Controlling risk, costs of catastrophes, and multitype branching processes for power flow

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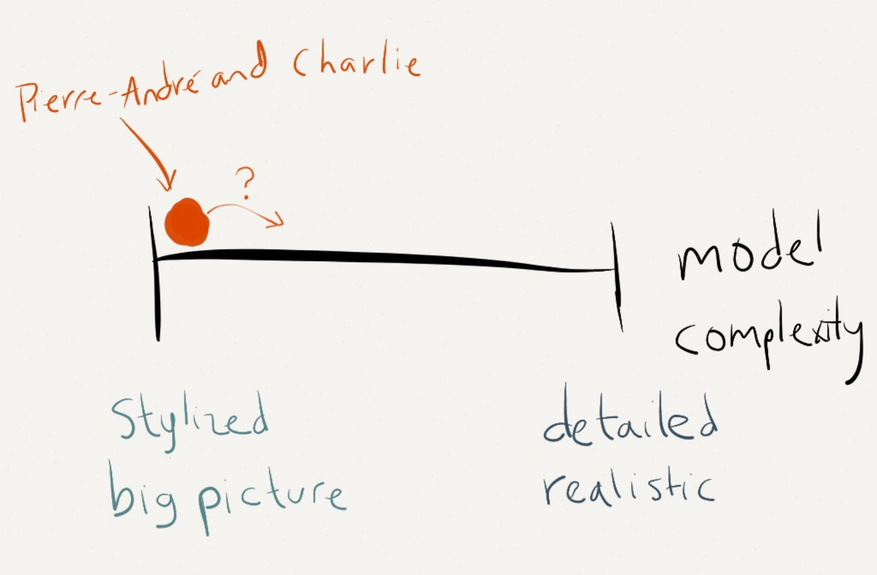
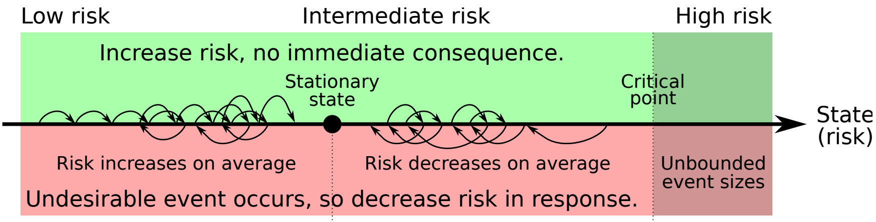
Scale of model complexity



Long-term dynamics of risk

- Undesirable events in infrastructures:
  - forest fires, avalanches, blackouts, financial crises
- Risk = probability or expected size of such events
- Dynamics over long timescales:
  - no events occur $\Longrightarrow$ risk may increase (e.g., for profits)
  - events occur $\Longrightarrow$ risk may decrease (e.g., less load, policy changes)
- May self-organize to a stationary state

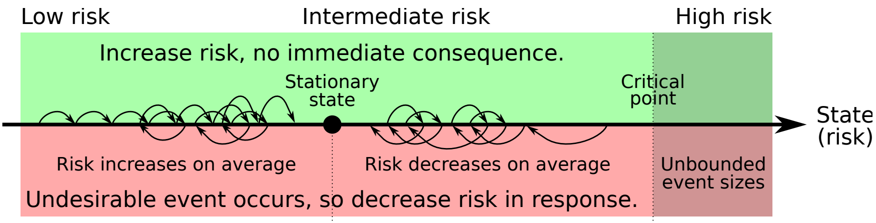


- When an event occurs, how much do we "pull back"?

Risk reduction

$\epsilon :=$ (amount of risk reduced) / (size of the event)

- Large ϵ: conservative. Small ϵ: reckless.
- Barely reduce risk ($\epsilon \to 0$): $\to$ critical point. *Self-organized criticality (SOC).*



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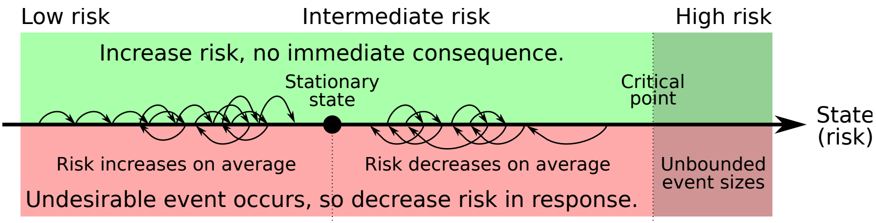

