Probabilistic analysis of power grids: how do large blackouts occur?

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based on T. Nesti, F. Sloothaak, B. Zwart. Emergence of scale-free blackout sizes in power grids. *Physical Review Letters* **125**, 058301, 2020.



The energy transition



Suggested solutions (renewables, demand response, ...) lead to

- Increased decentralization (e.g. rooftop solar panels)
- Increased complexity [e.g. between physical network and communication network]
- More uncertainty

More variability in supply



Wind, and also solar, are variable over many time-scales.

More variability in demand



More variability in prices



Applied probability and energy





Stella Kapodistria



Fiona Sloothaak



Maria Vlasiou



Vision: mathematics can help to transform the power grid into a smart grid, like it helped to transform phone networks into the Internet.

Specific topics:

- Distribution grids with EV charging
- RL, preventive maintenance (e.g. for wind turbines)
- Reliability, rare events, rare-event simulation

Mathematical challenges

- Optimization
- Dynamics/control
- Complex systems
- Probability/Statistics
- Al
- Market design (traditional, P2P,...)



Community building: co-organized semester on mathematics for energy networks at the Isaac Newton Institute, Cambridge UK, spring 2019.

Todays focus: understanding large blackouts



80B of annual economic damage to US economy from blackouts

Unrest in South Australia (2016 - 2017)



- Rolling blackouts during heat wave. Renewable energy (wrongfully) blamed. Problems mitigated by 100 MW Tesla battery
- Other controversial disruptions: Los Angeles (2018), Texas (2021), UK (2019, concurrent disruptions at wind park + classical generator)

Successful squirrel attacks

1/23/2017

CyberSquirrel1.com





TOTAL SUCCESSFUL CYBER WAR OPS AS OF 2017.01.08 - 1748

Agent	Success		
Squirrel	879		
Bird	434		
Snake	83		
Raccoon	72		
Rat	36		
Marten	22		

ABOUT THIS MAP

This map lists all unclassified Cyber Squirrel Operations that have been released to the public that we have been able to confirm. There are many more executed ops than displayed on this map however, those ops remain classified.

Confirmation for all ops has been preserved by the Internet Archive's WayBack Machine whenever possible.

"I don't think paralysis [of the electrical grid] is more likely by cyberattack than by natural disaster.

MOST RECENT UNCLASSIFIED OPS

Tweets by @CyberSquirrel1



Linemen are not our enemies, much resp

Can we mathematically understand blackouts?

- We cannot model everything
- Statistical physics of complex networks: aim to understand how macroscopic phenomena evolve out of microscopic interactions.
- Some quote made by some of my colleagues:
 - "It is not complex, but complicated"
 - "It is not possible to come up with a both interesting and useful result"
- It can take a long time to determine the cause of a blackout even after it occurred.
- To understand, predict and/or detect anomalies, should we use simple black box methods from machine learning or sophisticated mathematical models?
- At least one feature of blackouts is not complicated

Pareto laws in power grids (Hines 09)



Goal: provide explanation using rare event analysis.

Probabilistic analysis of rare events

- Large deviations theory:
 - compute (analytically) the probability that a rare event occurs
 - determine the most likely way a rare event occurs, if it occurs
- 2 Extreme value theory:
 - growth rate of maxima
 - how to extrapolate from data
- **(2)** 'Dutch' application: determining dike heights as part of Deltawerken
- Other Applications
 - dimensioning safety/buffer/storage levels in finance, insurance, computer, communication networks, ...
 - vulnerability assessment: finding weakest links in complex systems

Light-Tailed Distributions

- Extreme Values are Very Rare
- Normal, Exponential, etc



Heavy-Tailed Distributions

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- Pareto Law, Weibull, etc



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Heavy tails are not as well understood as light tails.

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Systemwide rare events

arise because

EVERYTHING goes wrong.

(Conspiracy Principle)

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Systemwide rare events

arise because of

A FEW Catastrophes.

(Catastrophe Principle)

Heavy tails are not as well understood as light tails.

New book



Free pdf at https://adamwierman.com/book/

Heavy Tails are Everywhere:



How do heavy tails occur?

- Queues: exogenous factors (e.g. job sizes)
- Finance: nonlinear internal dynamics (e.g. compounding losses)
- Growing social networks: preferential attachment
- Power systems: not well understood.
 Most popular narrative to date: self-organized criticality

Heavy tails and critical phenomena

Consider a Branching Process with $Z_0 = 1$ and

$$Z_{n+1}=\sum_{i=1}^{Z_n}C_{ni}.$$

If $\mathbf{E}[C_{ni}] = 1$ the branching process is said to be critical. The total size and depth of the tree are heavy-tailed.

