Power Grid Failures - Renewable Energy

How fluctuations in solar and wind affect grid security in Germany

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July 2019

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Transmission network of Germany

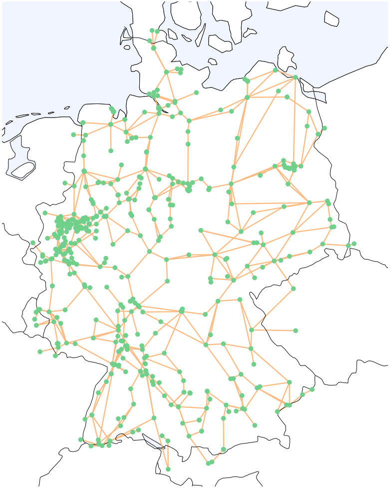

Figure 1: The $n = 585$ nodes and $k = 695$ lines of the SciGRID dataset.

Power injection

At each node $i \in \{1, \ldots, n\}$:

$$p_i := S_i^{green} + S_i^{grey} - S_i^{load}$$

	green	grey
Operation costs	**0-10 €/MWh**	30-35 €/MWh
CO2eq-emissions	**0 kg/MWh**	490 - 820 kg/MWh[1]
Controllable?	wind & hydro	**yes**
Output	stochastic	**deterministic**

[1] IPCC 2014

Line limits

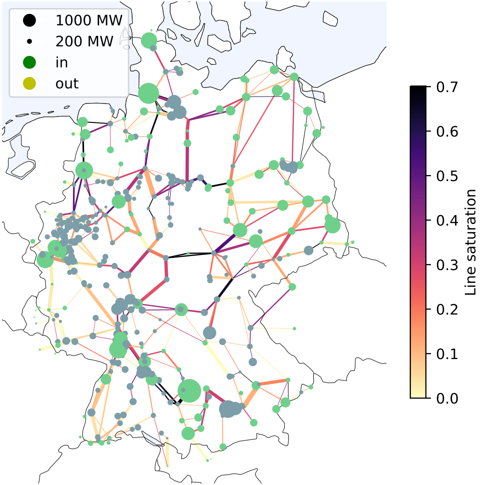

Figure 2: Line saturation at 11am, 1 Jan 2011.

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Summary

Given:

- Grid structure
- Hourly load
- Hourly generation

Predict:

- **‘Top 10’** of lines most likely to fail
- For each risky line: the most likely **cascading line failures**

NIEUWS STROOMNETTEN

Elektriciteitsnetwerk kan stroom uit lokale groene projecten niet aan

Lokale groene energieprojecten kunnen niet doorgaan doordat zij hun stroom niet kwijt kunnen. Netbeheerder Enexis moet in Groningen en Drenthe ‘nee’ verkopen aan boeren, bedrijven en verenigingen die zonnepanelen op hun daken willen, door een gebrek aan capaciteit op het elektriciteitsnet. Ook aansluiting van nieuwe grootschalige zonneweiden is in bepaalde gebieden niet meer mogelijk.

Jurre van den Berg 11 januari 2019, 2:00

Emergent failures and cascades in power grids: a statistical physics perspective

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(Dated: April 23, 2018)

We model power grids transporting electricity generated by intermittent renewable sources as complex networks, where line failures can emerge indirectly by noisy power input at the nodes. By combining concepts from statistical physics and the physics of power flows, and taking weather correlations into account, we rank line failures according to their likelihood and establish the most likely way such failures occur and propagate. Our insights are mathematically rigorous in a small-noise limit and are validated with data from the German transmission grid.

PACS numbers: 89.75.Hc,89.20.-a,88.80.-q

Understanding cascading failures in complex networks is of great importance and has received a lot of attention in recent years [1–17]. Despite proposing different mechanisms for their evolution, a common feature is that cascades are triggered by some *external* event. This initial attack is chosen either (i) deliberately, to target the most vulnerable or crucial network component or (ii) uniformly at random, to understand the average network reliability. This distinction led to the insight that complex networks are resilient to random attacks, but vulnerable to targeted attacks [7, 18, 19]. However, both lead to the *direct* failure of the attacked network component.

In this Letter, we focus on networks in which edge failures occur in a fundamentally different manner. Specifically, we consider networks where fluctuations of the node

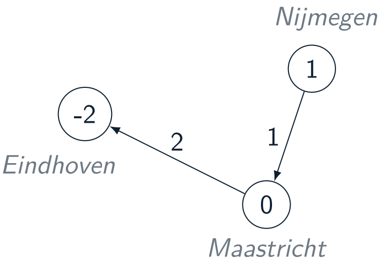
Previous works applying large-deviations techniques to problems in complex networks dynamics, such as epidemic extinction and biophysical networks, include [23, 24].