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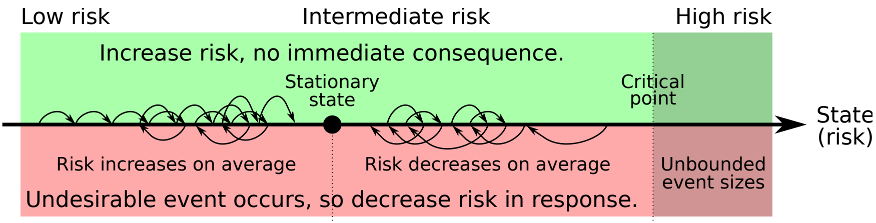

Questions

Power grids appear to be near a critical point.

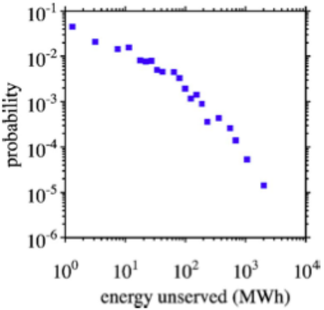

FIG. 1. (Color online) Log-log plot of scaled pdf of energy unserved during North American blackouts 1984 to 1998.

Blackout size distribution [Dobson et al. *Chaos* **17** (2007)].

- Safe distance from critical point? Depends on costs of events.
- Can we move further away from the critical point?

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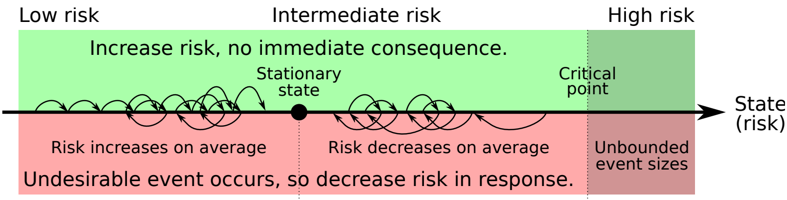
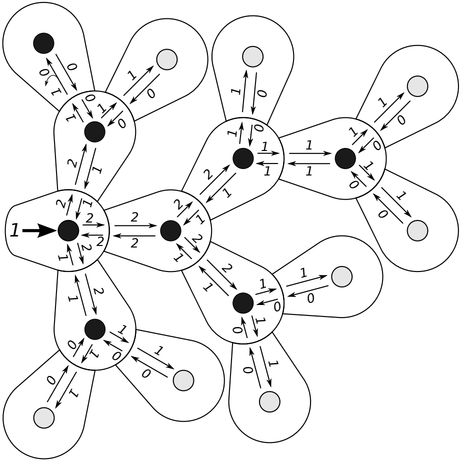
Sandpile model on a network

- A tool for thinking about risk in complex systems
- Given a graph, drop sand on the nodes, who move it to their neighbors if they have too much. Cascades (avalanches) of sand.
- Risk = amount of sand
- A fraction ϵ of sand moved in a cascade is deleted.
  - Self-organizes to a critical point as $\epsilon \to 0$.



Analytical framework

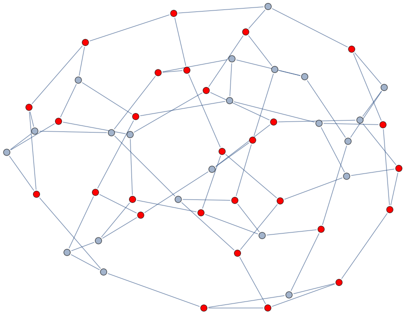
- Multitype branching process
  - Consider pairwise correlations
  - “Types” track exchanges between neighboring nodes
  - Bootstrap the pairwise correlations by enforcing steady state



P.-A. Noël, C. D. Brummitt and R. M. D’Souza, Physical Review Letters **111**, 078701 (2013).

Triggering cascades in the sandpile model

After cascade ends, some nodes are barely below their capacity, i.e., they would cause a cascade if they were to receive another grain of sand.