Self-organized criticality: many natural and man-made systems appear to be self-organizing and also behave like critical systems

Attempts have been made to model cascading failures as branching processes.

A better explanation

Let C be the size of a city, in terms of number of people, and let T be the size of a blackout, in terms of number of customers affected Both have statistically significant, almost identical power law for US:

$$P(C > x) \approx x^{-1.37}$$
 $P(T > x) \approx x^{-1.31}$

German city sizes: power law with index 1.28

2015 rank \$	City 🗢	State +	2015 Estimate 🗢	2011 Census 🗢	Change ¢	2015 land area 🗢	2015 p
1	<u> -</u> Berlin	Eerlin	3,520,031	3,292,365	+6.91%	891.68 km ² 344.28 sq mi	
2	Hamburg	Hamburg	1,787,408	1,706,696	+4.73%	755.3 km ² 291.6 sq mi	
3	Munich (München)	🕵 Bavaria	1,450,381	1,348,335	+7.57%	310.7 km ² 120.0 sq mi	
4	Cologne (Köln)	North Rhine-Westphalia	1,060,582	1,005,775	+5.45%	405.02 km ² 156.38 sq mi	
5	🚛 Frankfurt am Main	Hesse	732,688	667,925	+9.70%	248.31 km ² 95.87 sq.mi	

log-log plots and Hill plots



US city size data (2000 census) and US outage data (NERC, 2002-2018). Cutoff chosen according to the PLFIT method of Clauset et. al (2009).

Mathematical model - main features

- Graph with *n* nodes, fixed topology. Demand at node *i*: X_i , with $P(X_i > x) \sim cx^{-\alpha}$. $\mathbf{X} = (X_1, \dots, X_n)$.
- To model electricity, we use the DC load flow model.
- We consider three stages in our model:
 - Planning: determine line capacities/limits
 - \bullet Operation: determine network flows, keeping some slack, quantified by a parameter $\lambda.$
 - Emergency: failure propagation, starting from a random line failure

Main result

Let X be a generic city size, with $P(X > x) \sim C_X x^{-\alpha}$.

Note that T is the blackout size [in terms of number of customers affected]

$$P(T > x) \sim C_T x^{-\alpha}, \qquad x \to \infty,$$
 (1)

$$C_T = C_X n \sum_{j=1}^n P(|A_1| = j) (1 - j\lambda/n)^{\alpha}.$$
 (2)

 A_1 denotes the (random) set of nodes making up the island with the largest city in the network once the cascade is over.

Proof challenge: reduce network to the case of a single big city, and many small cities, reducing the problem to the analysis of a cascade to a single-sink network.

Numerical studies

Our result holds up against several simulation studies

- Generation constraints
- Extending DC to AC
- No heavy tailed blackout size if city sizes are uniformly distributed
- IEEE test networks
- Synthetic scalable networks, tailored to power grids [Wang, Scaglione, and co-authors]

Critical assumption: frozen vs random city sizes [quenched vs annealed] becomes irrelevant if network is sufficiently large

SciGRID case study - Impact of λ



Figure: Dissection of biggest blackout for loading factors $\lambda = 0.7$ (left panels), $\lambda = 0.8$ (middle) and $\lambda = 0.9$ (right) in terms of the cumulative number of affected customers at each consecutive stage as displayed in the top charts with the biggest jump colored red.

Number of load shedding events during cascade



Figure: Histogram of the total number of load shedding events in the SciGRID network. For a moderate loading factor $\lambda = 0.7$, nearly 99% of the blackouts only involved a single jump. Even for a high loading factor $\lambda = 0.9$, 87% of the blackouts involve just a single jump. The fraction of blackouts with four or more jumps remains below 5%

Insights

$$P(T > x) \sim C_T x^{-\alpha}, \qquad x \to \infty,$$

• Using our methods, we can compute

P(blackout starts with failure at line $i \mid$ large blackout occurs)

This helps to determine the most vulnerable lines.

- However, line upgrades only make C_T smaller. α will not chance. Thus: upgrades provide limited effect in preventing large blackouts.
- Duration of blackout is light-tailed, and seems independent of size.
- It makes more sense to invest in making cities more resilient (e.g. be capable to operate in islanded mode for several hours in case of need).

- What would be a fair price for an insurance against blackouts?
- How much storage do we need if we are (close to) 100 percent renewables, and want to limit shortages to, say, 30 minutes per year?
- What is the value of storage as mitigation against future rare events?
- Can we design congestion management schemes with probabilistic reliability guarantees?