We model a transmission network by a connected graph G with n nodes representing the *buses* and m directed edges modeling *transmission lines*. The nominal values of net power injections at the nodes are given by $\boldsymbol{\mu} = \{\mu_i\}_{i=1,\dots,n}$. We model the stochastic fluctuation of the power injections around $\boldsymbol{\mu}$, due to variability in renewable generation, by means of the random vector $\mathbf{p} = \{p_i\}_{i=1,\dots,n}$, which is assumed to follow a multivariate Gaussian distribution with density

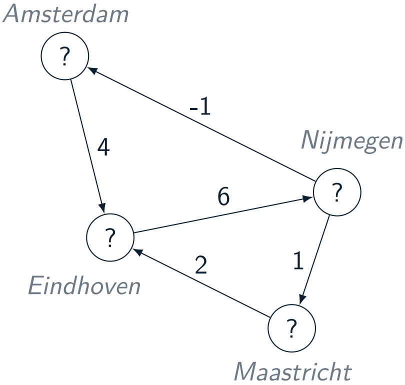
$$\varphi(\mathbf{x}) = \frac{\exp(-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu})^T(\varepsilon\boldsymbol{\Sigma}_p)^{-1}(\mathbf{x}-\boldsymbol{\mu}))}{(2\pi)^{\frac{n}{2}}\det(\varepsilon\boldsymbol{\Sigma}_p)^{\frac{1}{2}}}, \quad (1)$$

Power Flow

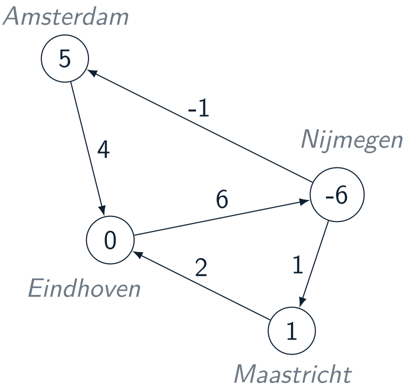
Digraph flow



Puzzle!

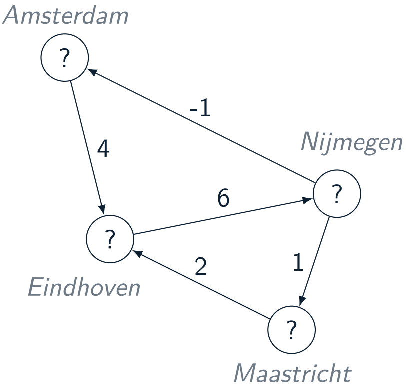


Solution



Transmission

$$\boldsymbol{f} = \begin{pmatrix} 1 \\ 2 \\ 6 \\ -1 \\ 4 \end{pmatrix} \in \mathbb{R}^k, \quad \boldsymbol{p} = \begin{pmatrix} ? \\ ? \\ ? \\ ? \end{pmatrix} \in \mathbb{R}^n$$



Power transmission is linear

$$\boldsymbol{p} = \boldsymbol{C} \cdot \boldsymbol{f}$$

$$\boldsymbol{C} \in \mathbb{R}^{n \times k}$$

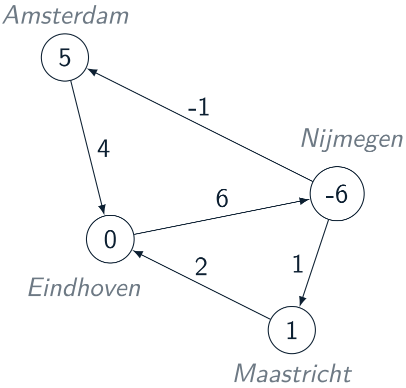
Transmission

Power transmission is linear

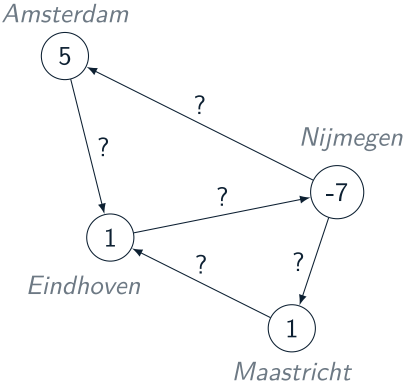
$$\boldsymbol{p} = \boldsymbol{C} \cdot \boldsymbol{f}$$

$$\boldsymbol{C} = \begin{pmatrix} +1 & 0 & -1 & +1 & 0 \\ 0 & 0 & 0 & -1 & +1 \\ 0 & -1 & +1 & 0 & -1 \\ -1 & +1 & 0 & 0 & 0 \end{pmatrix}$$

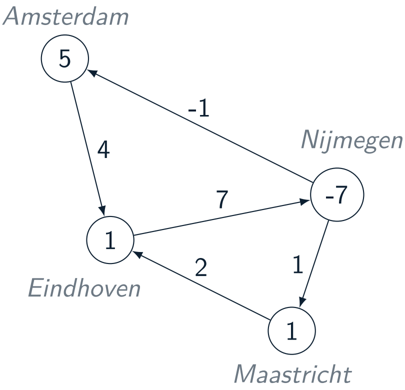
we get: $\boldsymbol{p} = \boldsymbol{C} \cdot \boldsymbol{f} = \begin{pmatrix} -6 \\ 5 \\ 0 \\ 1 \end{pmatrix}$