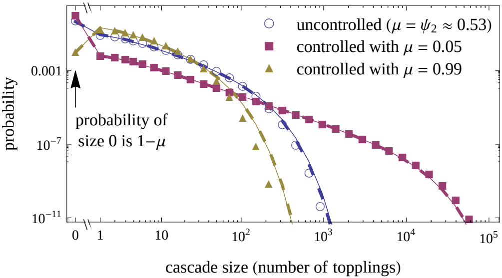
Traditional rule

Drop sand on a uniformly random node.

Control scheme

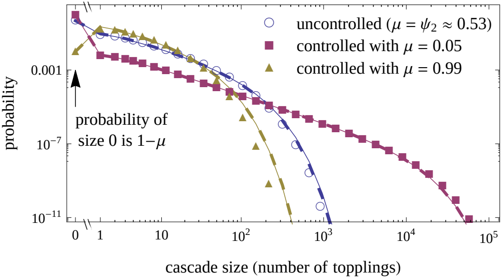
With probability μ, drop sand on a node that will cause a cascade.

Cascade size distributions



- Large μ: frequently trigger cascades
  - Example: snow avalanches, controlled forest fires
  - Reduces large cascades but makes more small ones.
- Small μ: avoid cascades
  - Example: "Yellowstone effect" (forest fires), avoiding blackouts.
  - Reduces small but exacerbates large.
- What frequency of cascades μ is best?

Cascade size distributions



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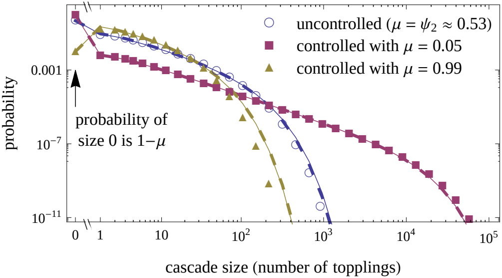

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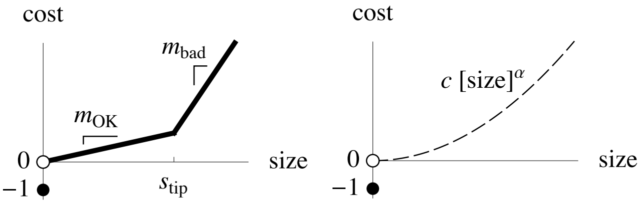
Costs of cascades determine the optimal μ^*

- Optimal control strategy $\mu^* = \min_\mu \langle costs \rangle$
- $cost(size) = ?$
- A big event could be disproportionately more costly:
  - We are well prepared for small catastrophes
  - Risk aversion
  - Government penalties for starting catastrophes
  - Costs from interdependence with other infrastructure



In this case, μ^* is not one of the extremes $0, 1$

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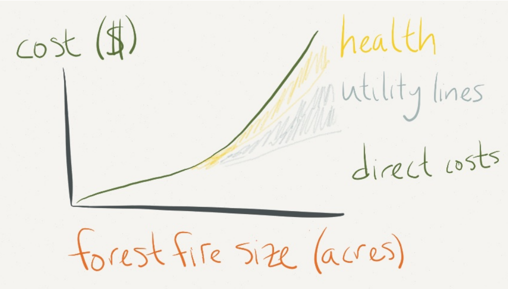
Costs of forest fires, blackouts

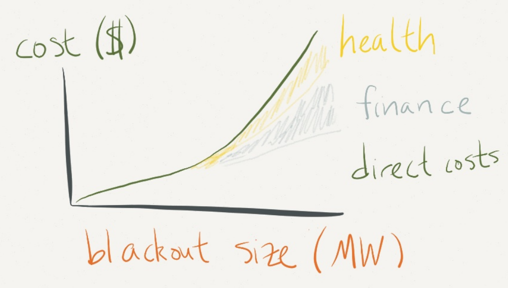
Forest fire costs:

- Direct: firefighters, property, utility lines, timber, aid
- Indirect: tax revenue, property value, human health

Blackout costs:

- Direct: productivity, costly generators
- Indirect: water, hospitals, finance?, transport?





