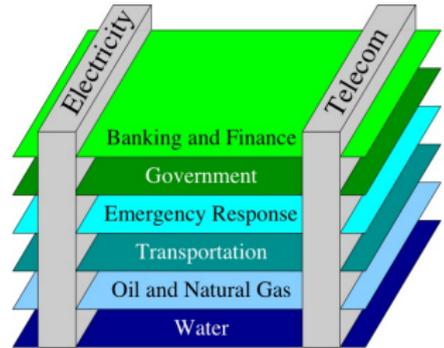
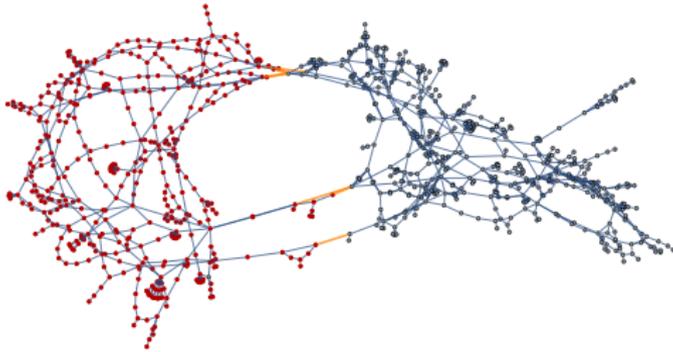


# Suppressing cascades by tuning interdependence between networks



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*Complexity Sciences Center*

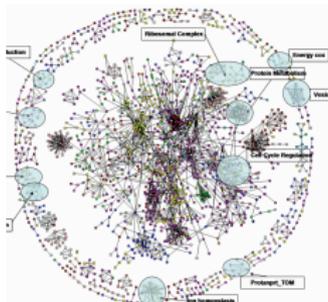
*External Professor, **Santa Fe Institute***



## Networks:



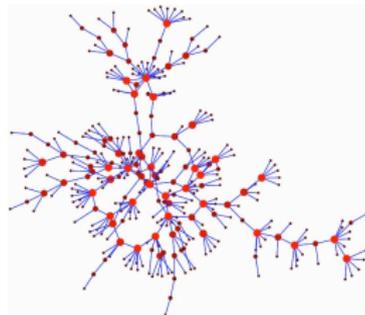
**Transportation  
Networks/  
Power grid**  
(distribution/  
collection networks)



### **Biological networks**

- protein interaction
- genetic regulation
- drug design

### **Computer networks**

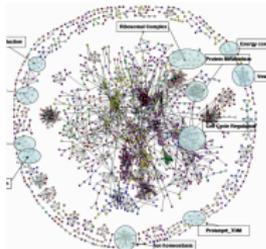


### **Social networks**

- Immunology
- Information
- Commerce

# In reality, a collection of interacting , dynamic networks

## Networks:



### Biological networks

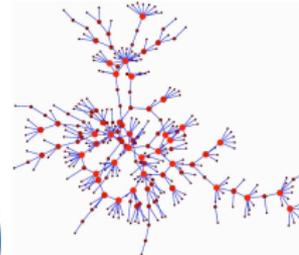
- protein interaction
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### Transportation Networks/ Power grid

(distribution/  
collection networks)

### Computer networks



### Social networks

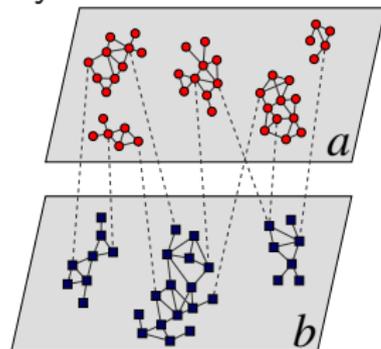
- Immunology
- Information
- Commerce

- E-commerce → WWW → Internet → Power grid → River networks.
- Biological virus → Social contact network → Transportation nets → Communication nets → Power grid → River networks.

