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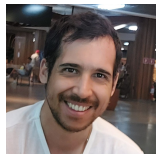
School of Engineering

Data-driven network inference: from transmission to distribution grids



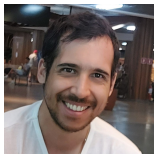
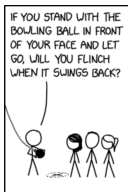
Inference of...

1. Transmission grids



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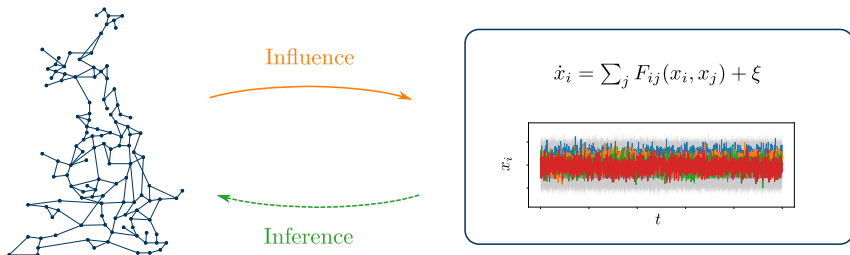
1. Transmission grids



2. Distribution grids



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)], ...

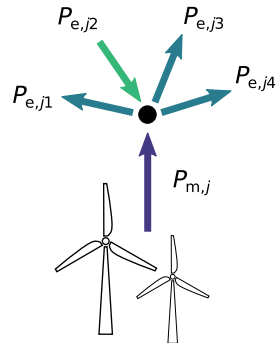
Statistical properties of trajectories: [Dahlhaus et al., *J. Neurosci. Methods* **77** (1997)], [Sameshima and Baccalá, *J. Neurosci. Methods* **94** (1999)], [Ren et al., *Phys. Rev. Lett.* **104** (2010)], [Newman, *Nature Physics* **14** (2018)], [Peixoto, *Phys. Rev. Lett.* **123** (2019)], ...

Power flow equations

Power flow equations:

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

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



Transmission grid inference



Melvyn Tyloo
Uni Exeter



Philippe Jacquod
HES-SO Sion

doi.org/10.1063/5.0058739

Simplified problem

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

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In transmission grids (high voltage):

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

$$G_{jk} \approx 0$$

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

The voltage phases evolve following the mismatch of the latter equation (swing equations).

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

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

where

$$\mathcal{J}_{ij} = \begin{cases} B_{ij} \cos(\theta_i^* - \theta_j^*), & i \neq j, \\ -\sum_k B_{ik} \cos(\theta_i^* - \theta_k^*), & i = j, \end{cases}$$

and $\boldsymbol{\xi}$ is the noise.

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

Correlated noise and two-point correlator

Consider a time-correlated noise ξ :

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

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

and look at $\mathbb{E}[\dot{x}_j\dot{x}_k]$.

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and look at $\mathbb{E}[\dot{\xi}_j\dot{\xi}_k]$.

Then for $\tau_0 \ll 1$,

$$\mathbb{E}[\dot{\xi}_j\dot{\xi}_k] = \delta_{jk} + \sum_{m=1}^{\infty} (-\tau_0)^m (\mathcal{J}^m)_{jk}$$

and for $\tau_0 \gg 1$,

$$\mathbb{E}[\dot{\xi}_j\dot{\xi}_k] = \frac{1}{n} - \sum_{m=1}^{\infty} (-\tau_0)^{-m} (\mathcal{J}^{-m})_{jk}$$

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 in CH.

Pros:

- ▶ Structure is usually simple (tree).

Cons:

- ▶ Data quality.
- ▶ Actual data availability.

One among many algorithms

Under "**reasonable**" assumptions, Park, Deka, and Chertkov (2018) can estimate the inverse of the resistance and reactance Laplacian matrices: $L_{1/r}^\dagger$ and $L_{1/x}^\dagger$.