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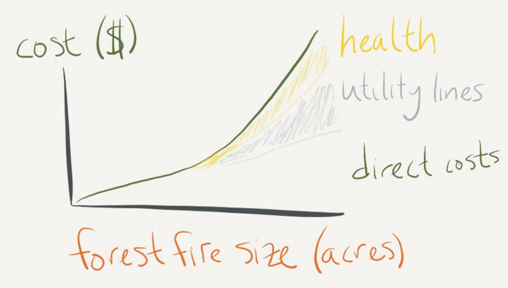

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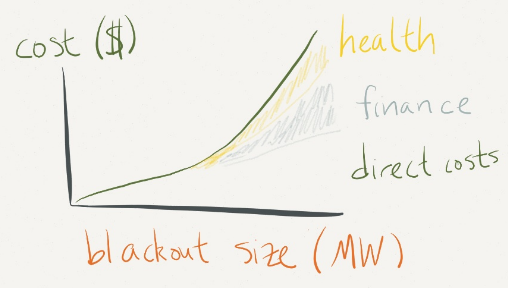

Challenges and goal

Conjecture

The super-linearity of *cost*(*event size*) is a measure of interdependence.

Goal

Use data on costs of catastrophes to

- measure interdependence among infrastructures
- inform our models to determine how much to "control" risk in our infrastructure

Challenges

- Less data on indirect costs
- Cost also depends on location
  - near cities, industry, key infrastructure?

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Our understanding of the problem

- As we understand it, past random graphs models of power grids are of little use to power grid engineers because:
  - they model the wrong dynamics (e.g., percolation, not flows); and
  - they do so on the wrong networks (e.g., treelike, no loops).
- We have ideas on how to address these problems (to some extent), but we would appreciate your feedback before proceeding further.
- Some questions to keep in mind.
  - What is a minimal caricature that could bear interesting results?
  - Is there a niche for a mature implementation of these ideas?
  - Concerning other types of infrastructures where flows matter: do you see any potential for these methods?
    - (For simplicity, this presentation considers only power grids.)
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The wrong dynamics

- Past random graphs models of power grids assumed that cascades propagate from node to node in a local manner (percolation etc.).
  - This is fundamentally wrong: local changes in the grid's state may have global impacts on how the currents flow.
  - Also, being disconnected is not intrinsically bad (e.g., islanding).
- As we understand it, any model that aims for some level of realism should implement one of the following incarnations of load flow.
  - Steady state DC flows.
    - (*Nominal voltages, small phase differences, negligible dissipation.*)
  - Steady state AC flows.
    - (*Full AC equations without transient, all at same frequency.*)
  - Non-stationary AC flows.
    - (*Has transient behavior, possible coupling of frequencies and flows.*)

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The wrong network

- Past random graphs models of power grids typically assume tree-like network structure, which is fundamentally wrong.
  - The network is not a tree: it contains loops, and they matter.
  - The network was designed with some principles in mind.

- These are not fundamental shortcomings of random graph methods, but instead reflect that the "wrong" random graph is used.

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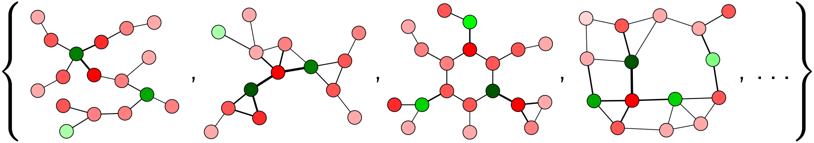
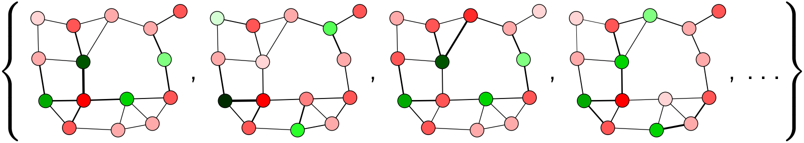
What is a random graphs?

- G is said to be a random graph if it has been sampled from an ensemble of possible configurations.

$G \in$ 

- "How random" the graph is depends on how the elements of the sampled set are similar among themselves.

$G \in$ 

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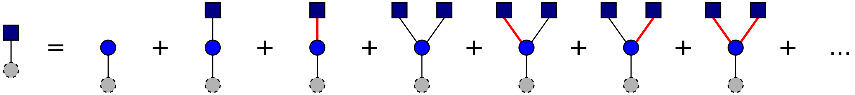
The "trivial" case of a tree

- A typical way to "solve" a branching process is to recursively define the solution in terms of itself.
  - Node (bus), where power is injected and/or drawn.
  - Reference node (slack bus) that has to balance everything else.
  - Represents "whatever lies ahead".