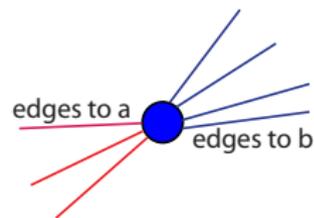
# Configuration model for interacting networks (NetSci 2009)

(E. Leicht and R. D'Souza, arXiv:0907.0894)

System of two networks



Connectivity for an individual node



- Degree distribution for nodes in network  $a$ :  $p_{k_a k_b}^a$
- For the the system:  $\{p_{k_a k_b}^a, p_{k_a k_b}^b\}$
- Generating functions to calculate properties of the ensemble of such networks.

# Dynamical processes on interdependent networks

## Motivation: interconnected power grids

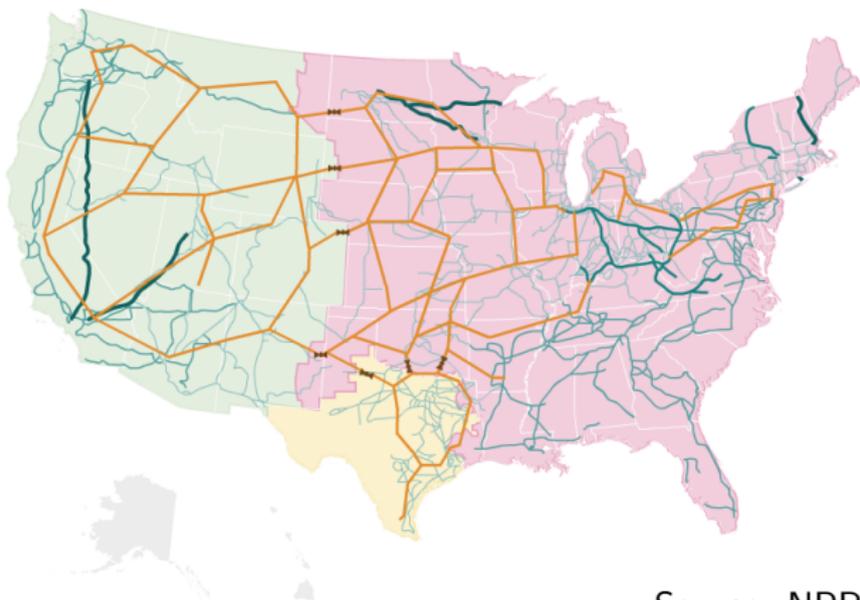
C. Brummitt, R. M. D'Souza and E. A. Leicht *PNAS* 109 (12), 2012.

Power grid: a collection of **interdependent** grids.  
(Interconnections built originally for emergencies.)

Blackouts **cascade** from one grid to another (in a non-local manner).

Building more **interconnections**  
(Fig: planned wind transmission).

**Increasingly distributed**



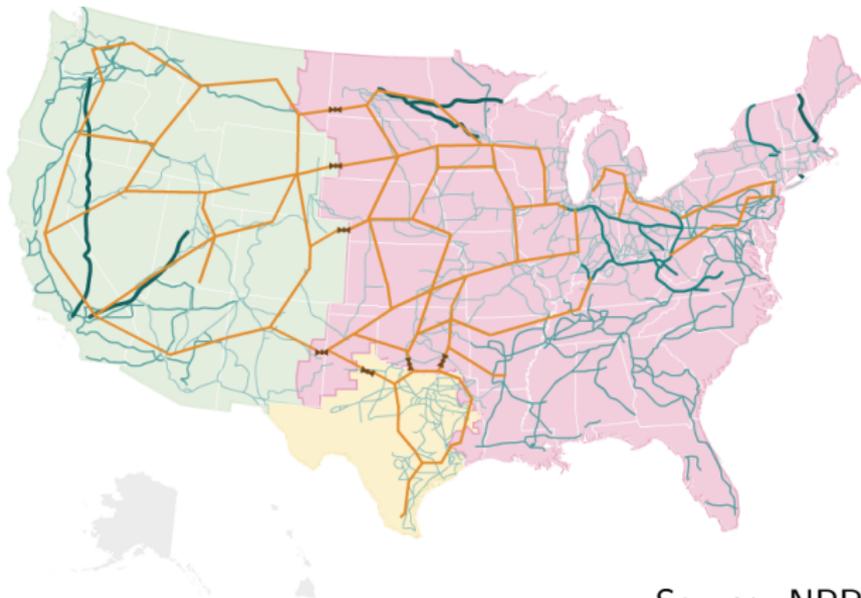
Source: NPR

# Motivation cont.: interconnected power grids

What is the effect of **interdependence** on **cascades**?

