavin Platt and Kate Weinberger

*Oberlin College, Lewis Center for Environmental Studies, Oberlin, Ohio, USA*

Used a combination of natural social networks, competition and web-based visuals to incent energy efficiency

# The value of social pressure

## Utilities Turn Their Customers Green, With Envy


Max Whittaker for The New York Times

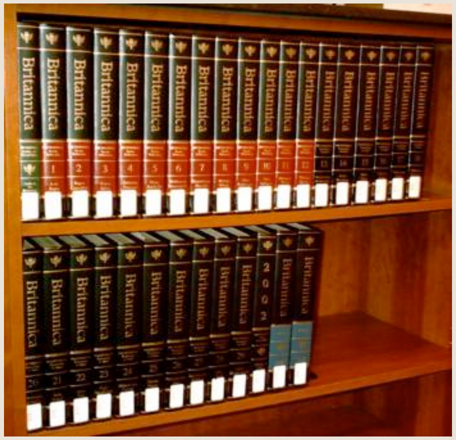
A desire to keep up with neighbors is spurring conservation.

# Online Social Networking

# Research question

- Can we design a voluntary social network that allows people to understand their energy consumption better, without top-down organization?

# Top-down vs. bottom-up modeling



WIKIPEDIA
The Free Encyclopedia

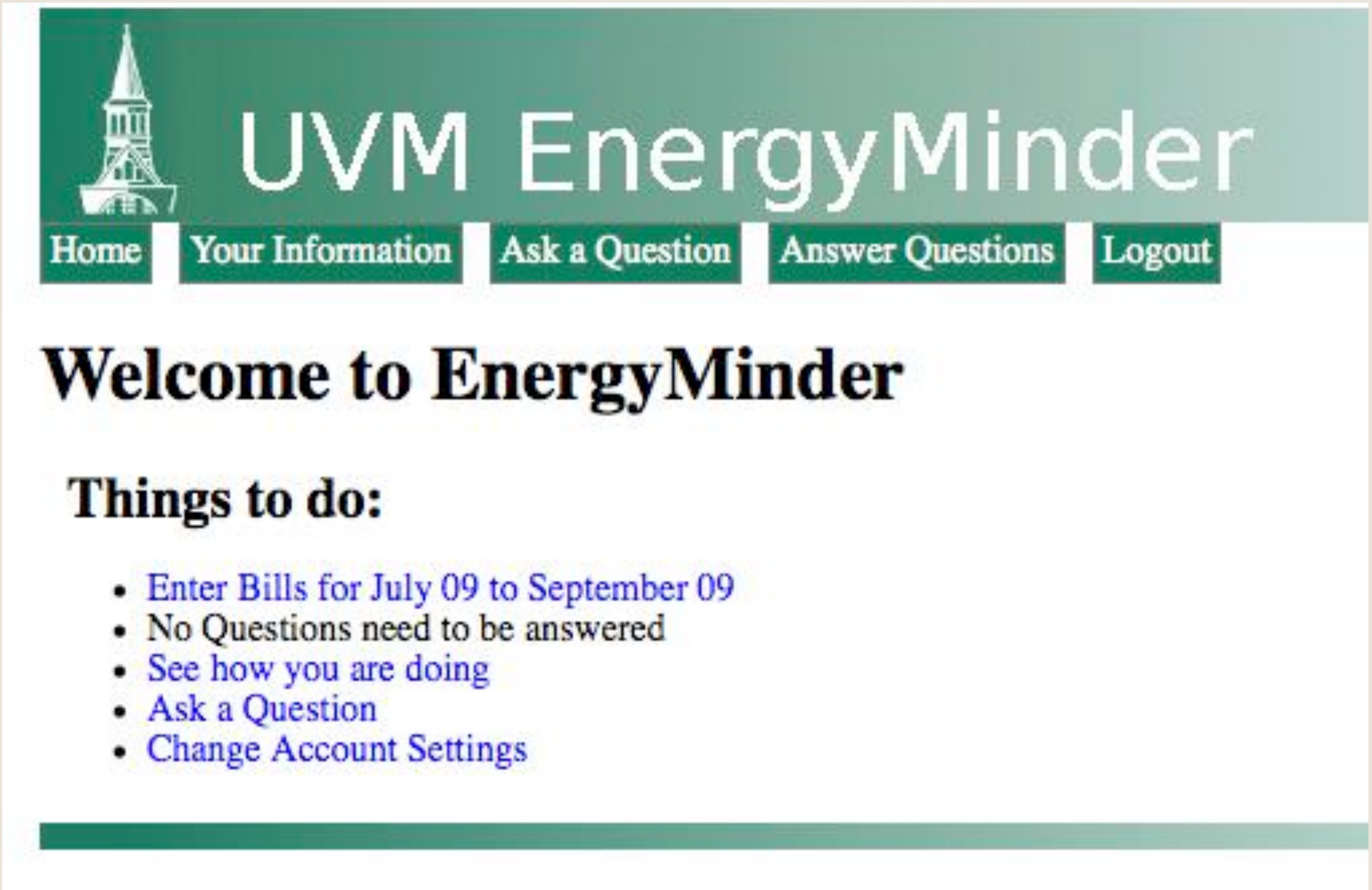
Top down (Microsoft Hohm)

Participants provide data. Microsoft builds an efficiency model and tells users about their efficiency, how to be more efficient.

Bottom up (EnergyMinder)

Users ask questions of one another. A (regression) model “emerges,” and is presented to participants.

# E-Minder


UVM EnergyMinder
Home
Your Information
Ask a Question
Answer Questions
Logout
Welcome to EnergyMinder
Things to do:
Enter Bills for July 09 to September 09
No Questions need to be answered
See how you are doing
Ask a Question
Change Account Settings

# Results from preliminary trial (N~30)

- Users interested to ask/answer questions.
- Very little interest in retrieving billing data
  - Next trial will link to AMI

The significant factors are as follows:

| Factor Number | Description |
|---|---|
| 1 | Number of adults living in the house |
| 2 | Own an electric dryer |
| 3 | Own an electric water heater |

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