

Robin Delabays

[www.delabays.xyz](http://www.delabays.xyz)

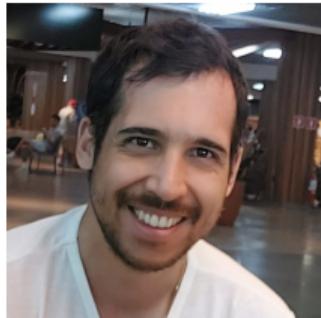
**Hes·so** VALAIS  
WALLIS

$\pi$  School of Engineering

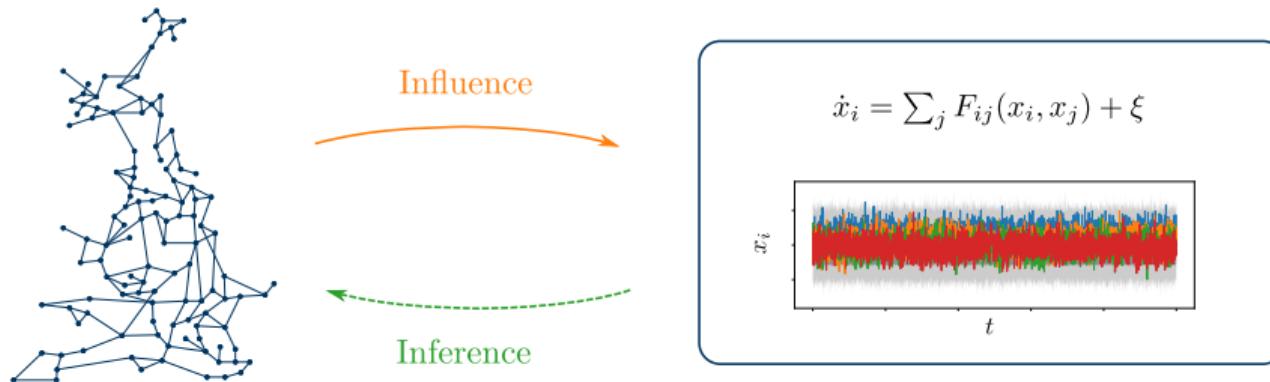
# Data-driven inference of power grids: challenges and opportunities



# People



# The graph impacts dynamics... and vice versa



W.-X. Wang, Y.-C. Lai, and C. Grebogi, *Phys. Rep.* **644** (2016).

I. Brugere, B. Gallagher, and T. Y. Berger-Wolf, *ACM Comput. Surv.* **51** (2018).

## Various approaches

**Probing:** [Yu et al., *Phys. Rev. Lett.* **97** (2006)], [Timme, *Phys. Rev. Lett.* **98** (2007)], [Dong et al., *PLoS ONE* **8** (2013)], [Basiri et al., *Phys. Rev. E* **98** (2018)], [Tyloo and D., *J. Phys. Complexity* **2** (2021)], ...

**Maximum likelihood/cost minimization:** [Hoang et al., *Phys. Rev. E* **99** (2019)], [Makarov et al., *J. Neurosci. Methods* **144**(2005)], [Shandilya and Timme, *New J. Phys.* **13** (2011)], [Panaggio et al., *Chaos* **29** (2019)], ...

**Statistical properties of trajectories:** [Dahlhaus et al., *J. Neurosci. Methods* **77** (1997)], [Sameshima and Baccalá, *J. Neurosci. Methods* **94** (1999)], [Ren et al., *Phys. Rev. Lett.* **104** (2010)], [Newman, *Nature Physics* **14** (2018)], [Peixoto, *Phys. Rev. Lett.* **123** (2019)], ...