It is thought power grids organize to a **“critical” state**

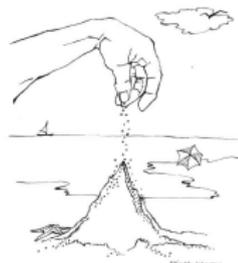
- power law distribution of black out sizes
- maximize profits while fearing large cascades



Source: NPR

# Sandpile models: “Self-organized criticality”

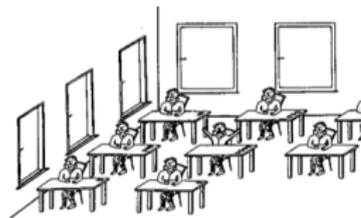
- Drop grains of **sand** (“load”) randomly on nodes.
- Each node has a **threshold** for sand.
- **Load** > **threshold**  $\rightsquigarrow$  node **topples** = sheds sand to neighbors.
- These neighbors may **topple**. And their neighbors. And so on.
- **Cascades** of **load/stress** on a system.



The **classic Bak-Tang-Wiesenfeld** sandpile model:

(Neuronal avalanches, banking cascades, earthquakes, landslides, forest fires, blackouts...)

- Finite square **lattice** in  $\mathbb{Z}^2$
- Thresholds 4
- **Open boundaries** prevent inundation



**Avalanche size follows power law distribution**  $P(s) \sim s^{-3/2}$

# Sandpile model on arbitrary networks

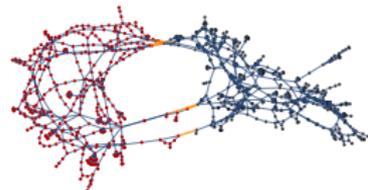
Sandpile model on **arbitrary networks**:

- Thresholds = **degrees**  
(shed one grain per neighbor)
- Boundaries: shedded sand are **deleted**  
independently with probability  $f$  ( $\approx 10/N$ )
- **Mean-field behavior** ( $P(s) \propto s^{-3/2}$ ) robust.  
(Goh et al. PRL 03, Phys. A 2004/2005, PRE 2005. PLRGs with  $2 < \gamma < 3$  not mean-field.)



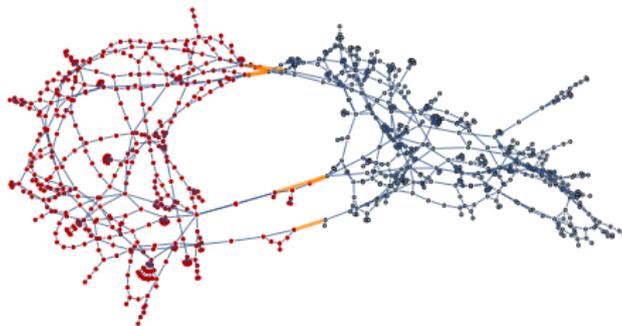
Sandpiles on **interacting networks**:

- **Sparse connections** between random graphs.
- Configuration model with **multi-type** degree distribution.



# Sparsely coupled networks

Two-type network:  $a$  and  $b$ .



Degree distributions:  $p_a(k_a, k_b)$ ,  $p_b(k_a, k_b)$

$p_a(k_a, k_b)$  = fraction of  $a$ -nodes with  $k_a, k_b$  neighbors in  $a, b$ .

**Configuration model:** create degree sequences until valid (even total intra-degree, same number of **inter-edge stubs**), then connect edge stubs at random.

# Measures of avalanche size

- **Topplings:**

Drop a grain of sand. How many nodes eventually topple?

**Avalanche size** distributions:  $s_a(t_a, t_b)$ ,  $s_b(t_a, t_b)$

e.g.,  $s_a(t_a, t_b)$  = chance an avalanche begun in  $a$  topples  
 $t_a$  many  $a$ -nodes,  $t_b$  many  $b$ -nodes.

To study this, we need a more basic distribution...

- **Sheddings:** Drop a grain of sand. How many grains are eventually shed from one network to another?

