

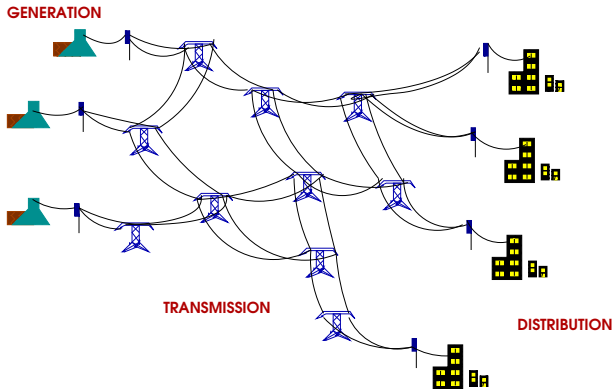
# Power grid vulnerability analysis

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Dimacs 2010

## Background: a power grid is three systems



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- Power grids can exhibit non-monotone behavior as a result of control or adversarial actions.
- Power grids can cascade.

## AC power flows – polar coordinates

→ Voltage at a node (“bus”)  $k$  is of the form  $U_k e^{j\theta_k}$ , where  $j = \sqrt{-1}$

→ Power flowing on edge (“line”)  $\{k, m\}$  equals  $p_{km} + jq_{km}$ , where

$$p_{km} = U_k^2 g_{km} - U_k U_m g_{km} \cos \theta_{km} - U_k U_m b_{km} \sin \theta_{km}$$

$$q_{km} = -U_k^2 (b_{km} + b_{km}^{sh}) + U_k U_m b_{km} \cos \theta_{km} - U_k U_m g_{km} \sin \theta_{km}$$

Here,  $\theta_{km} \doteq \theta_k - \theta_m$

$g_{km}$ ,  $b_{km}$ ,  $b_{km}^{sh}$  are known *parameters* (series conductance, series reactance, shunt susceptance)



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and, ideally, meet thermal constraints (flow limits) on the power lines

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- Do we have **fast** and **reliable** algorithm for the power flow problem?
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- What if all solutions are “bad”?



## Solution methodologies

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- **New result:** Low et al (2010). Some (many?) optimal power flow problems can be solved using semidefinite programming.

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- $x_{ij} f_{ij} - \theta_i + \theta_j = 0$  for all  $(i, j)$ . ( $x_{ij}$  = “reactance”)

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**Lemma:** Given a choice for  $\mathbf{b}$  with  $\sum_i \mathbf{b}_i = \mathbf{0}$  (a requirement), the system has a **unique** (in  $\mathbf{f}$ ) solution.



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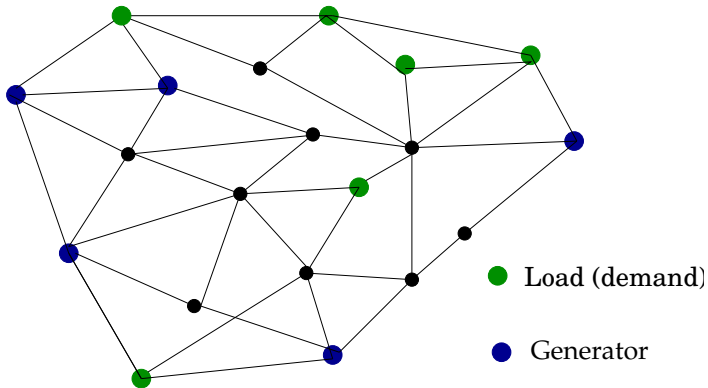
Cause 1 was “inadequate system understanding” – stated 20 times

Cause 2 was “inadequate situational awareness” – stated 14 times

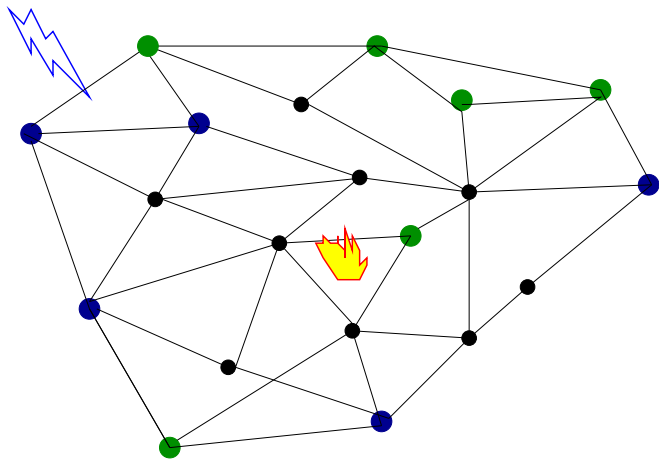
Cause 3 was “inadequate tree trimming” – stated 4 times