- The different terms of the sum account for different eventualities:
  - the degree of the reached node;
  - whether failures occur or not;
  - the power injected and/or drawn at the reached node; etc.
- We may recursively compute the flows entering/leaving nodes.
  - The "types" of the branching process specify the flows.
- Can account for failures and operator decisions (local information).

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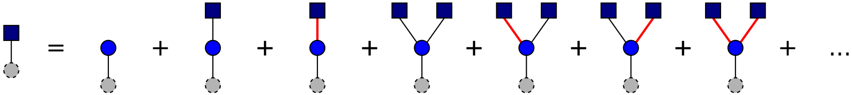

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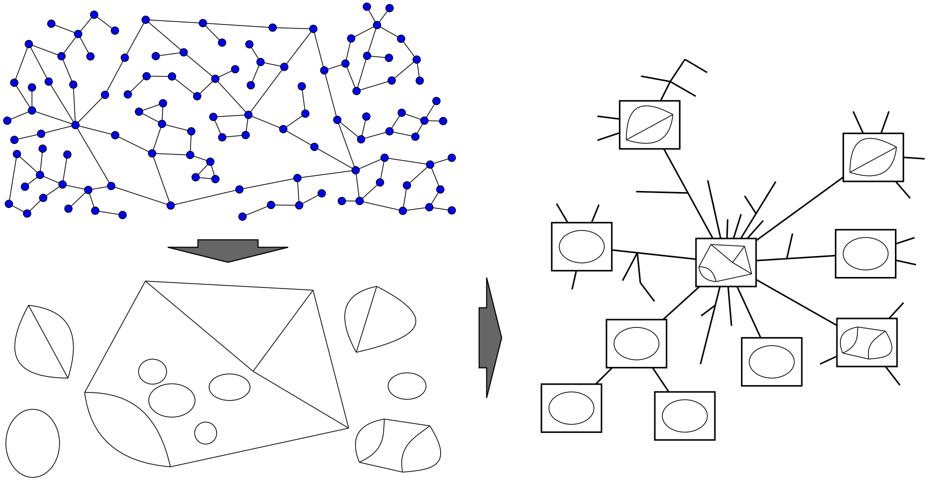
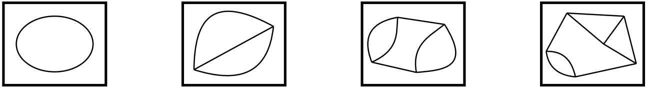
Cycles as motifs: tree of motifs



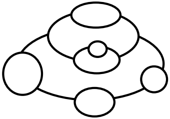
- Hence, even if the network is not a tree, taking a "tree of motifs" perspective allows us to use the same recursive approach.

Solvable (?!) motifs

- Motifs involving a sufficiently small number of loops may be solvable by "analytical brute force".



- Certain classes of motifs with a larger number of loops may be amenable to analysis (e.g., "fractal-like" structures).



"Tricks" related to weighting configurations

- Some of the random graph configurations may make no sense, so we may want to enforce additional constraints.
  - The generated power should be sufficient to supply the load.
  - Links/nodes do not "spontaneously fail" without prior failures.
  - No additional links/nodes fail after a single failure ($N - 1$ feasibility).
- $\hookrightarrow$ Give zero weight to "bad configurations", then renormalize.

- The same weighting approach could be used to enforce some "global optimization" requirements (specifiable through local information).
  - E.g., minimize total squared flow along links.
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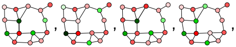
Summary of what we could do (Would that be enough?)

- Steady state AC/DC flows (possibility to emulate transients etc.).
- Network structure including loops through motifs.
  - In particular, we could specify the whole graph as a single motif (for small networks). $G \in \Big\{$  $, \dots \Big\}$
- Account for failures and/or for operator decisions.
  - Based on local information (directly in the branching process).
  - Global optimization (weighting configurations with local information).
- We do not claim that random graphs methods could replace the intensive simulations that currently keep the grid on.
  - What we propose could become a different tool for a different purpose.

Questions? Comments?