**Shedding size** distributions:  $\rho_{od}(r_{aa}, r_{ab}, r_{ba}, r_{bb})$

= chance a grain shed from network  $o$  to  $d$  eventually causes  
 $r_{aa}, r_{ab}, r_{ba}, r_{bb}$  many grains to be shed from  $a \rightarrow a, a \rightarrow b, b \rightarrow a, b \rightarrow b$

\*Approximate shedding and toppling as multi-type branching processes. (Will explain in detail.)

# Overview of the calculations

From **degree** distribution to **avalanche size** distribution:

**Input:** degree distributions  $p_a(k_a, k_b), p_b(k_a, k_b)$

↓ *compute*

**shedding** branching distributions  $q_{aa}, q_{ab}, q_{ba}, q_{bb}$

↓ *compute*

**toppling** branching distributions  $u_a, u_b$

↓ *plug in*

**toppling** branching generating functions  $\mathcal{U}_a, \mathcal{U}_b$

↓ *plug in*

equations for **avalanche size** generating functions  $\mathcal{S}_a, \mathcal{S}_b$

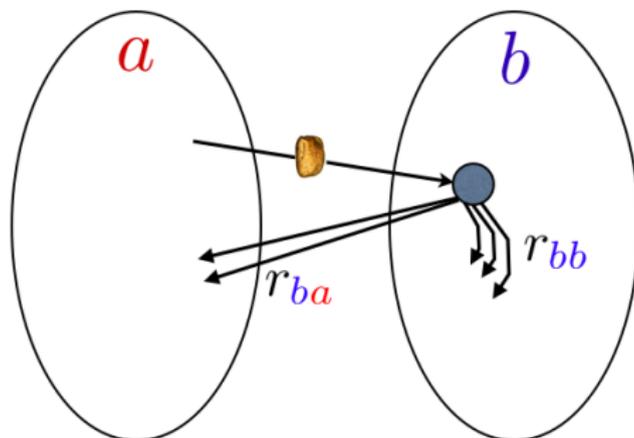
↓ *solve numerically, asymptotically*

**Output:** **avalanche size** distributions  $s_a, s_b$

# Shedding branch distribution, $q_{od}$

**Example:**

$q_{ab}(r_{ba}, r_{bb}) :=$  the branch (children) distribution for an  $ab$ -shedding.



Probability a single grain shed from  $a$  to  $b$  results in  $r_{ba}$   $a$ -sheddings and  $r_{bb}$   $b$ -sheddings.

# Shedding branch distributions $q_{od}$

The crux of the derivation

$q_{od}(r_{da}, r_{db})$  := chance a grain of sand shed from network  $o$  to  $d$  topples that node, sending  $r_{da}, r_{db}$  many grains to networks  $a, b$ .

$$q_{od}(r_{da}, r_{db}) = \underbrace{\frac{r_{do} p_d(r_{da}, r_{db})}{\langle k_{do} \rangle}}_{\text{I}} \underbrace{\frac{1}{r_{da} + r_{db}}}_{\text{II}} \quad \text{for } r_{da} + r_{db} > 0.$$

- I: chance the grain lands on a node with degree  $p_d(r_{da}, r_{db})$  (Edge following.)
- II: empirically, sand on nodes is  $\sim \text{Uniform}\{0, \dots, k-1\}^\dagger$
- Chance of no children =  $q_{od}(0, 0) := 1 - \sum_{r_{da}+r_{db}>0} q_{od}(r_{da}, r_{db})$  (Probability a neighbor of any degree sheds, properly weighted.)
- Chance at least one child =  $1 - q_{od}(0, 0)$ .