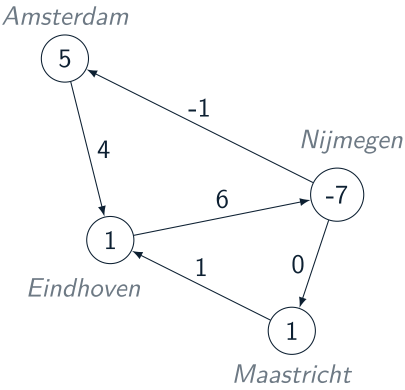
Inverse problem: Linear Power Flow (LPF)



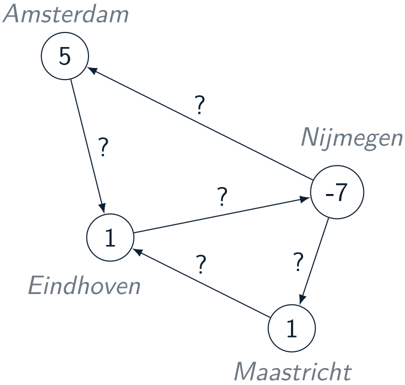
Solution



Another solution



Inverse problem: Linear Power Flow (LPF)



Inverse problem: Linear Power Flow (LPF)

The $\boldsymbol{LPF}$ is a (linear) *right-inverse* of $\boldsymbol{C}$:

$$\boldsymbol{C} \cdot \boldsymbol{LPF} = \boldsymbol{I}.$$

Many linear maps satisfy this property, but there is only one *right* $\boldsymbol{LPF}$ that satisfies **Kirchoff's Circuit Laws** and **Ohm's Law**.

The $\boldsymbol{LPF}$ is difficult to compute: requires *Singular Value Decomposition* of a $k \times k$ matrix.

Electric model - HV Layer

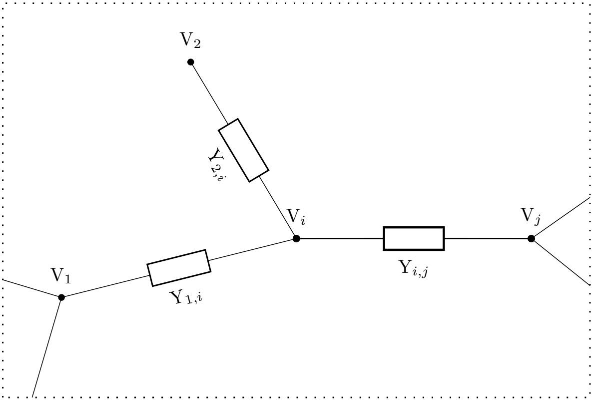
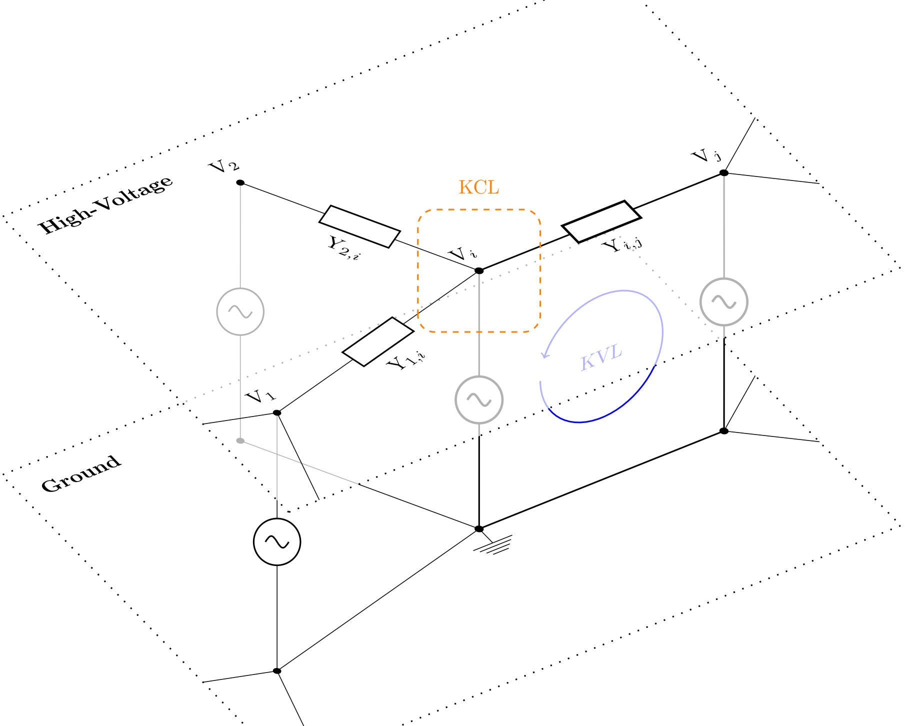
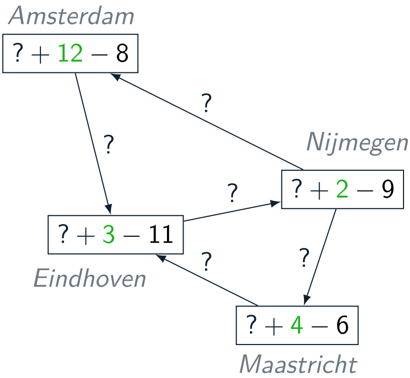


Figure 3: Top layer of the electric circuit used in the model. Transmission lines are modelled as impedances.

