New ways to measure and mitigate risk in complex power networks

Paul Hines
University of Washington
October 2015

Credits
Funding: National Science Foundation, MITRE, Dept. of Energy, DTRA
Errors and omissions: Paul Hines
Electricity is amazing. With it we can move energy made from almost anything, almost anywhere, at almost the speed of light. But…
US Northeast and Canada
August 14, 2003
50 million people
California, Arizona, Mexico
September 8, 2011
5 million people
Northern India
July 30, 2012: 350 million people
July 31, 2012: 700 million people
Officials said it would take at least 12 hours to repair the system and restore power to the capital Dhaka [AP]
Washington DC, April 7, 2015
And the Internet is great, but it also has vulnerabilities
Several questions

• Can we identify useful statistical signs of risk in high-sample rate (PMU) grid data?

• Can we use models of cascading failure to find actionable measures of blackout risk?

• Will cyber-physical interdependence make the grid more or less vulnerable to attacks and failures?
Can we identify useful statistical signs of risk in high-sample rate (PMU) grid data?

Paul Hines
University of Washington
October 2015

Situational Awareness

U.S.-Canada Power System Outage Task Force

Final Report on the August 14, 2003 Blackout in the United States and Canada:
Causes and Recommendations

Arizona-Southern California Outages on September 8, 2011
Causes and Recommendations

Inadequate Situational Awareness
The 2003 Blackout Report stated, “A principal cause of the August 14 blackout was a lack of situational awareness, which was in turn the result of inadequate reliability tools and backup capabilities.” Similarly, the instant inquiry determined that inadequate real-time situational awareness contributed to the cascading outages. In

\[ v(t) = 120\sqrt{2}\cos(2\pi 60t - \pi/4) \]
Early-warning signals for critical transitions

Marten Scheffer\textsuperscript{1}, Jordi Bascompte\textsuperscript{2}, William A. Brock\textsuperscript{3}, Victor Brovkin\textsuperscript{5}, Stephen R. Carpenter\textsuperscript{4}, Vasilis Dakos\textsuperscript{1}, Hermann Held\textsuperscript{6}, Egbert H. van Nes\textsuperscript{1}, Max Rietkerk\textsuperscript{7} & George Sugihara\textsuperscript{8}
Sure enough... statistics are (sometimes) useful indicators.
"Our results demonstrate that claims on the universality of early warning signals are not correct, and that catastrophic collapses can occur without prior warning. In order to correctly predict a collapse and determine whether early warning signals precede the collapse, detailed knowledge of the mathematical structure of the approaching bifurcation is necessary."
How can we find the useful* statistical early warning signs?

*Useful: A sign that shows up early enough that we might actually be able to do something about it, even if there is measurement noise
First let’s define our SDEs

\[ \dot{x} = f(x, y) \]  
\[ 0 = g(x, y, u) \]

Differential equations. (swing eqs., governors, exciters, etc.)

Algebraic equations

r.v. for stochastic load perturbations

\[ \dot{u} = -Eu + C\xi \]

Loads modeled as Ornstein–Uhlenbeck process

Ind. Gaussian r.v.s, 1% std. dev.

Encodes corr. time of load fluctuations
Choose an operating point, and linearize around that point

\[
\Delta y = \begin{bmatrix} -g_y^{-1}g_x & -g_y^{-1}g_u \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta u \end{bmatrix}
\]

\[
\begin{bmatrix} \Delta \dot{x} \\ \Delta \dot{u} \end{bmatrix} = \begin{bmatrix} f_x & f_y g_y^{-1} g_x & -f_y g_y^{-1} g_u \\ 0 & -E \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta u \end{bmatrix} + \begin{bmatrix} 0 \\ C \end{bmatrix} \xi
\]

Jacobian matrix: \( df/dx \)

Which gives us a system of SDEs in Ornstein–Uhlenbeck form:

\[
\dot{z} = Az + B\xi
\]
Now solve the SDEs

I’d like to tell you that we came up with new, elegant mathematics from scratch. In reality…

\[ A\sigma_{\tilde{z}} + \sigma_{\tilde{z}} A^T = -BB^T \]  \hspace{1cm} \text{Lyapunov eq.}

\[ \mathbb{E} \left[ \tilde{z} (t) \tilde{z}^T (s) \right] = \exp \left[ -A|t - s| \right] \sigma_{\tilde{z}} \]

And then reverse the Kron reduction to compute the variance and autocorrelation of voltage and current magnitudes.
Check to make sure that the analytical and numerical line up
And add measurement noise

Which we can subsequently filter to largely regain our original signal, with the interesting side-effect that some of the variance now appears as autocorrelation.
Now, sometimes we can see the difference between high and low load; sometimes we can’t.

