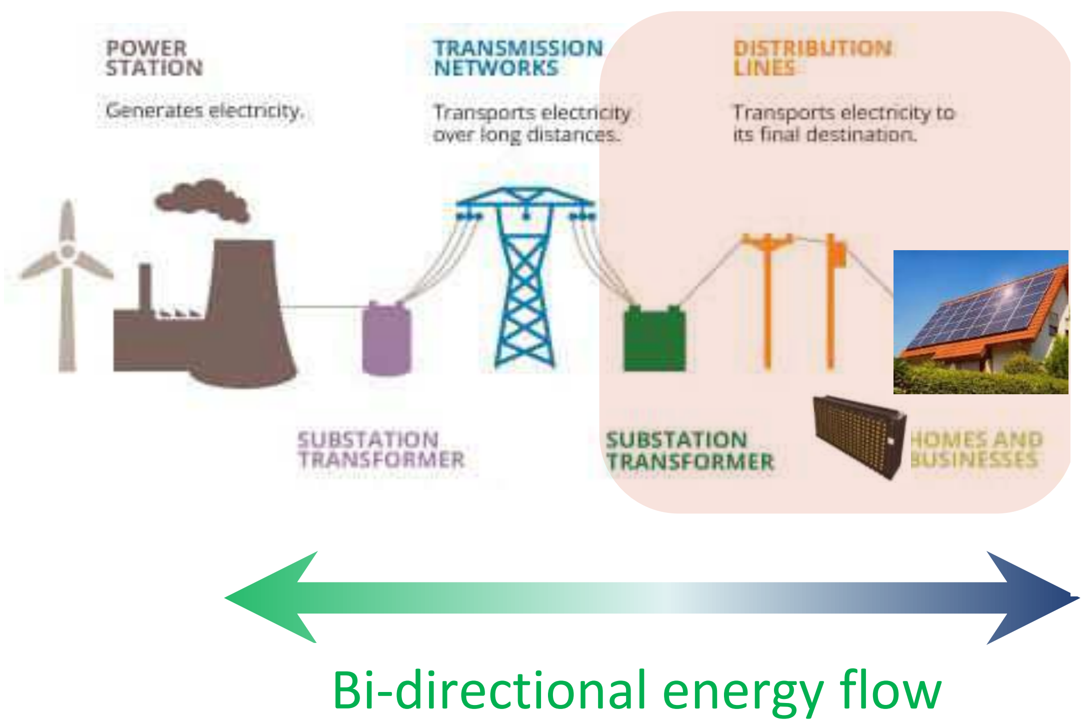
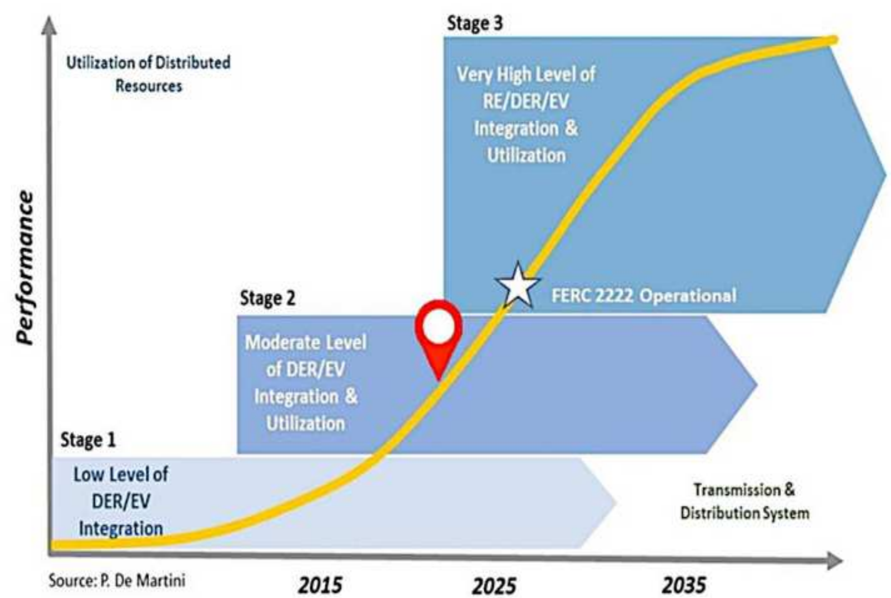
Trackable topology and parameter estimation in distribution grids with limited edge-data