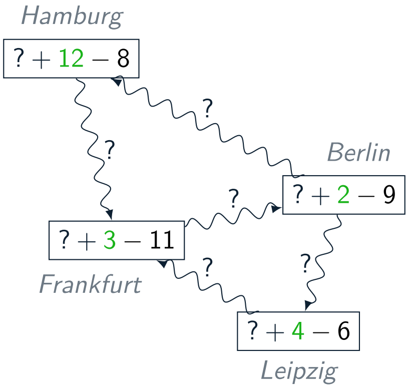


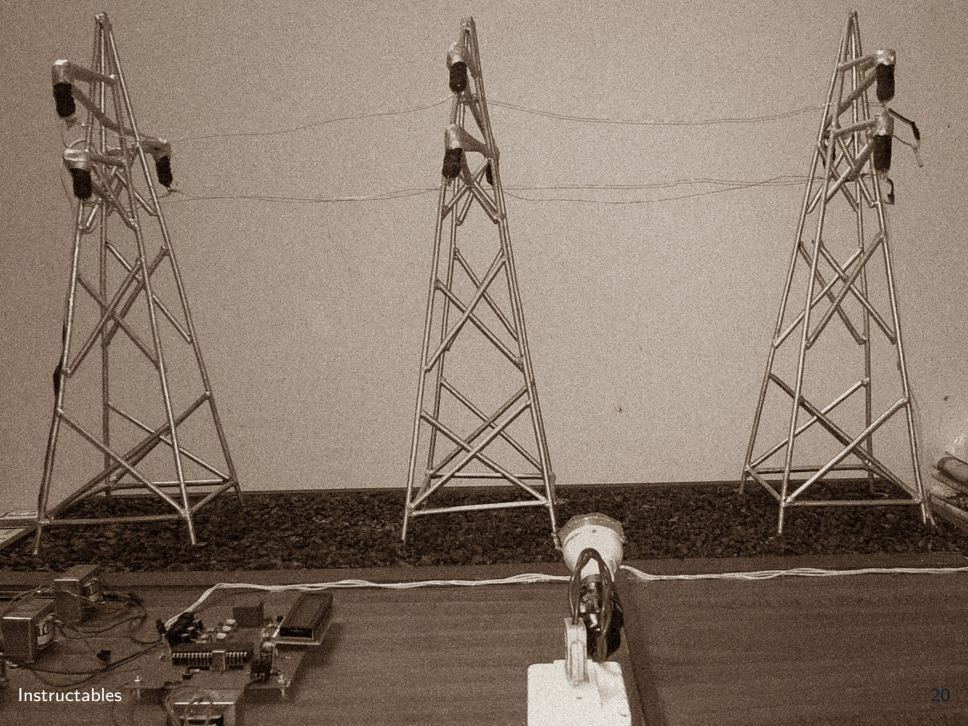
High-Voltage
Ground
KCL
KVL
V_2
V_i
V_j
V_1
$Y_{2,i}$
$Y_{i,j}$
$Y_{1,i}$

Unknown generation: Linear Optimum Power Flow (LOPF)



Unknown generation: Optimum Power Flow (OPF)





OPF to supplement data

Available:

- Grid structure
- Hourly load
- Hourly solar and wind generation

Not available:

- Hourly grey generation

$\xrightarrow{\text{OPF}}$

Available:

- Grid structure
- Hourly load
- Hourly generation

OPF accuracy

OPF is used to generate an hourly power injection dataset, by assuming that the cheapest generation profile is used at all times.

OPF is a fair approximation, because

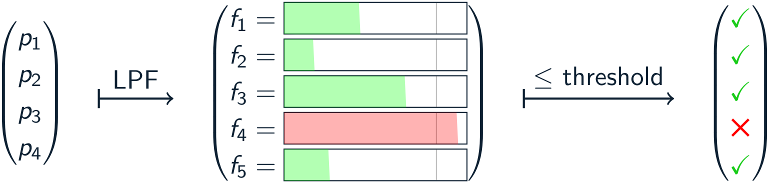
grid operators actually use OPF algorithms to minimise costs

Stochastic power injections

Deterministic power injection $\boldsymbol{p}$

Given a power injection $\boldsymbol{p} \in \mathbb{R}^n$:

- **Linearised Power Flow** computes *line current*
- $>100\%$ saturated $\Rightarrow$ **line failure**

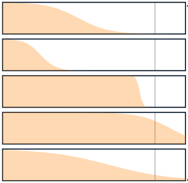


Stochastic power injection P

When the power injection $\boldsymbol{P}$ is **stochastic**:

- **LPF** now gives the line current *distribution*
- For each line, we have:
  - the failure *probability*
  - the *most likely power injection* $\tilde{\boldsymbol{p}}$ that would cause that failure

$$\begin{pmatrix}P_1\\P_2\\P_3\\P_4\end{pmatrix} \xmapsto{\text{LPF}} \begin{pmatrix}F_1\sim\\F_2\sim\\F_3\sim\\F_4\sim\\F_5\sim\end{pmatrix} \longmapsto \begin{pmatrix}0.001\%\\0.0001\%\\0.1\%\\60.0\%\\10.0\%\end{pmatrix}, \begin{pmatrix}\tilde{\boldsymbol{p}}\mid F_1>1\\\tilde{\boldsymbol{p}}\mid F_2>1\\\tilde{\boldsymbol{p}}\mid F_3>1\\\tilde{\boldsymbol{p}}\mid F_4>1\\\tilde{\boldsymbol{p}}\mid F_5>1\end{pmatrix}$$