How do we measure “detectability” to distinguish useful statistical signals from non-useful ones?
Define a formal measure of “detectability”

detectability:

\[ q_{95/80} = \left[ \text{Probability to mistake 80\%b for 95\%b} \right] + \left[ \text{Probability to mistake 95\%b for 80\%b} \right] \]

\[ = \int_{-\infty}^{\infty} f_X(80\%) \, dx + \int_{-\infty}^{a} f_X(95\%) \, dx \]
Which statistics provide useful (detectable) early warning?
Variance of voltages
Why is variance in voltage useful?
Autocorrelation of currents

Not useful

Detectability

Useful

0.3

0.2

0.1

0
In summary

• Statistics like **Autocorrelation** and **variance** can be useful indicators of proximity to instability, just as they are in many other complex systems.

• Particularly useful indicators:
  
  • Variances of **voltages near loads**
  
  • Autocorrelations of **currents near generators**

• Fluctuations can frequently **identify the locations** of emerging problems in the network
Can we use models of cascading failure to find actionable measures of blackout risk?

Paul D. H. Hines
University of Vermont

[2] Paul Hines, Ian Dobson and Pooya Rezaei, Cascading Power Outages Propagate Locally in an Influence Graph that is not the Actual Grid Topology, in review.
Because of complex interactions among nature, components and people we get power laws in blackout sizes.

Size of the 100-year blackout: 186 GW

We need new tools for understanding risk.
Let us say we have a power grid model, and we want to measure cascading failure risk.
But all real blackouts have come from unexpected combinations of outages (including cyber-human ones)

• We try to operate power grids with n-1 security, but
  • The probability of a single line outage is $\sim 10^{-4}$
  • Large systems have $\sim 10^4$ lines; $\sim 1$ failure/hour
  • Even if outages are uncorrelated (false) N-2 events are $\sim 1x/\text{year}$

• ~1970s, Monte Carlo methods were developed for probabilistic reliability analysis

• But, Monte Carlo is super-slow:
  • combinatorial number of possible triggering combinations, each with very small probabilities
  • event costs (blackout sizes) span 3-4 orders of magnitude
But most combinations are benign, only a few are “malignant”

Evidence
There are 4.2 million n-2 combinations in the “Polish” grid. Only 300-400 of these cause large blackouts.

Can we somehow quickly find the malignant combinations, and then use their probabilities to estimate risk?
The Random Chemistry algorithm

\[ O(\log_2 N) \]

Number of unique molecules/tube:

- 40 outages
- 20 outages
- 10 outages
- 5 outages
- 2-3 outages
Estimating risk with RC

\[ \hat{R}_{RC}(x) = \sum_{k=2}^{k_{\text{max}}} \sum_{m \in \Omega_{RC,k}} \hat{M}_k \Pr(m) S(m, x) \]

The estimated number of malignancies of size \( k \)

The number of malignancies of size \( k \) found by RC

Blackout sizes

Probability of (multiple) contingency
Comparing RC to Monte Carlo

![Graph comparing RC to Monte Carlo simulations. The graph shows the risk (expected blackout size in kW) over the number of calls to the cascading failure simulator. The x-axis represents the number of calls to the simulator, scaled by $10^7$. The y-axis represents risk in kW. The graph includes lines for RC and MC simulations with different thresholds for the size of cascading failures ($S \geq 5\%$ and $S \geq 40\%$).]
Can we use these results to reduce risk?
Finiding critical components

Some triggering events are way, way more important than the average
An experiment

- Take the 3 lines that contribute most to blackout risk
- Re-dispatch generators to leave more margin between the flow on these lines and the limit (cut the limit in half)
- Fuel costs increase by 1.6%
- Large (S>5%) blackout risk decreases by 61%
- Very large (S>40%) blackout risk decreases by 83%
And now we have reams of data from cascading failure simulations

- Organize cascading failure data
- Carefully count the number of times that outages result in other outages
- Translate these into an “influence graph.”
- Study the graph to gain insight
Upgrading

- Find the 10 lines that contribute most to risk, inside of cascades.
- Beautiful mathematics tragically omitted.
- Upgrade (protection systems, tree trimming) so that they are 1/2 as likely to trip on overload.
- Recompute blackout risk
Will cyber-physical interdependence make the grid more or less vulnerable to attacks and failures?