Deep Deka
Research Scientist,
MIT Energy Initiative

Distribution Grid

- Final Tier in electricity transfer
  - More active devices, more opportunities for control/services

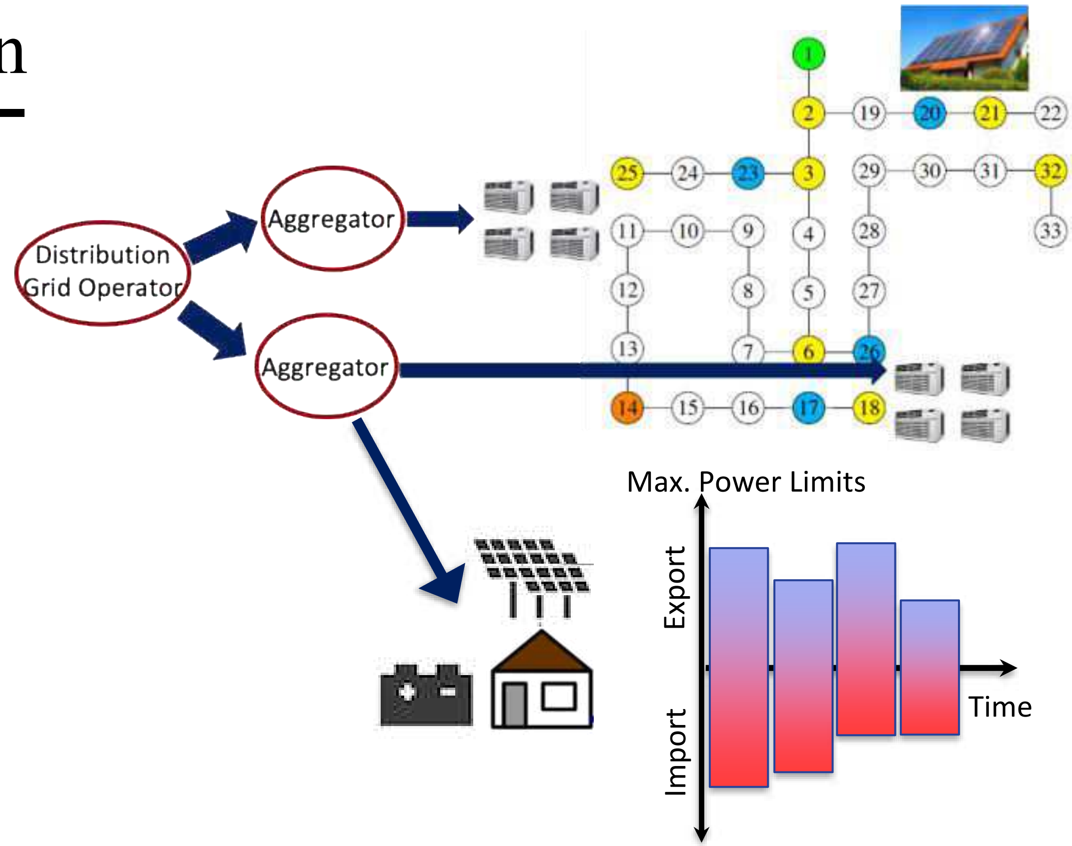




DOE Office of Electricity Report "Distribution System Evolution", April 2024

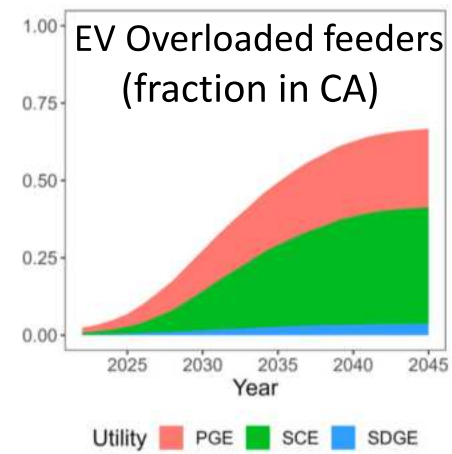
Distribution Grid Evolution

- New operating paradigms:
  - Virtual power Plants
  - Operating Envelopes
  - New markets,