# Notations

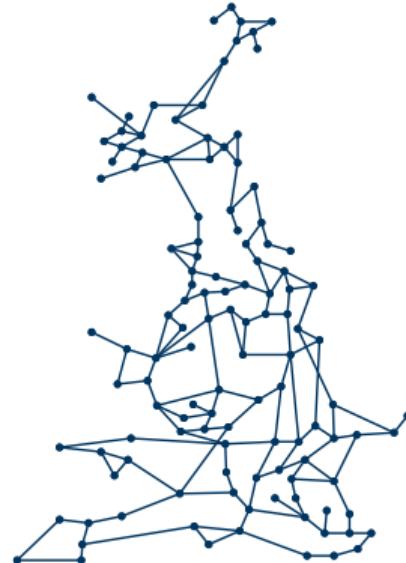
A graph

$$\mathcal{G} = (V, E)$$

The adjacency matrix  $A \in \mathbb{R}^{n \times n}$

The degree matrix  $D \in \mathbb{R}^{n \times n}$

The Laplacian matrix  $L = D - A$



## Power grid analysis

In AC power grids, all quantities become complex:

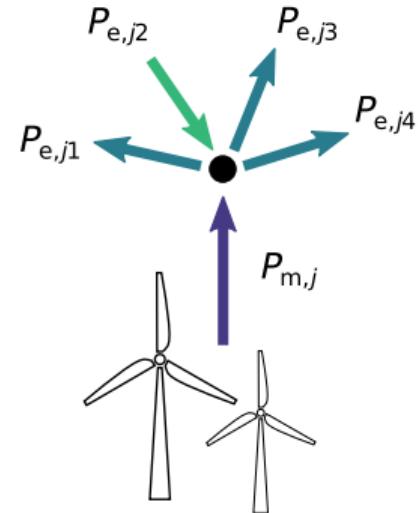
- ▶ Voltage:  $\underline{V}_j = V_j e^{i\omega_j}$
- ▶ Current:  $\underline{I}_j = I_j e^{i\phi_j}$
- ▶ Power:  $S_j = P_j + iQ_j$
- ▶ Impedance:  $Z_{jk} = R_{jk} + iX_{jk}$
- ▶ Admittance:  $Y_{jk} = 1/Z_{jk} = G_{jk} + iB_{jk}$

## Power flow equations

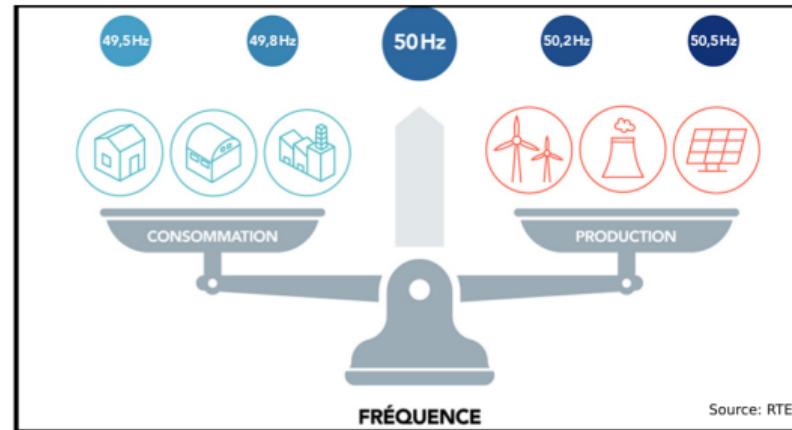
Power flow equations:

$$P_j = \sum_k \underbrace{V_j V_k [B_{jk} \sin(\theta_j - \theta_k) + G_{jk} \cos(\theta_j - \theta_k)]}_{P_{e,jk}}$$

$$Q_j = \sum_k V_j V_k [B_{jk} \cos(\theta_j - \theta_k) - G_{jk} \sin(\theta_j - \theta_k)]$$