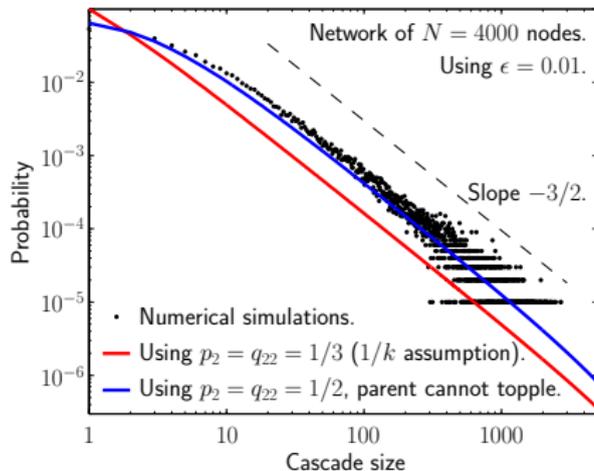
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<sup>†</sup>Reason for **criticality (SOC)** in isolated networks. Expected number of children sheddings:  $\langle q \rangle = \sum_k k \frac{k p(k)}{\langle k \rangle} \frac{1}{k} = 1$ .

## Aside: Revisiting the “1/k” assumption

Pierre-Andre Noël, C. Brummitt, R. D’Souza  
**Poster** here at NetSci

A node that just toppled is  
actually less likely to topple on  
the next time step.  
(prob zero sand  $\neq 1/k$ )



# Summary of distributions and their generating functions

	distribution	generating function
degree	$p_a(k_a, k_b), p_b(k_a, k_b)$	$G_a(\omega_a, \omega_b), G_b(\omega_a, \omega_b)$
shedding branch	$q_{od}(r_{da}, r_{db})$	
toppling branch	$u_a(t_a, t_b), u_b(t_a, t_b)$	$\mathcal{U}_a(\tau_a, \tau_b), \mathcal{U}_b(\tau_a, \tau_b)$
toppling size	$s_a(t_a, t_b), s_b(t_a, t_b)$	$\mathcal{S}_a(\tau_a, \tau_b), \mathcal{S}_b(\tau_a, \tau_b)$

Self-consistency equations:

$$\mathcal{S}_a = \tau_a \mathcal{U}_a(\mathcal{S}_a, \mathcal{S}_b), \quad (1)$$

$$\mathcal{S}_b = \tau_b \mathcal{U}_b(\mathcal{S}_a, \mathcal{S}_b). \quad (2)$$

Want to solve (1), (2) for  $\mathcal{S}_a(\tau_a, \tau_b), \mathcal{S}_b(\tau_a, \tau_b)$ .

Coefficients of  $\mathcal{S}_a, \mathcal{S}_b =$  avalanche size distributions  $s_a, s_b$ .

In practice, Eqs. (1), (2) are transcendental and difficult to invert.

# Numerically solving $\vec{S}(\vec{\tau}) = \vec{\tau} \cdot \vec{U}(\vec{S}(\vec{\tau}))$

Methods for computing  $s_a, s_b$  for **small avalanche size**:

**Method 1:** Iterate starting from  $S_a = S_b = 1$ ; **expand**.

**Method 2:** Iterate symbolically; use **Cauchy's integration formula**

$$s_a(t_a, t_b) = \frac{1}{(2\pi i)^2} \iint_D \frac{S_a(\tau_a, \tau_b)}{\tau_a^{t_a+1} \tau_b^{t_b+1}} d\tau_a d\tau_b,$$

where  $D \subset \mathbb{C}^2$  encloses the origin and no poles of  $S_a$ .

**Method 3:** **Multidimensional Lagrange inversion** (IJ Good 1960):

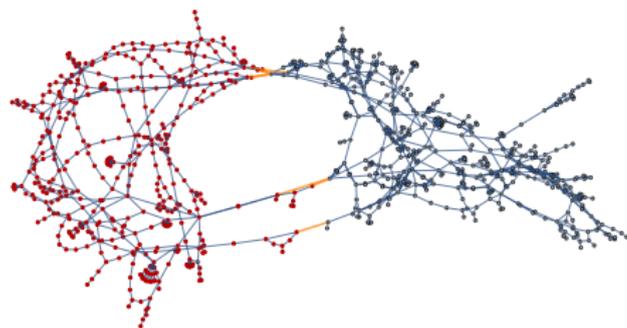
$$S_a = \sum_{m_a, m_b=0}^{\infty} \frac{\tau_a^{m_a} \tau_b^{m_b}}{m_a! m_b!} \left[ \frac{\partial^{m_a+m_b}}{\partial \kappa_a^{m_a} \partial \kappa_b^{m_b}} \left\{ h(\vec{\kappa}) \mathcal{U}_a(\vec{\kappa})^{m_a} \mathcal{U}_b(\vec{\kappa})^{m_b} \left\| \left\| \delta_{\mu}^{\nu} - \frac{\kappa_{\mu}}{\mathcal{U}_{\mu}} \frac{\partial \mathcal{U}_{\mu}}{\partial \kappa_{\mu}} \right\| \right\} \right]_{\vec{\kappa}=0},$$

if the types  $\mu, \nu \in \{a, b\}$  have a **positive chance of no children**.

