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

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2010 DOE Peer Review Meeting
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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

<table>
<thead>
<tr>
<th>Date</th>
<th>Location</th>
<th>MW</th>
<th>Customers</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>14-Aug-2003</td>
<td>Eastern US, Canada</td>
<td>57,669</td>
<td>15,330,850</td>
<td>Cascading failure</td>
</tr>
<tr>
<td>18-Apr-1988</td>
<td>Eastern US, Canada</td>
<td>18,500</td>
<td>2,800,000</td>
<td>Ice storm</td>
</tr>
<tr>
<td>10-Aug-1996</td>
<td>Western US</td>
<td>12,500</td>
<td>7,500,000</td>
<td>Cascading failure</td>
</tr>
<tr>
<td>18-Sep-2003</td>
<td>Southeastern US</td>
<td>10,067</td>
<td>2,590,000</td>
<td>Hurricane Isabel</td>
</tr>
<tr>
<td>23-Oct-2005</td>
<td>Southeastern US</td>
<td>10,000</td>
<td>3,200,000</td>
<td>Hurricane Wilma</td>
</tr>
<tr>
<td>27-Sep-1985</td>
<td>Southeastern US</td>
<td>9,956</td>
<td>2,991,139</td>
<td>Hurricane Gloria</td>
</tr>
<tr>
<td>29-Aug-2005</td>
<td>Southeastern US</td>
<td>9,652</td>
<td>1,091,057</td>
<td>Hurricane Katrina</td>
</tr>
<tr>
<td>29-Feb-1984</td>
<td>Western US</td>
<td>7,901</td>
<td>3,159,559</td>
<td>Cascading failure</td>
</tr>
<tr>
<td>4-Dec-2002</td>
<td>Southeastern US</td>
<td>7,200</td>
<td>1,140,000</td>
<td>Ice/wind/rain storm</td>
</tr>
<tr>
<td>10-Oct-1993</td>
<td>Western US</td>
<td>7,130</td>
<td>2,142,107</td>
<td>Transmission failure, cascade</td>
</tr>
<tr>
<td>14-Dec-2002</td>
<td>Western US</td>
<td>6,990</td>
<td>2,100,000</td>
<td>Winter storm</td>
</tr>
<tr>
<td>4-Sep-2004</td>
<td>Southeastern US</td>
<td>6,018</td>
<td>1,807,881</td>
<td>Hurricane Frances</td>
</tr>
<tr>
<td>25-Sep-2004</td>
<td>Southeastern US</td>
<td>6,000</td>
<td>1,700,000</td>
<td>Hurricane Jeanne</td>
</tr>
<tr>
<td>14-Sep-1999</td>
<td>Eastern US</td>
<td>5,525</td>
<td>1,660,000</td>
<td>Hurricane Floyd</td>
</tr>
</tbody>
</table>
Blackouts by time of day

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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Catastrophic cascade of failures in interdependent networks

Sergey V. Buldyrev, Roni Parshani, Gerald Paul, H. Eugene Stanley & Shlomo Havlin

The New York Times, 15 April 2010

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

LETTERS

Catastrophic cascade of failures in interdependent networks

Sergey V. Buldyrev, Roni Parshani, Gerald Paul, H. Eugene Stanley & Shlomo Havlin

fety Science, 2009

Hines, 3 Nov. 2010
But cascades in power grids are different...

By Kirchhoff’s laws

Safety science model
Results for 40 areas in the Eastern Interconnect

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

Random Failure Statistics:
- \( \mu = 14.04 \)
- \( \sigma = 19.45 \)
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...

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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As systems approach “collapse” they show 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?
1-machine, infinite bus model results

Frequency components of the phase angle at bus 1

Autocorrelation

Time before critical transition (minutes)

Hines, 3 Nov. 2010
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

Time before critical transition (minutes)

Autocorrelation

Filtered freq.

Freq.

0 0.16 0.38 0.67 0.76 -0.45 -0.54 0.03

-0.63 -0.34 -0.11 0.38 0.38 0.76 0.76

Hines, 3 Nov. 2010
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.

Cascading failure costs as decentralized controllers work with more information

Increasing quantity of cooperation among agents →

Hines, 3 Nov. 2010
Prelim. work plan. Currently in Q1 of 8.

- **Project management**
  - Task 0.1. Complete project mgmt. plan
  - Task 0.5. Collect industry data
  - Task 0.6. Complete final report
  - Task 1. Cascading failure risk research

- **Sampling methods**
  - Task 1.2. Dynamic Simulation
    - Task 1.2.1. Two-bus modeling
      - Task 1.2.2. Cascading failure model
  - Task 1.3. Decentralized Control

- **Simple grid modeling**
  - Task 1.2.1.1. Basic model
  - Task 1.2.1.5. Model governor

- **Cascading failure modeling**
  - Task 1.2.2.4. Integrate model & sampling
  - Task 1.2.3. Critical Slowing Down
    - Task 1.2.3.1. Complete preliminary analysis

- **Critical Slowing Down**
  - Task 1.3. Decentralized Control

- **Control Methods**
  - Task 1.3.4. Test impact on C.F. risk

- **Development & Testing**
  - Task 2. Dev. & Test System Models
    - Task 2.1. Apply cascade model to regional syste

- **Conference & Commercialization plan**
  - Task 5.2. Conference

Hines, 3 Nov. 2010
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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