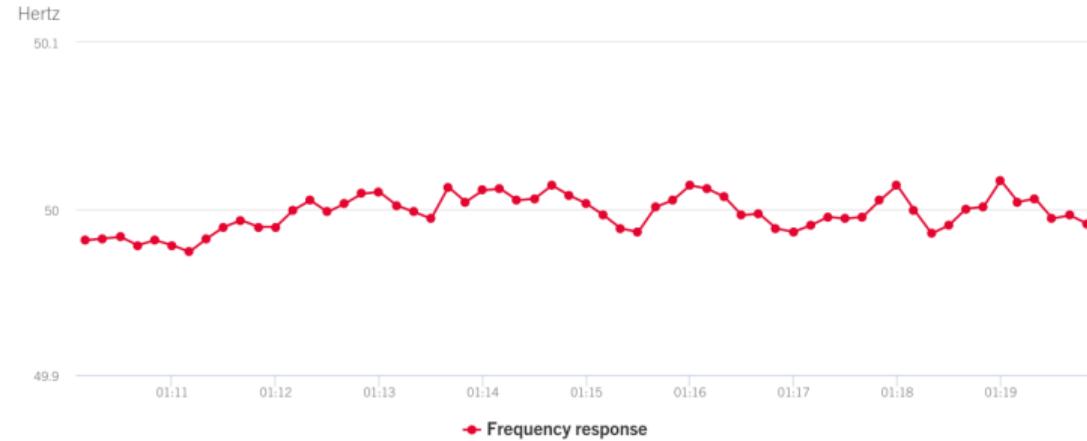
# The swing equations



$$\dot{\theta}_j = P_j - \sum_k P_{e,jk}$$

# Grid frequency

Current frequency 49.991 Hz  
Current grid time deviation 13.195 s



# Transmission grid inference



Melvyn Tyloo  
Uni Exeter



Philippe Jacquod  
HES-SO Sion

[doi.org/10.1063/5.0058739](https://doi.org/10.1063/5.0058739)

## Simplified problem

$$P_j = \sum_k V_j V_k [B_{jk} \sin(\theta_j - \theta_k) + G_{jk} \cos(\theta_j - \theta_k)]$$

## Simplified problem

$$P_j = \sum_k V_j V_k [B_{jk} \sin(\theta_j - \theta_k) + G_{jk} \cos(\theta_j - \theta_k)]$$

In transmission grids (high voltage):

$$V_j \approx \text{constant}$$

$$G_{jk} \approx 0$$

$$P_{m,j} = \sum_k B_{jk} \sin(\theta_j - \theta_k)$$

## Simplified problem (bis)

The swing equations look like the Kuramoto model:

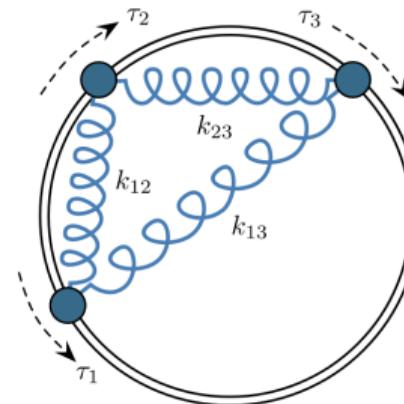
$$\dot{\theta}_j = P_j - \sum_k B_{jk} \sin(\theta_j - \theta_k)$$

## Simplified problem (bis)

The swing equations look like the Kuramoto model:

$$\dot{\theta}_j = P_j - \sum_k B_{jk} \sin(\theta_j - \theta_k)$$

Most likely converges to a steady state  $\theta^*$ .



# Network inference from ambient noise

Considering deviations from the fixed point

$$\mathbf{x}(t) = \boldsymbol{\theta}(t) - \boldsymbol{\theta}^*$$

# Network inference from ambient noise

Considering deviations from the fixed point

$$\mathbf{x}(t) = \boldsymbol{\theta}(t) - \boldsymbol{\theta}^*$$

The dynamics is approximated as

$$\dot{\mathbf{x}} \approx \mathcal{J}\mathbf{x} + \boldsymbol{\xi}$$

**Remark:** The Jacobian  $\mathcal{J}$  is a (weighted) Laplacian matrix, in particular symmetric.

## Correlated noise

**Idea:** Extract information from the noise.

## Correlated noise

**Idea:** Extract information from the noise.

Consider a time-correlated noise  $\xi$ :

$$\mathbb{E}[\xi_j(t)] = 0$$

$$\mathbb{E}[\xi_j(t)\xi_k(t')] = \delta_{jk} e^{-\tau_0|t-t'|}$$

Measure its impact at the vertices  $\mathbf{x}$  (actually we look at  $\dot{\mathbf{x}}$ ).