- Unfortunately for **large avalanches** need to use simulation.  
(Asymptotic approximations used for isolated networks do not apply.)

# Plugging in degree distributions: A real world example

Two geographically nearby **power grids** in the southeastern US.



	Grid c	Grid d
# nodes	439	504
$\langle k_{int} \rangle$	2.4	2.9
$\langle k_{ext} \rangle$	0.02	0.01
clustering	0.01	0.08

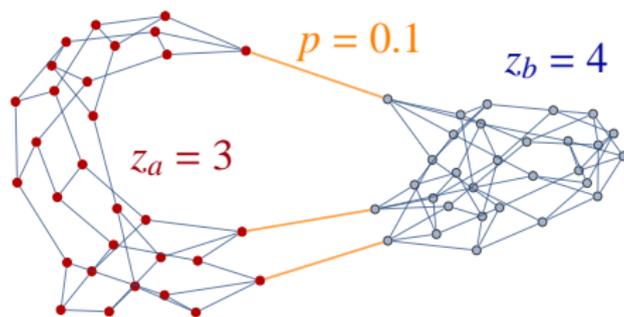
**8 links** between these two distinct grids.

Different average internal degree  $\langle k_{int} \rangle$ . Long paths.

(Low clustering – approximately locally tree-like.)

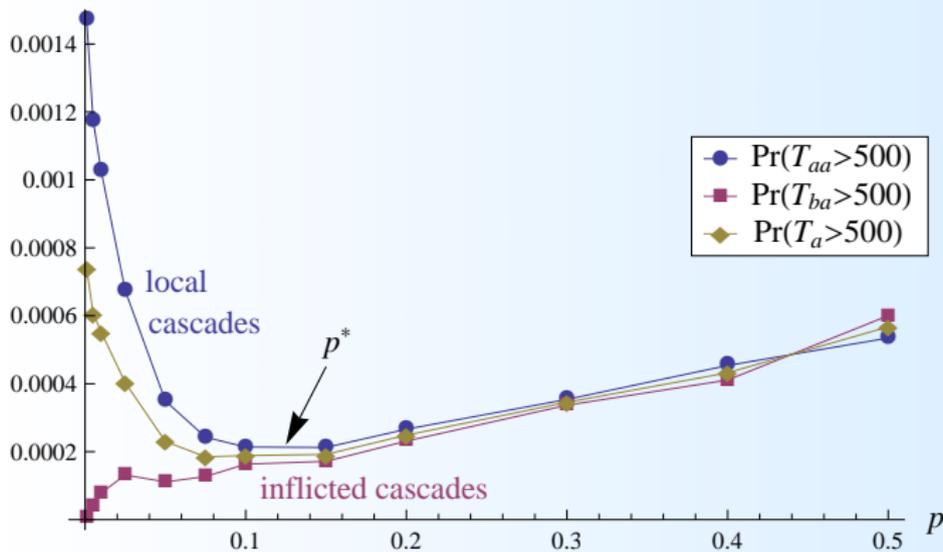
# A canonical idealization: Random regular graphs

Two random  $z_a$ -,  $z_b$ -regular graphs with “Bernoulli coupling”:  
each node gets an external link independently with probability  $p$ .  
These  $\approx$  power grids.



$$\mathcal{U}_a(\tau_a, \tau_b) = \frac{(p - p\tau_a + (z_a + 1)(\tau_a + z_a - 1))^{z_a}(1 + p(\tau_b - 1) + z_b)}{(z_a + 1)^{z_a} z_a^{z_a} (z_b + 1)}$$