Cause 4 was “inadequate RC diagnostic support” – stated 5 times

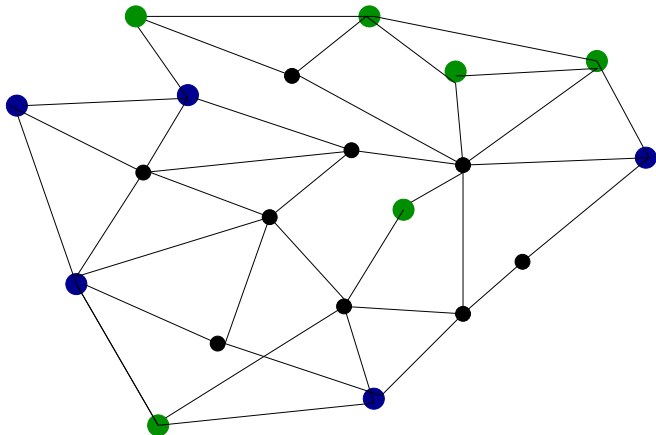
## Cascades



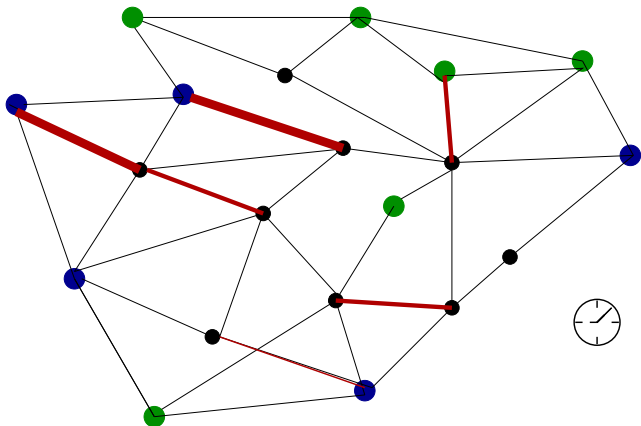
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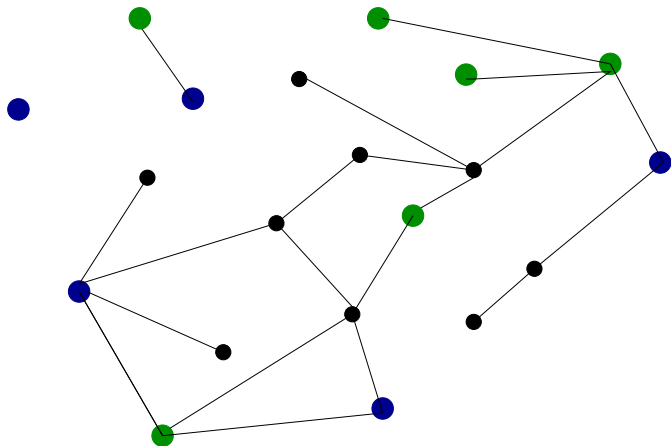


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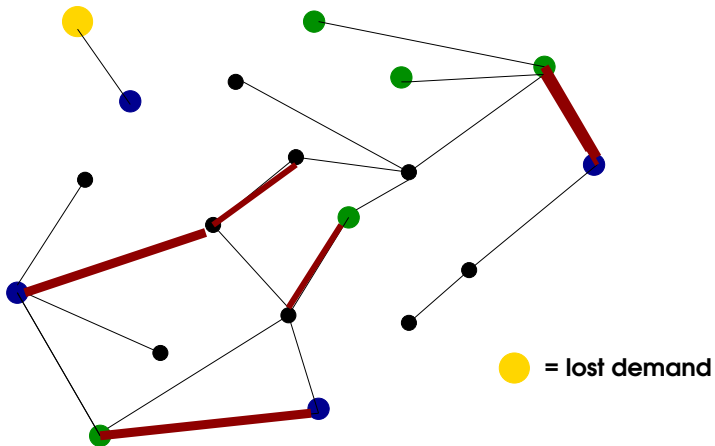