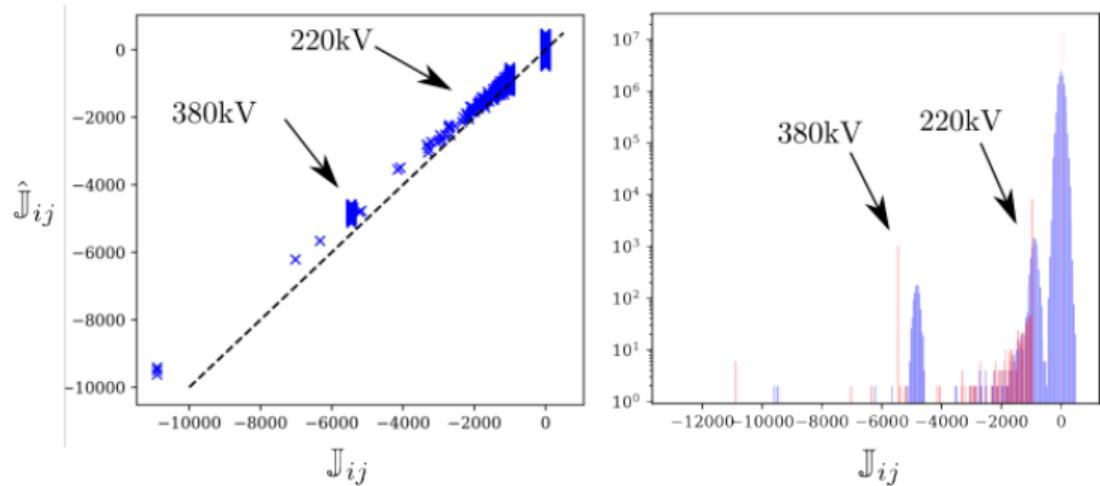
## Two-point correlators

The Jacobian's  $\ell$ -th eigenvalue and eigenvector are  $\lambda_\ell$  and  $\mathbf{u}^{(\ell)}$ .

Then for  $\lambda_\ell \tau_0 < 1$ ,

$$\begin{aligned}\mathbb{E}[\dot{x}_j \dot{x}_k] &= \delta_{jk} - \sum_{\ell=2}^n \mathbf{u}_j^{(\ell)} \mathbf{u}_k^{(\ell)} \frac{\lambda_\ell \tau_0}{1 + \lambda_\ell \tau_0} = \delta_{jk} - \sum_{\ell=2}^n \mathbf{u}_j^{(\ell)} \mathbf{u}_k^{(\ell)} \lambda_\ell \tau_0 \sum_{m=0}^{\infty} (-\lambda_\ell \tau_0)^m \\ &= \delta_{jk} + \sum_{m=1}^{\infty} (-\tau_0)^m \sum_{\ell=2}^n \mathbf{u}_j^{(\ell)} \lambda_\ell^m \mathbf{u}_k^{(\ell)} \\ &= \delta_{jk} + \sum_{m=1}^{\infty} (-\tau_0)^m (\mathcal{J}^m)_{jk}\end{aligned}$$

# Results



In practice, we can only determine existence of edges, not their weight.

# Distribution grid inference



Marc Gillioz  
HES-SO Sion

# Distribution grid vs. transmission grid

## Relevance:

- ▶ Line parameters are often not known.
- ▶ Sometimes even the structure is not clear.
- ▶ Grid operators are interested in accurate models.
- ▶ By 2027, 80% of deployment.

## Pros:

- ▶ Structure is usually simple (tree).

## Cons:

- ▶ Actual data availability.
- ▶ Data quality.