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Stochastic power injection $\boldsymbol{P}$

When the power injection $\boldsymbol{P}$ is **Gaussian**:

$$\boldsymbol{P} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma),$$

then then line flow vector $\boldsymbol{F}$ is also Gaussian:

$$\begin{aligned} &\boldsymbol{F} = \boldsymbol{LPF} \cdot \boldsymbol{P} \\ &\boldsymbol{F} \sim \mathcal{N}(\boldsymbol{LPF} \cdot \boldsymbol{\mu}, \quad \boldsymbol{LPF} \cdot \Sigma \cdot \boldsymbol{LPF}^T). \end{aligned}$$

Correlated injections, night-time

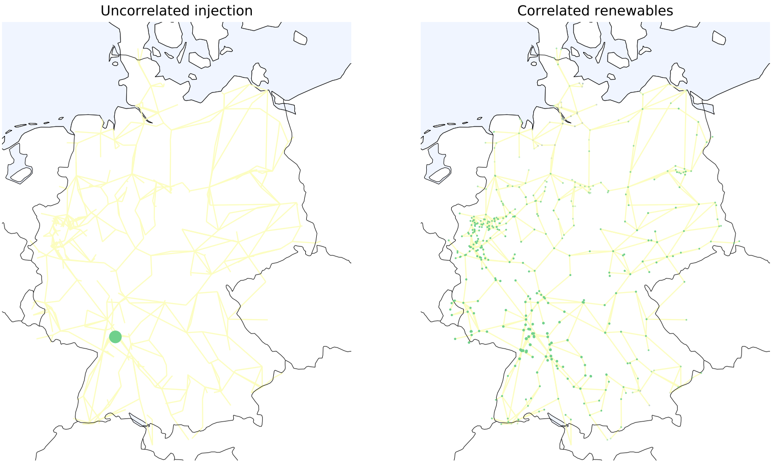


Figure 4: Covariance relative to bus 345, wind only.

Correlated injections, daytime

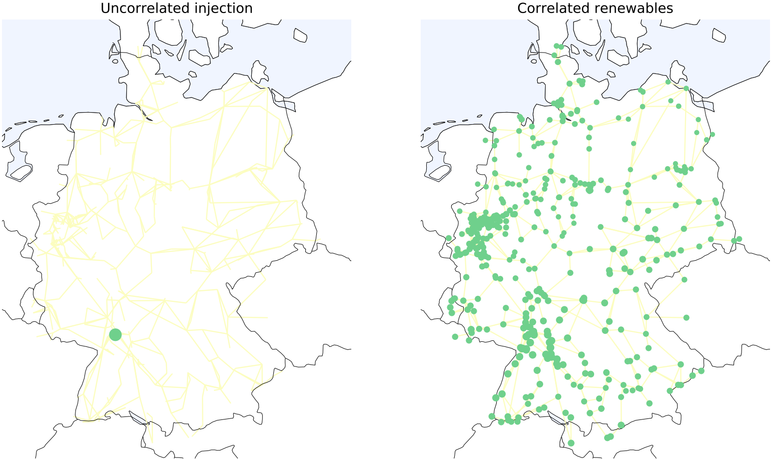


Figure 5: Covariance relative to bus 345, wind & solar.

Correlated flow, daytime

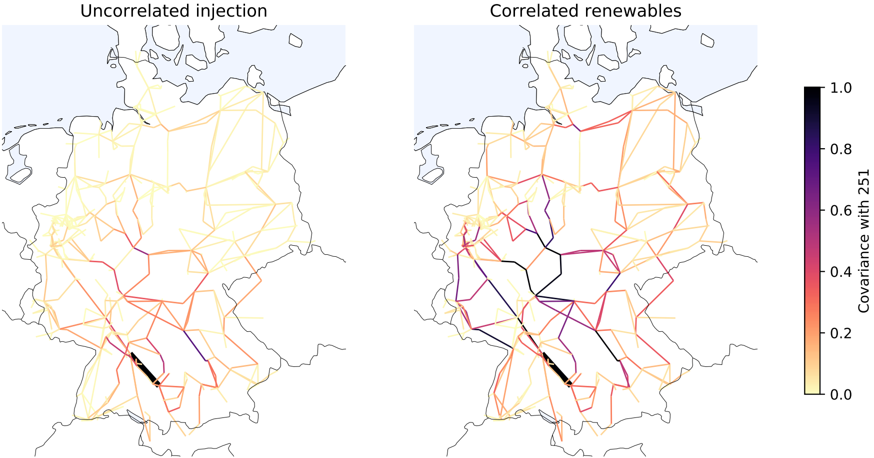


Figure 6: Covariance relative to line 251.