Linear coupled power flow (LC-PF)

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

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

$$\mathbf{P} = L_{1/x}\boldsymbol{\theta} + L_{1/r}\mathbf{V}$$

$$\mathbf{Q} = L_{1/x}\mathbf{V} - L_{1/r}\boldsymbol{\theta}$$

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$$\mathbf{Q} = L_{1/x}\mathbf{V} - L_{1/r}\boldsymbol{\theta}$$

leads to

$$\mathbf{V} = L_{1/r}^\dagger \mathbf{P} + L_{1/x}^\dagger \mathbf{Q}$$

$$\boldsymbol{\theta} = L_{1/x}^\dagger \mathbf{P} - L_{1/r}^\dagger \mathbf{Q}$$

Extracting information from correlations

Taking the voltage to power correlations:

$$\mathbb{E}(V_j P_k) = (L_{1/r}^\dagger)_{jk} \mathbb{E}(P_k^2) + (L_{1/x}^\dagger)_{jk} \mathbb{E}(P_k Q_k)$$

$$\mathbb{E}(V_j Q_k) = (L_{1/r}^\dagger)_{jk} \mathbb{E}(P_k Q_k) - (L_{1/x}^\dagger)_{jk} \mathbb{E}(Q_k^2)$$

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All (co)variances can be estimated empirically.

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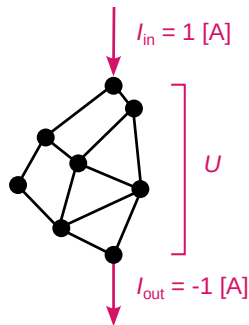
All (co)variances can be estimated empirically.

Then one can solve for $L_{1/r}^\dagger$ and $L_{1/x}^\dagger$.

Effective resistance

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

$$d_r(i, j) = (L_{1/r}^\dagger)_{ii} + (L_{1/r}^\dagger)_{jj} - 2(L_{1/r}^\dagger)_{ij}.$$



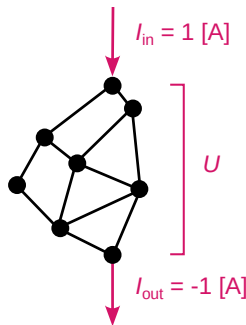
Effective resistance

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As the graph is a tree,

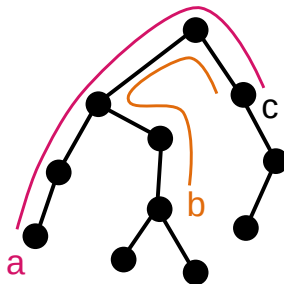
$$d_r(i, j) = \sum_{e \in \mathcal{P}_{ij}} R_e$$



Recursive grouping algorithm

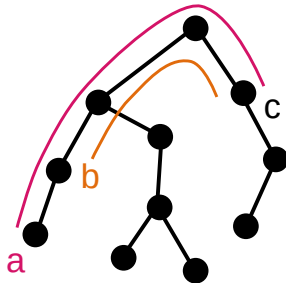
Given pairwise distances $d(a, b)$ and assuming **the graph is a tree**. Compute

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



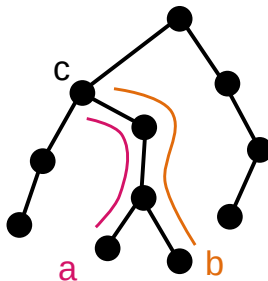
Recursive grouping algorithm: parent-child

If $d(a, b) = \Phi_{abc}$ for all c , then b is a parent to a .



Recursive grouping algorithm: siblings

If $\Phi_{abc} = \Phi_{abc'}$ for all c, c' , then a and b are siblings.

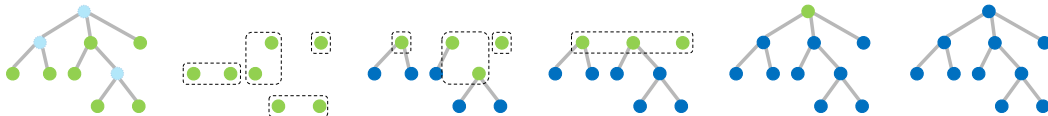


Then a new parent h is added,

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

$$d(c, h) = d(a, c) - d(a, h)$$

Recursive grouping algorithm



Let's run the algo on real data

Semi-synthetic data:

Smart meter measurements from
GOFLEX...