BUT

- Needs:
  - Metering for estimation
  - Co-ordination



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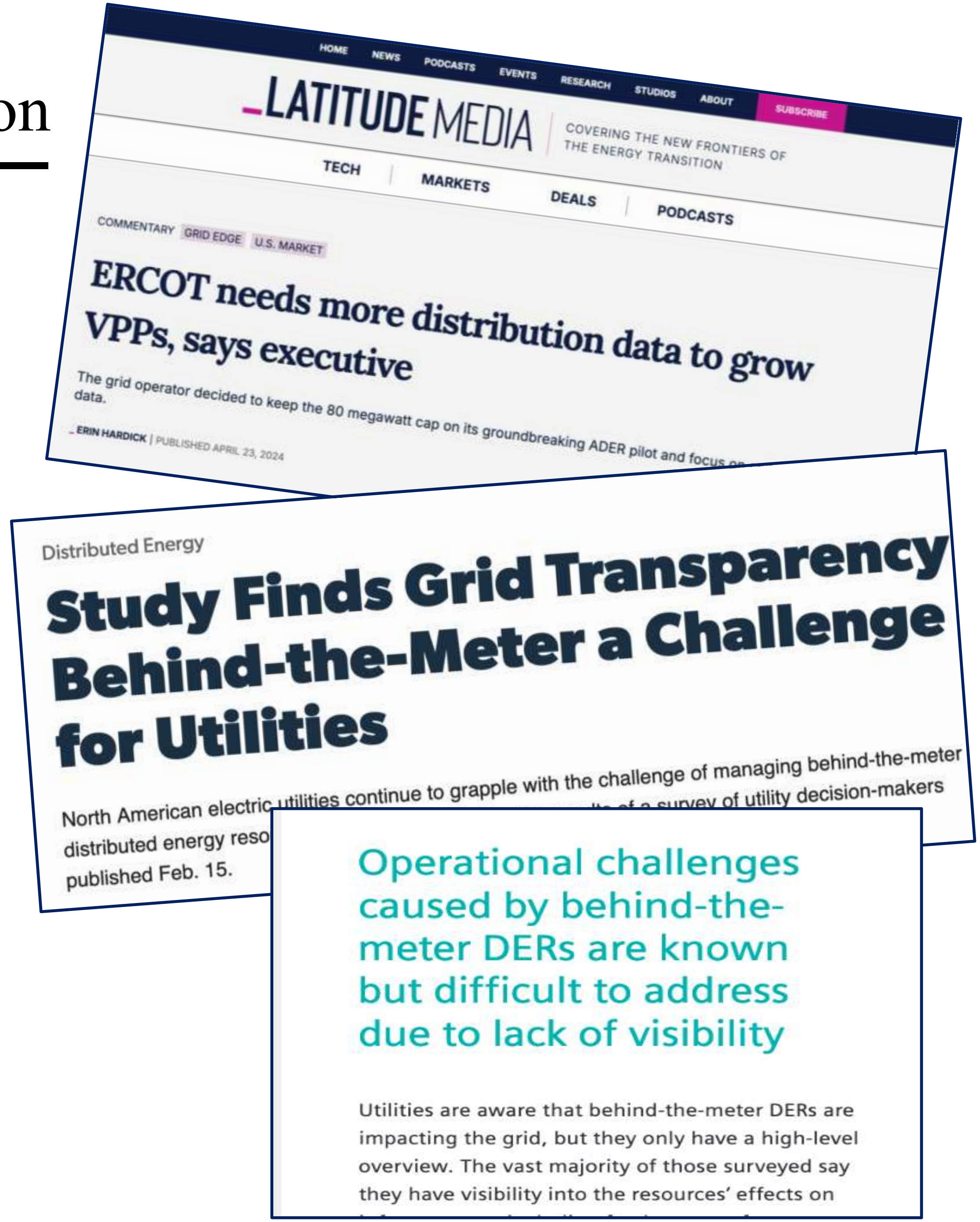
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COMMENTARY GRID EDGE U.S. MARKET