Correlated flow, daytime

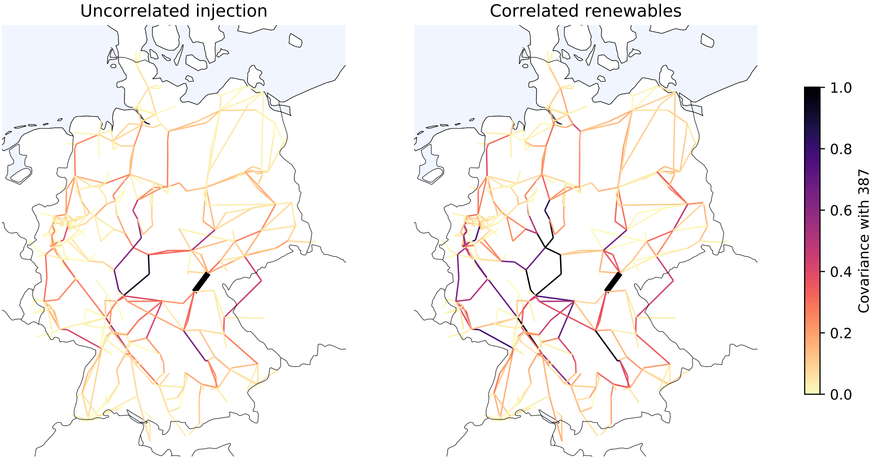


Figure 7: Covariance relative to line 387.

Long-range correlations

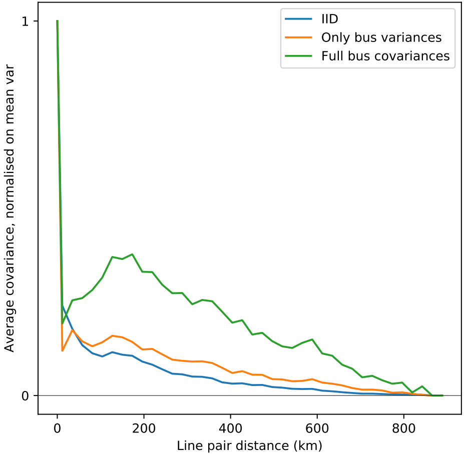
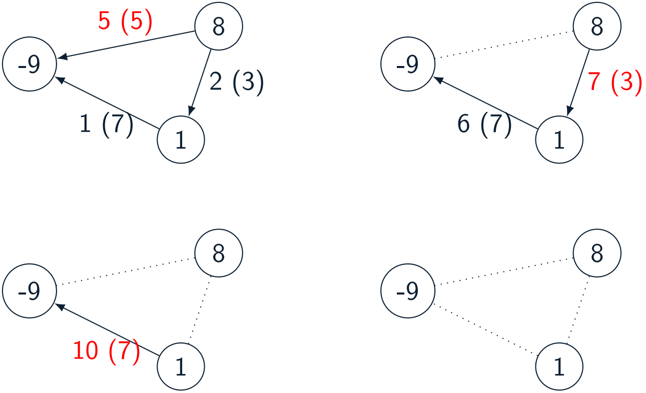


Figure 8: Covariances of 10^5 random line pairs, versus their distance.

Cascading failures

Cascades

Flow redistributions cause new failures!



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Top 10 risky lines!

line	$\mathbb{P}[\lvert F_l \rvert \geq 1]$	cascaded
651	9.56 %	1
652	8.96 %	1
411	7.06 %	1
54	6.21 %	1
298	3.45 %	13
473	3.13 %	1
213	2.37 %	1
25	2.11 %	2
645	2.02 %	32
74	1.96 %	1

Less risky lines: lower top 50

line	$\mathbb{P}[\lvert F_l \rvert \geq 1]$	cascaded
459	$9.51 \cdot 10^{-7}$	137
280	$7.90 \cdot 10^{-7}$	185
481	$7.61 \cdot 10^{-7}$	216
337	$5.82 \cdot 10^{-7}$	3
22	$3.47 \cdot 10^{-7}$	125
416	$3.12 \cdot 10^{-7}$	178
144	$2.69 \cdot 10^{-7}$	198
654	$1.26 \cdot 10^{-7}$	175
188	$1.02 \cdot 10^{-7}$	152
18	$6.43 \cdot 10^{-8}$	162

Conclusions

Conclusions

- **Long-distance correlations** in line currents are **increased** because of correlated weather.
- If an emergent failure occurs, it can **coincide with** or **cause** other failures.