<https://goflex-project.eu/>

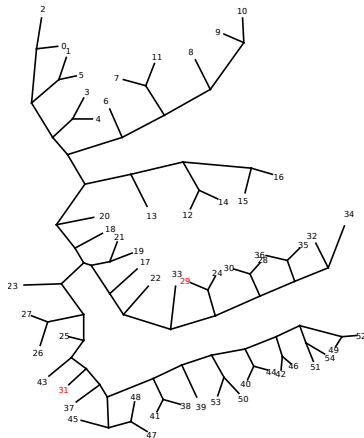
Khan and Hayes, *2022 IEEE PESGM* (2022), doi: 10.1109/PESGM48719.2022.9916806

Let's run the algo on real data

Semi-synthetic data:

Smart meter measurements from
GOFLEX...

... on a standard distribution grid.



<https://goflex-project.eu/>

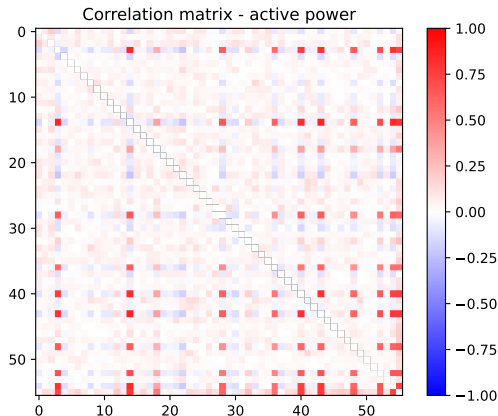
Khan and Hayes, 2022 IEEE PESGM (2022), doi: 10.1109/PESGM48719.2022.9916806

Issue...

Park et al. (2018) require

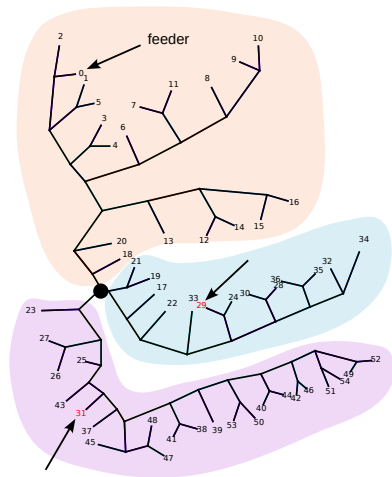
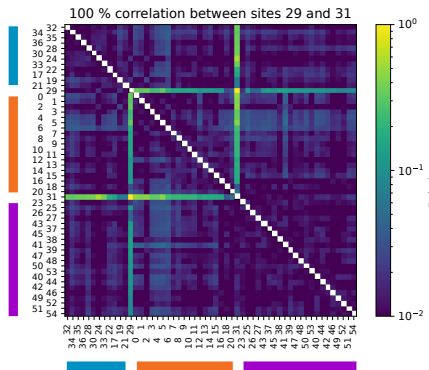
$$\mathbb{E}(P_j P_k) = 0,$$

which is not always true.



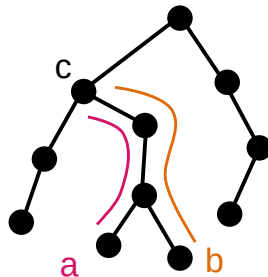
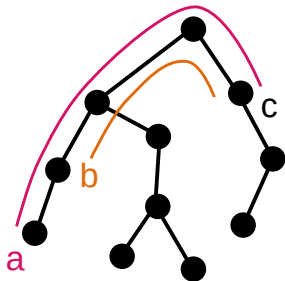
Let's go back to synthetic data

Same grid, but Gaussian time series with controlled correlations.