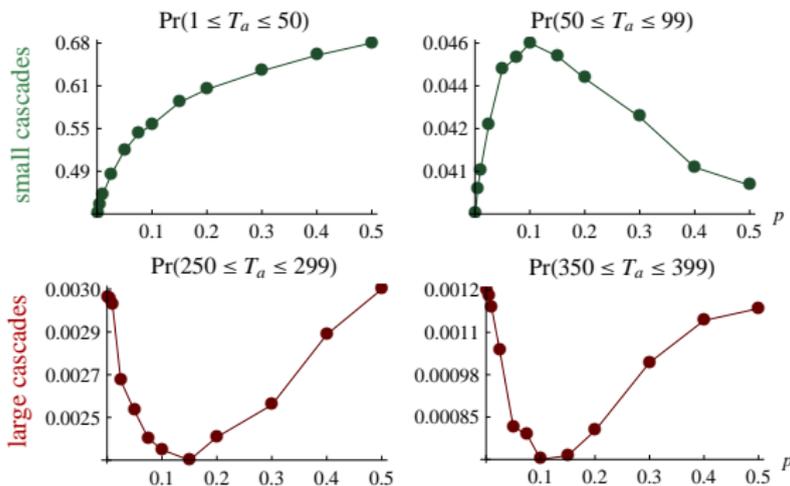
# Main findings: For an individual network, optimal $p^*$



- (Blue curve) Initially increasing  $p$  decreases the largest cascades started in that network (second network is reservoir for load).
- (Red curve) Increasing  $p$  increases the largest cascades inflicted from the second network (two reasons: new channels and greater capacity).
- (Gold curve) Neglecting the origin of the cascade, the effects balance at a stable critical point,  $p^* \approx 0.1$ . (Reduced by 75% from  $p=0.001$  to  $p=0.1$ )

# Main findings: Individual network, “Yellowstone effect”

Suppressing largest cascades amplifies small and intermediate ones!  
(Suppressing smallest amplifies largest (Yellowstone and Power Grids\*))



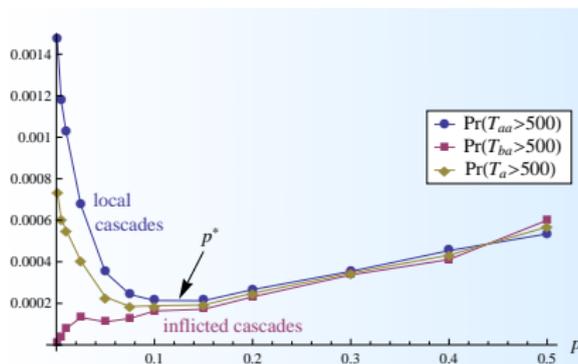
- To suppress smallest, isolation  $p = 0$ .
- To suppress intermediate (10% of system size) either  $p = 0$  or  $p = 1$ .
- To suppress cascades  $> 25\%$  of system size then  $p = p^* \approx 0.11$ .

\*Dobson I, Carreras BA, Lynch VE, Newman DE *Chaos*, (2007).

# Main findings: System as a whole

## More interconnections fuel larger system-wide cascades.

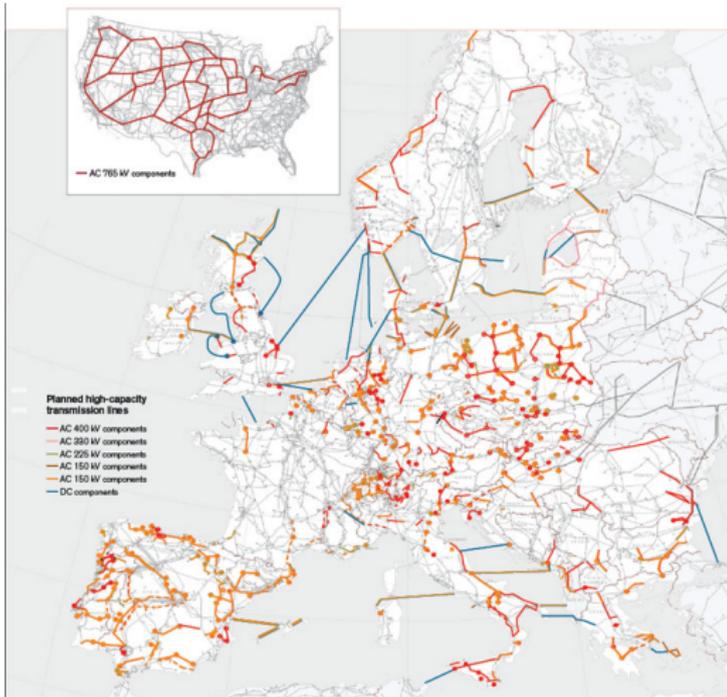
- Each new interconnection adds capacity and load to the system (Here capacity is a node's degree, interconnections increase degree)