- Complex behaviour of transmission networks arises from simple, *elegant* mathematical structure

Appendix

LPF accuracy

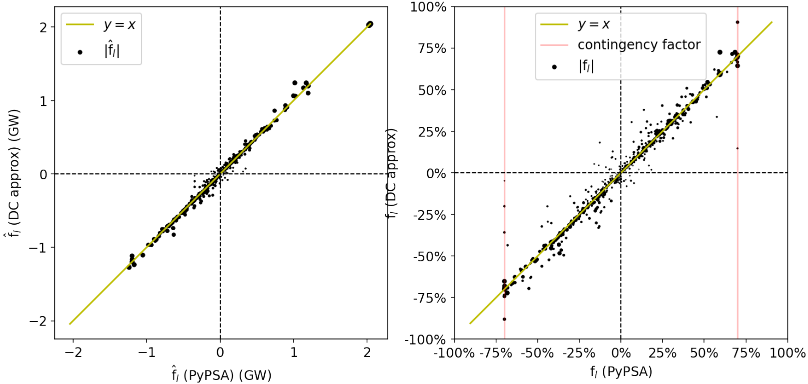


Figure 9: Line flow (left) and saturation (right) computed using LPF and (non-linear) PF

Solar model

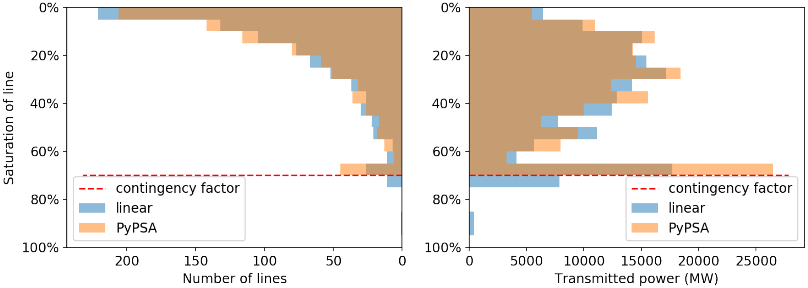


Figure 10: Histogram of line flow (left) and saturation (right) computed using LPF and (non-linear) PF

Solar model

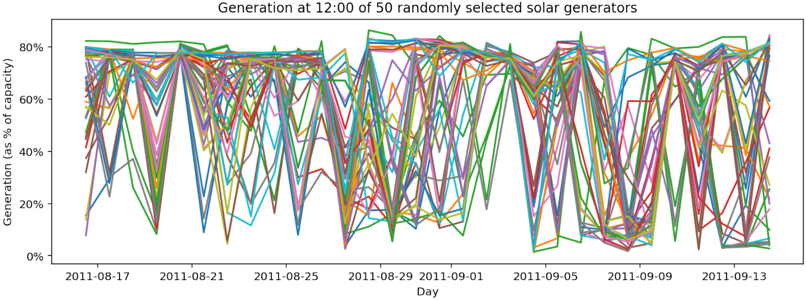
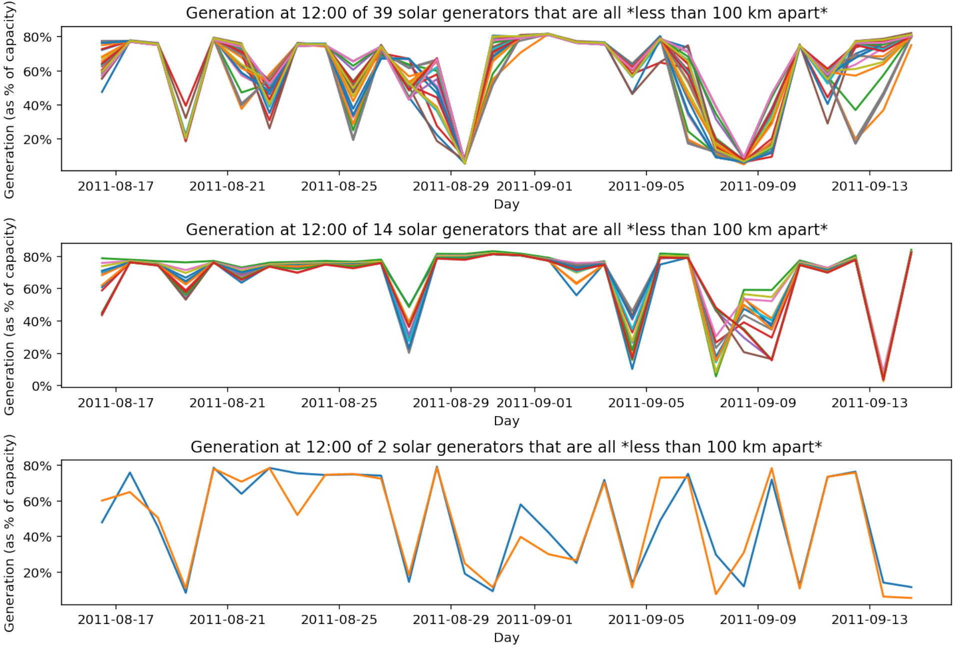


Figure 11: Daily solar generation at random nodes


Generation at 12:00 of 39 solar generators that are all *less than 100 km apart*
Generation at 12:00 of 14 solar generators that are all *less than 100 km apart*
Generation at 12:00 of 2 solar generators that are all *less than 100 km apart*
Generation (as % of capacity)
0%
20%
40%
60%
80%
2011-08-17
2011-08-21
2011-08-25
2011-08-29
2011-09-01
2011-09-05
2011-09-09
2011-09-13
Day

ARMA?