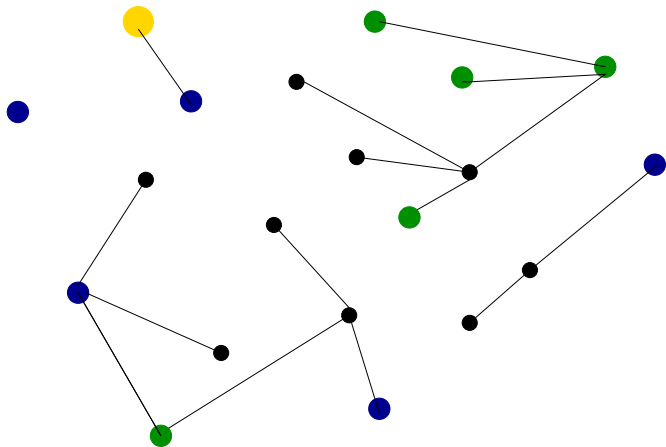
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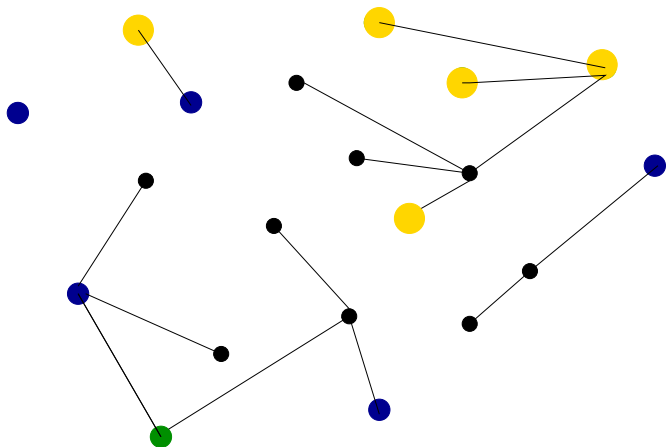
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## Formal cascade model (Dobson et al)

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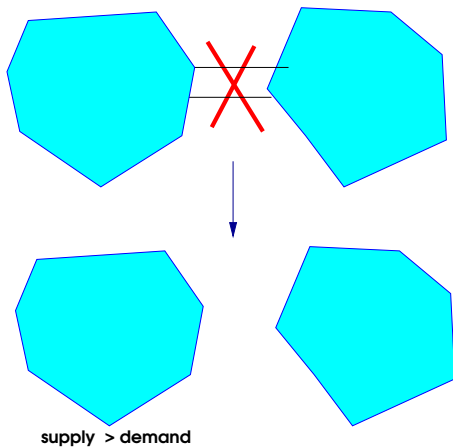
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if  $(1 - \gamma)u_e \leq \tilde{f}_e^r \leq u_e$  then **e** fails with probability 1/2

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→ If no more faults occur or too much demand has been lost, STOP



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At round  $R$ , reduce demands so as to remove any line overloads.

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- $f_j^r$  = flow on arc  $j$  at round  $r$
- $y_j^r = 1$ , if arc  $j$  fails in round  $r$ ,  $0$  otherwise
- $d_i^r$  = demand at node  $i$  in round  $r$
- and many other variables

$$\max \sum_{i \in \mathcal{D}} d_i^R$$

Subject to:

$$\sum_{j \in \delta^+(i)} f_j^r - \sum_{j \in \delta^-(i)} f_j^r = \begin{cases} s_i^r & i \in \mathcal{G} \\ -d_i^r & i \in \mathcal{D} \\ 0 & \text{otherwise} \end{cases} \quad \forall 1 \leq r \leq R \quad (1)$$

$$f_j^r = \pi_j^r - \nu_j^r \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R \quad (2)$$

$$\pi_j^r \leq \tilde{D} p_j^r, \quad \nu_j^r \leq \tilde{D} n_j^r, \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R \quad (3)$$

$$p_j^r + n_j^r = 1 - \sum_{h=1}^{r-1} y_j^h, \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R \quad (4)$$

$$\pi_j^r + \nu_j^r - u_j \leq \tilde{D} y_j^r \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R \quad (5)$$

$$\pi_j^r + \nu_j^r \geq u_j y_j^r \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R-1 \quad (6)$$

$$\pi_j^R + \nu_j^R \leq u_j \quad \forall j \in \mathcal{A} \quad (7)$$

$$|\phi_i^r - \phi_j^r - x_j f_j^r| \leq M_j \sum_{h=1}^{r-1} y_j^h \quad \forall j \in \mathcal{A} \quad (8)$$

$$0 \leq s_i^r \leq \tilde{s}_i \quad \forall i \in \mathcal{G}, \quad 0 \leq d_i^r \leq \tilde{d}_i \quad \forall i \in \mathcal{D}, \quad (9)$$

$$p_j^r, n_j^r, y_j^r = 0 \text{ or } 1, \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R \quad (10)$$

$$0 \leq \pi_j^r, 0 \leq \nu_j^r, \quad \forall j \in \mathcal{A} \text{ and } 1 \leq r \leq R. \quad (11)$$

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## Adaptive affine controls

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The goal: pick control to maximize demand being served at the end of round  $R$ .