## One among many algorithms

Under "**reasonable**" assumptions, Park, Deka, and Chertkov (2018) can estimate the inverse of the resistance and reactance Laplacian matrices:  $L_r^\dagger$  and  $L_x^\dagger$ .

$$\mathbb{E}(V_j P_k) = (L_r^\dagger)_{jk} \mathbb{E}(P_k^2) + (L_x^\dagger)_{jk} \mathbb{E}(P_k Q_k)$$

$$\mathbb{E}(V_j Q_k) = (L_r^\dagger)_{jk} \mathbb{E}(P_k Q_k) + (L_x^\dagger)_{jk} \mathbb{E}(Q_k^2)$$

## Effective resistance

Hence, we get the **effective resistance**:

$$d_r(i, j) = (L^\dagger)_{ii} + (L^\dagger)_{jj} - 2(L^\dagger)_{ij}$$

which is a distance.

As the graph is a tree,

$$\Omega_{ij} = \sum_{e \in P_{ij}} R_e$$

## Recursive grouping algorithm

Given pairwise distances  $d(a, b)$  and assuming **the graph is a tree**. Compute

$$\Phi_{abc} = d(a, c) - d(b, c)$$

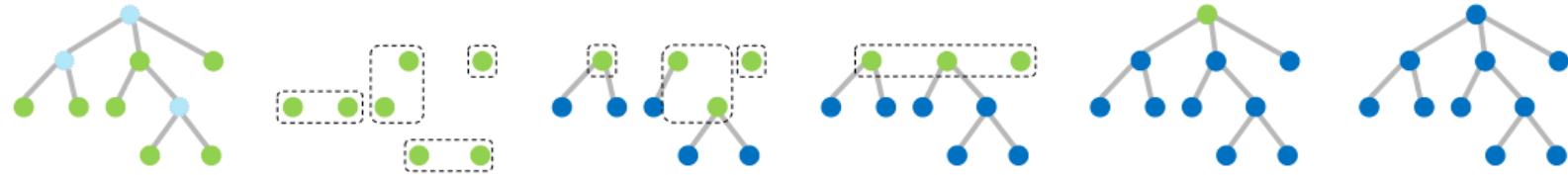
Then

1. If  $d(a, b) = \Phi_{abc}$  for all  $c$ , then  $b \rightarrow a$ .
2. If  $\Phi_{abc} = \Phi_{abc'}$  for all  $c, c'$ , then  $a \leftrightarrow b$ .

In case 2., a new parent  $h$  is added. Then

$$d(a, h) = \frac{1}{2}(d(a, b) + \Phi_{abc}) \quad d(c, h) = d(a, c) - d(a, h)$$

## Recursive grouping algorithm



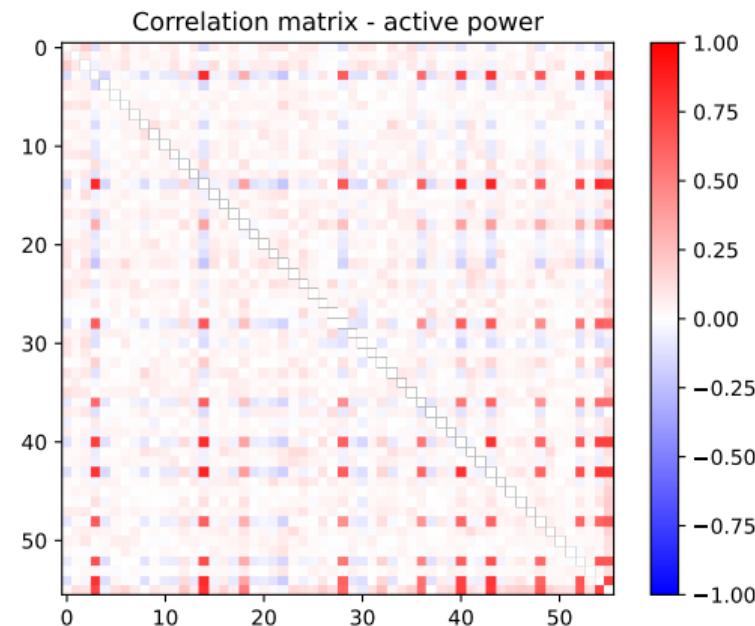
# Issue...