Paul Hines
University of Washington
October 2015

Perhaps coupling will cause risk to increase?

Catastrophic cascade of failures in interdependent networks

Sergey V. Buldyrev¹,², Roni Parshani³, Gerald Paul², H. Eugene Stanley² & Shlomo Havlin³
Perhaps coupling will cause risk to go down, and then up?
Or maybe coupling is useful?

Avoiding catastrophic failure in correlated networks of networks

Saulo D. S. Reis¹,², Yanqing Hu¹, Andrés Babino³, José S. Andrade Jr², Santiago Canals⁴, Mariano Sigman³,⁵ and Hernán A. Makse¹,²,³*
However the mechanics of cascading in the grid differ from contagion models.

Conventional models of contagion

Cascading in power grids
Non locality in a real cascade
Let’s use *reasonably* accurate grid models, and then couple them to a very simple comm. model.

*Model is very similar to work by Parandehgheibi, Modiano & Hay*
(roughly) Modeling human & cyber operators

**Measure** line flows and statuses

**Control** generators and loads with

minimize $-1^\top \Delta P_D + \lambda^\top f_{over}$ < Load shedding and overloads

subject to $\Delta f = X_b^{-1} A^\top \Delta \theta$ < Changes in flows*

$-f_{max} - f_{over} \leq f_0 + \Delta f \leq f_{max} + f_{over}$ < Limits on flows*

$B \Delta \theta = A_G \Delta P_G - A_D \Delta P_D$ < PF constraint

$\mathcal{P}_{G,\min} \leq P_{G,0} + \Delta P_G \leq \mathcal{P}_{G,\max}$ < Limits*

$-P_{D,0} \leq \Delta P_D \leq 0$

$\Delta \theta_i = 0$, $\forall i \in \Omega_{ref}$

$f_{over} \geq 0$ *Only the comm-connected subset
How does robustness change with the level of coupling? *Comparison result*

Coupled topological model with Polish grid coupled to Comm. network (10% rewired copy of grid)
How does robustness change with the level of coupling? *Power grid result*

![Graph showing robustness vs. amount of coupling for different power grid models.](image)
Optimal coupling

\[ \Pr(G_C > 0.5n) \]

Graph showing the probability \( \Pr(G_C > 0.5n) \) as a function of \( q \) for different values of \( f \):
- \( f = 0.19 \)
- \( f = 0.20 \)
- \( f = 0.21 \)
- \( f = 0.22 \)
- \( f = 0.23 \)
- \( f = 0.24 \)
- \( f = 0.25 \)
- \( f = 0.26 \)
Optimal coupling
Implications

- Overly simple models can be misleading.

- So long as the communication system provides benefits, and the probability of grid -> comm and comm -> grid propagation is low, increased coupling can be good.

- However, if we design the “Smart Grid” poorly (poor battery backup systems, inability to “carry on” if the sister network fails), coupling can be disastrous.
What is Smart Grid?

The smart grid uses modern information technology to make electric power systems work better – cleaner, cheaper, and more reliably. The smart grid is designed to allow greater usage of renewable resources, such as solar or wind, which are restricted in traditional grids by high variability and unpredictability of these sources. Smart grid operation requires active participation of power consumers, in promoting energy efficiency, in timing energy usage to help maintain a uniform electric load, and in operation of distributed small-scale solar and wind power generation units. Proactive government policies are needed to support and encourage these changes, and improved public education is needed to help the public appreciate the benefits and weigh the risks of the smart grid.
New ways to measure and mitigate risk in complex power networks

Paul Hines
University of Washington
October 2015

Credits
Funding: National Science Foundation, MITRE, Dept. of Energy, DTRA
Errors and omissions: Paul Hines