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Insist that for each  $r$ ,  $(\mathbf{c}_v^r, \mathbf{b}_v^r, \mathbf{s}_v^r) = (\mathbf{c}^r, \mathbf{b}^r, \mathbf{s}^r)$  for every  $\mathbf{v}$

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**Then, equivalent problem:**

- In round  $r$ , let  $\alpha^r(\mathbf{K}) \leq 1$  be chosen for each *component* of the network in round  $r$
- If node  $\mathbf{v} \in$  component  $\mathbf{K}$ , then its demand is scaled by  $\alpha^r(\mathbf{K})$



## Notation:

- $\hat{\beta}$  = supply/demand vector at time 0
- $\hat{f}$  = corresponding power flows at time 0
- $\Theta^R(t, \beta) : \mathcal{R}_+ \rightarrow \mathcal{R}_+$  = total demand, at the end of round  $R$ , using optimal control, if the supply/demand vector is  $t\beta$

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- Robust/stochastic version?

## General case: simulation-based optimization

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$\Theta(\tilde{\mathbf{u}})$  is obtained through a simulation

## Derivative-free optimization

Conn, Scheinberg, Vicente, others

Rough description:

- *Sample* a number of control vectors  $\tilde{\mathbf{u}}$
- Use the sample points to construct a convex approximation to  $\tilde{\Theta}$
- Optimize this approximation; this yields a new sample point

Scalability to large dimensionality?

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Given a control vector  $\tilde{u}$

- 1 Estimate the “gradient”  $\mathbf{g} = \nabla \tilde{\Theta}(\tilde{u})$  through finite differences.

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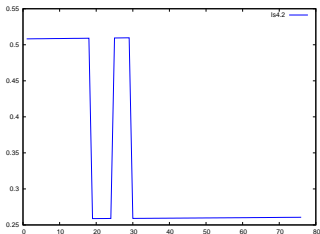
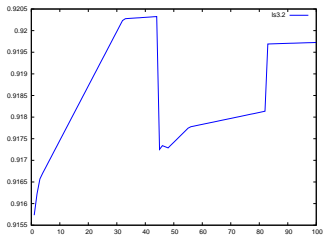
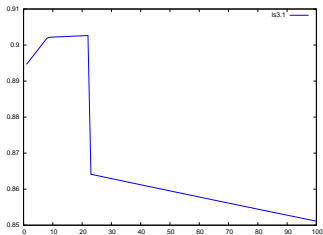
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→ Easily parallelizable



## Line searches



## Current parallel implementation: boss-nerd

- Boss carries out search algorithm
- Nerds simulate cascades with given control
- Communication using Unix sockets

## Scaling

**Example:** 10000 nodes, 19309 lines

5 gradient steps

8-core i7 CPUs (3 machines total)

cores	wall-clock sec
2	94379
4	47592
8	28136
16	14618
24	9918

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  - 3 At least three rounds of cascade after initial event

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Perform segmented gradient search starting from  $(\mathbf{c}^*, \mathbf{b}^*, \mathbf{s}^*)$ .

Look for a control with  $(\mathbf{c}_v^r, \mathbf{b}_v^r, \mathbf{s}_v^r) = \text{constant}$  for each given  $r$  and all  $v$  in a common  $\Sigma_j$ .

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- (3) Perform full gradient search starting from the output in (2).

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- **K** random lines taken out
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<b>K</b>	yield, (%) <b>no control</b>	yield, (%) <b>control</b>	wallclock (sec)
1	90.04	95.03	134
2	12.54	50.13	87
5	32.94	81.05	107
10	2.02	36.97	97
20	1.64	27.84	159
50	0.83	16.96	209

## Conjectures

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(Answer: both wrong)

## Details: cascade with 50 (highly loaded) random lines taken out

- No control  $\Rightarrow$  yield = **0%**
- Optimal round 1 only constant control  $\Rightarrow$  yield = **38%**
- Optimal scaling control  $\Rightarrow$  yield = **45%**
- Plus segmented gradient search  $\Rightarrow$  yield = **50%**



## Load distribution at time zero

(load of arc  $j = \frac{|f_j|}{u_j}$ )

load	no. of arcs
1505	1
58	1
48	2
32	1
22	2
19	1
11	1
7	2
6	2
5	4
4	6
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**Optimal** round 1 scale = **0.51**, so **44** faults

## Out-of-sample testing: use stochastic faults

at round  $r$ ,

$e$  fails if  $u_e < \tilde{f}_e^r$ ,

$e$  does not fail if  $(1 - \gamma)u_e > \tilde{f}_e^r$ , ( $\gamma = \text{tolerance}$ )

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What is the impact of  $\gamma$ ?

$\gamma = 0.03, 0.10, 0.20,$

10000 runs