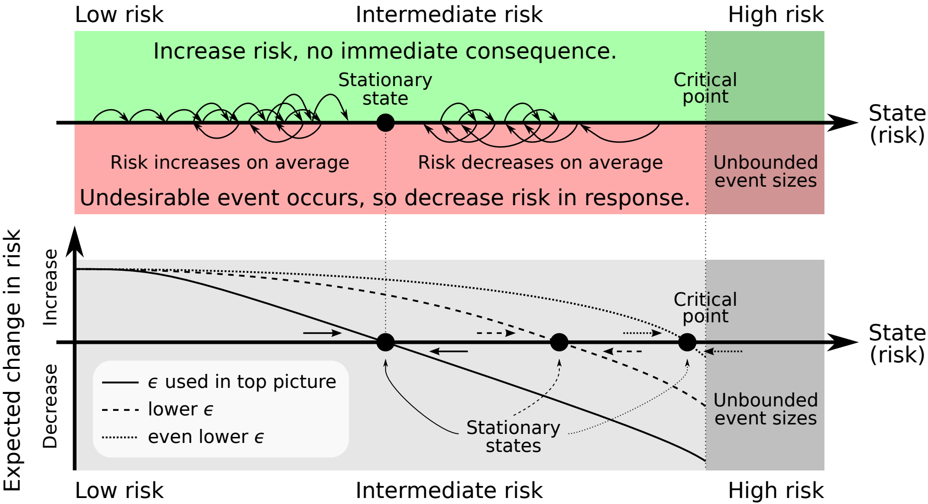
Systemic risk in a stylized model

- How does *cost* grow with *catastrophe size* in real systems?
- What factors affect costs of catastrophes?
  - Location, size, duration, ...
- Could interdependence be measured in dollars?

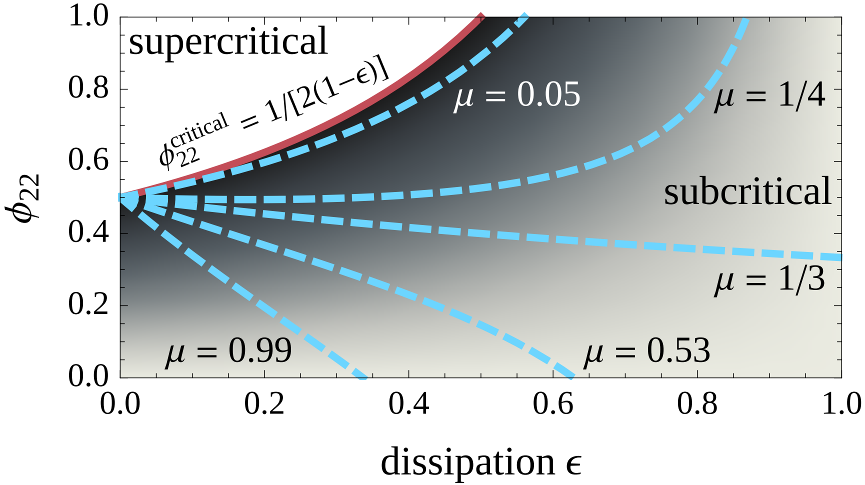
Branching flows: a work in progress

- What is a minimal caricature that could bear interesting results?
- Is there a niche for a mature implementation of these ideas?
- Could this apply to other types of infrastructures than power grids?

Risk and self-organized criticality



Phase diagram of dissipation and control



Literature on costs of catastrophes

1. The True Cost of Wildfire in the Western U.S. *Western Forestry Leadership Coalition* (2010).
2. What is the price of catastrophic wildfire? *J. Forestry* **99** (2001).
3. Do one percent of the forest fires cause ninety-nine percent of the damage? *Forest Science* **35** (1989).
4. Business Interruption Impacts of a Terrorist Attack on the Electric Power System of Los Angeles: Customer Resilience to a Total Blackout, *Risk Analysis* (2007).

Macroeconomic impact of natural catastrophes (e.g., earthquakes)

1. Natural Disasters: Mitigating Impact, Managing Risks. IMF Working Paper (2012).
2. The economics of natural disasters: concepts and methods. World Bank Policy Research Working Paper Series (2010).
3. Unmitigated disasters? New evidence on the macroeconomic cost of natural catastrophes. (2012).

Long-term costs of financial crises

1. Systemic crises and growth. *The Quarterly Journal of Economics* **123** (2008).

"Solving" cycle motifs