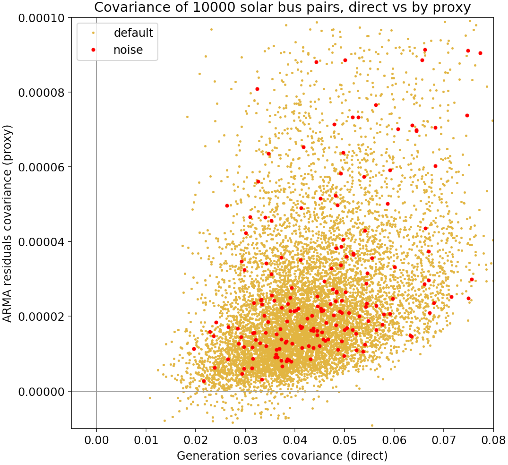
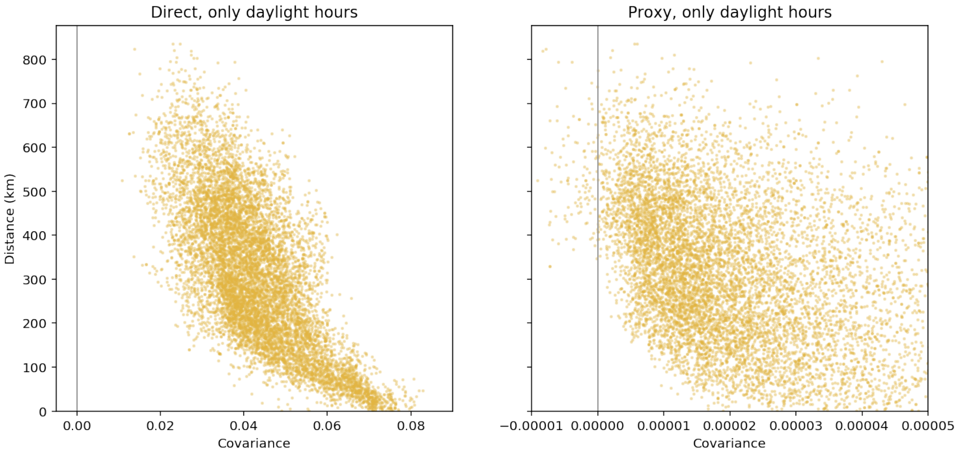


Figure 12: Two methods for estimating bus covariances



Direct, only daylight hours
Proxy, only daylight hours
Distance (km)
0
100
200
300
400
500
600
700
800
0.00
0.02
0.04
0.06
0.08
Covariance
−0.00001
0.00000
0.00001
0.00002
0.00003
0.00004
0.00005
Covariance

ARMA?

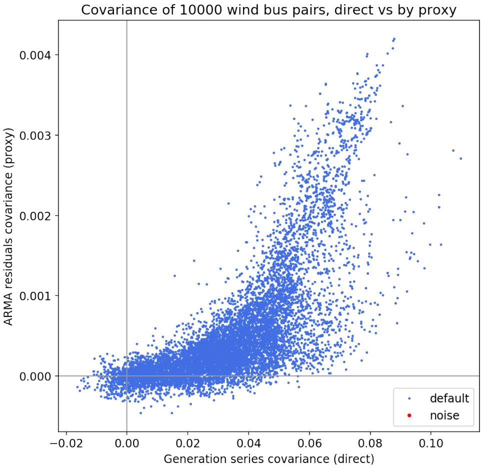
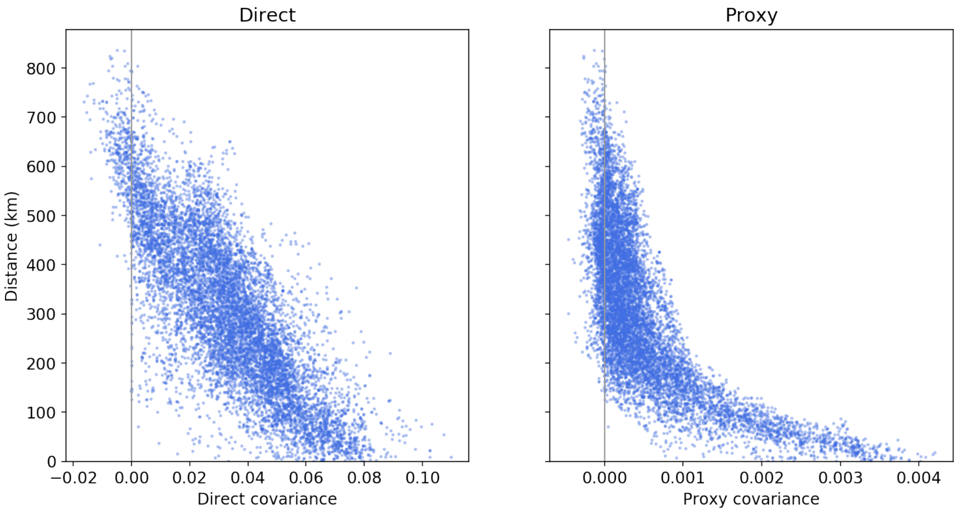


Figure 13: Two methods for estimating bus covariances


Direct
Proxy
Distance (km)
800
700
600
500
400
300
200
100
0
−0.02
0.00
0.02
0.04
0.06
0.08
0.10
Direct covariance
0.000
0.001
0.002
0.003
0.004
Proxy covariance

Github

github.com/fonsp/grid-analysis