Park et al. (2018) require

$$\mathbb{E}(P_j P_k) = 0,$$

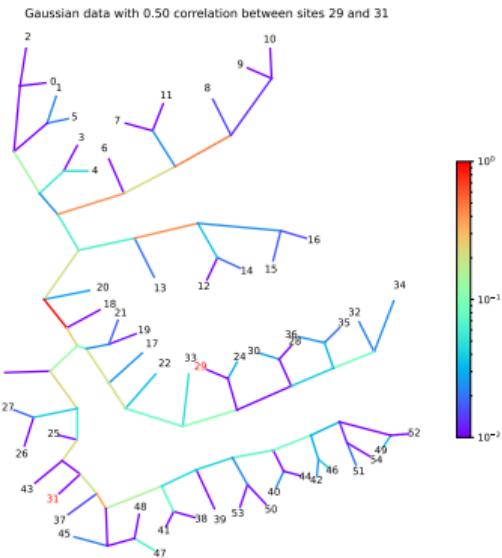
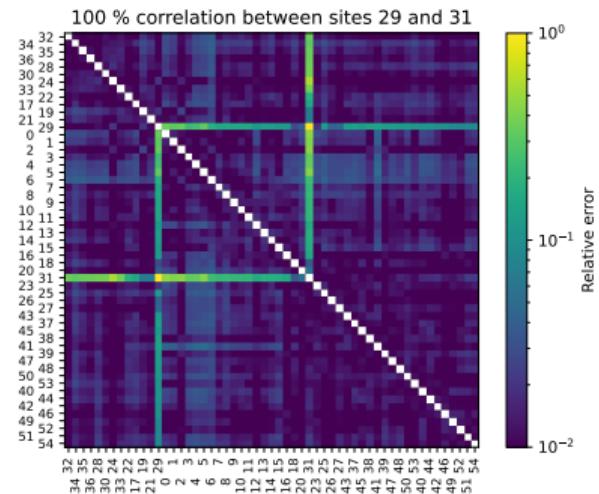
which is not always true.

**Idea:** Sub-sampling

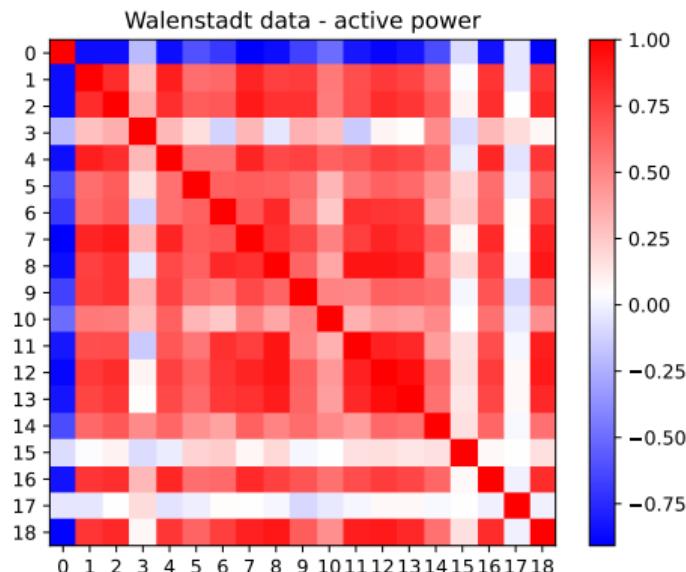


# Our hope

Correlation does not impedes all resistances.



Unfortunately...



# Conclusion

Correlations carry information about the underlying network...

## Conclusion

Correlations carry information about the underlying network...

but too much correlation impedes inference.

## Conclusion

Correlations carry information about the underlying network...

but too much correlation impedes inference.

Thank you!

# GeoCoW 2026

Geometry of Complex Webs

November 1 - 6, 2026

Les Diablerets

[https://swissmaprs.ch/events/  
geocow-geometry-of-complex-webs/](https://swissmaprs.ch/events/geocow-geometry-of-complex-webs/)