- Test this on coupled random-regular graphs by rewiring internal edges to be spanning edges (increase interconnectivity with out increasing degree). No increase in the largest cascades.
- Inflicted cascades (Red curve) increase mostly due to increased capacity.
- So an individual operator adding edges to achieve  $p^*$  may inadvertently cause larger global cascades.

# Larger cascades from increased interconnections: A warning sign?

- Financial markets
- Energy transmission systems



Source:  
*Technology Review*,  
“Joining the Dots”,  
Jan/Feb (2011).

## Main findings, continued: Frustrated equilibrium

Unless the coupled grids are identical, only one will be able to achieve its  $p^*$ .

- Coupled  $z_a \neq z_b$  regular random graphs (branching process and simulation).

$$\frac{\langle s_a \rangle_b}{\langle s_b \rangle_a} = \frac{1 + z_a}{1 + z_b}$$

If  $z_b > z_a$  inflicted cascades from  $b$  to  $a$  larger than those from  $a$  to  $b$ .

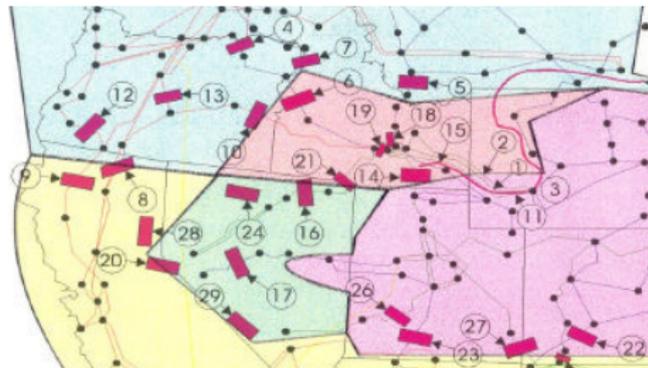
(An arm's race for capacity?)

## Summary: Sandpile cascades on interacting networks

- Some interconnectivity can be *beneficial*, but too much is *detrimental*. Stable optimal levels are possible.
- From perspective of *isolated network*, seek optimal interconnectivity  $p^*$ .
- This *equilibrium will be frustrated* if the two networks differ in their load or propensity to cascade.
- Tuning  $p$  to *suppress* large cascades *amplifies* to occurrence of small ones. (Likewise, suppressing small, amplifies large.)
- *Additional capacity* and overall load from new interconnections *fuels larger cascades* in the system as a whole.
- What might be good for an individual operator (adding edges to achieve  $p^*$ ), may be bad for society.

# Possible extensions – Real power grids

- Expand multi-type processes to encode for different types of nodes (buses, transformers, generators)
- Linearized power flow equations – **cascades in real power grids are non-local:** e.g. fig: 3 to 4, 7 to 8
- Game theoretic/  
economic consideration  
(we assume adding connections is cost-free)



(1996 Western blackout NERC report)

(Power grids as “critical” – Balancing profit and fear of outages)

## Teams and social networks

- Tasks (sand) arriving on people (nodes)
- Each person has a capacity for tasks: sheds once overloaded
- Coupling to a second social network (team) can reduce large cascades

## Amplifying cascades

- Encourage adoption of new products
- Snowball sampling

## Airline networks

- Different carriers accepting load (bumped passengers)

# References and Acknowledgements

- C. Brummitt, R. M. D'Souza and E. A. Leicht, "Suppressing cascades of load in interdependent networks", *PNAS* 109 (12) 2012.
- Note **Author Summary** for high-level overview.
- Noël, Brummitt, D'Souza **poster** at NetSci.