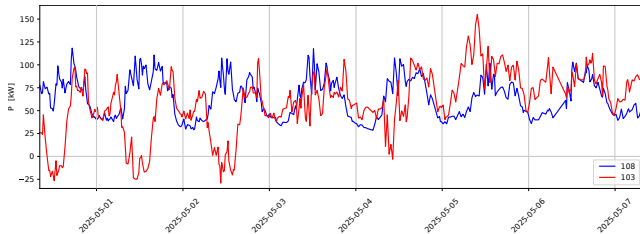
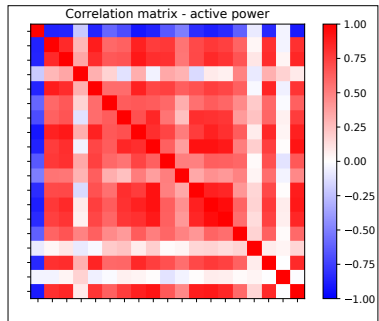


There is hope...

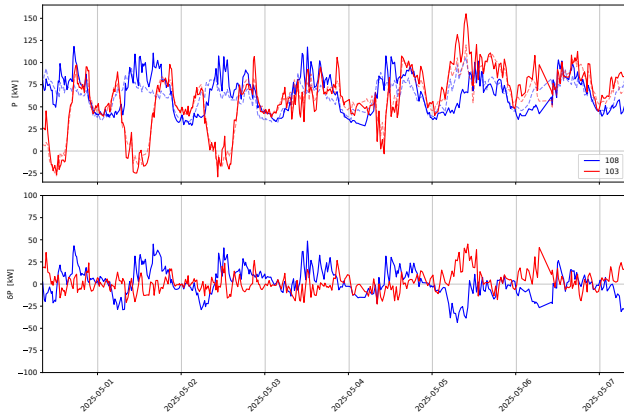
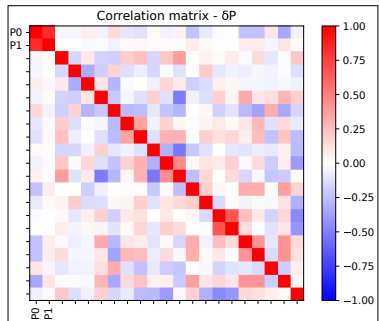
Recursive grouping algorithm



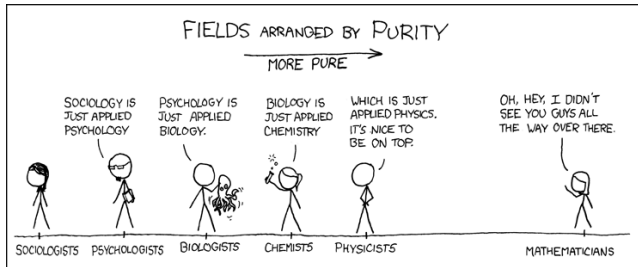
(Un)luckily...



Work in progress...



Conclusion



Main lesson learned:

- ▶ We are working at a sensitive spot in terms of SNR.
- ▶ Data are hard to find actually!

Correlated noise

Idea: Extract information from the noise.

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Consider a time-correlated noise ξ :

$$\mathbb{E}[\xi_j(t)] = 0 \qquad \mathbb{E}[\xi_j(t)\xi_k(t')] = \delta_{jk}e^{-\tau_0|t-t'|}$$

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

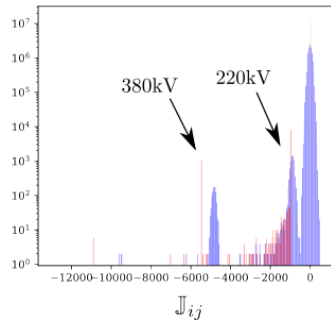
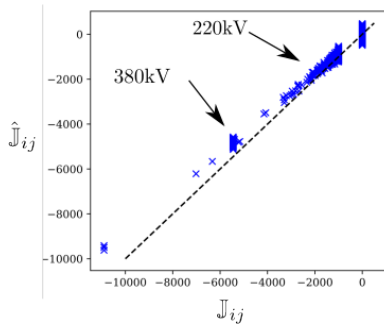
Two-point correlators

The Jacobian's ℓ -th eigenvalue and eigenvector are λ_ℓ 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.