ERCOT needs more distribution data to grow VPPs, says executive

The grid operator decided to keep the 80 megawatt cap on its groundbreaking ADER pilot and focus on data.

ERIN HARDICK | PUBLISHED APRIL 23, 2024

Distributed Energy

Study Finds Grid Transparency Behind-the-Meter a Challenge for Utilities

North American electric utilities continue to grapple with the challenge of managing behind-the-meter distributed energy reso... survey of utility decision-makers published Feb. 15.

Operational challenges caused by behind-the-meter DERs are known but difficult to address due to lack of visibility

Utilities are aware that behind-the-meter DERs are impacting the grid, but they only have a high-level overview. The vast majority of those surveyed say they have visibility into the resources' effects on

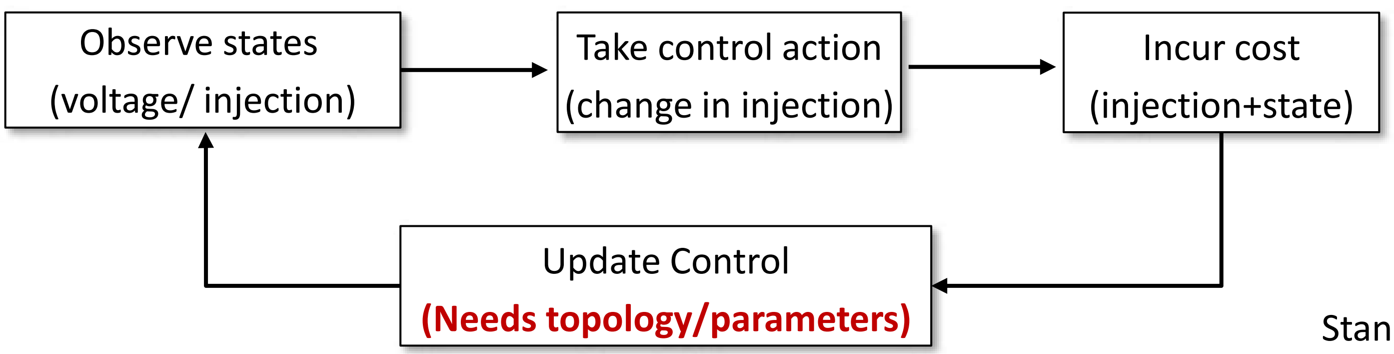
Distribution Grid Sensing

- Smart meters, PMUs, micro-PMUs, IoT, AMI
- Big Data: High fidelity measurements
- Sparse: Not everywhere in low voltage grids

Use cases with limited edge devices:

✓ Topology learning/ Phase identification

✓ Control/aggregation/VPP needs impedances



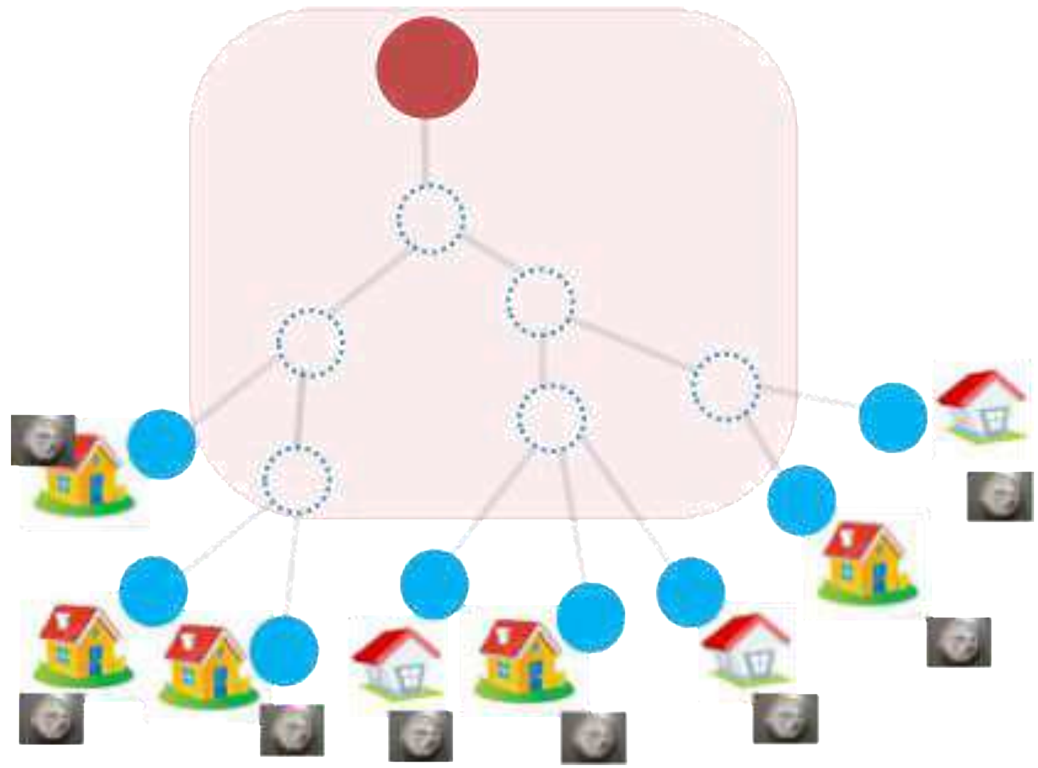
Standard Feedback loop

Problem: Learning with *end-users*

- Data: Time-series Nodal voltages (V) and injections (P,Q) at leaves
- Unobserved: all intermediate nodes & lines
- Estimate: Operational Topology + Line Impedance

Theoretical guarantees via statistical Machine Learning

- what length of observations?
- how much observability?
- how much noise?



Grid Model:

- Distribution grid features
  1. Structure of the grid: **Radial**
  2. Flow Physics (Static regime)

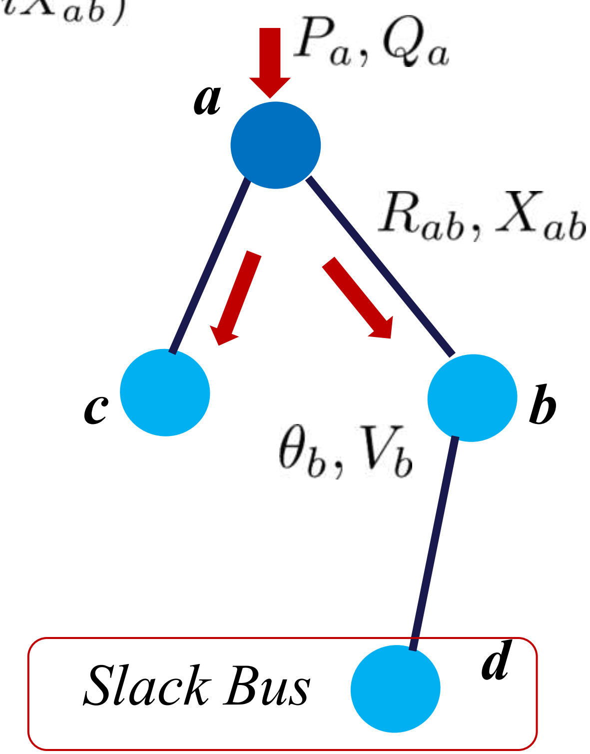
$$P_a + \hat{i}Q_a = \sum_{(a,b)} V_a e^{\hat{i}\theta_a} \frac{(V_a e^{-\hat{i}\theta_a} - V_b e^{-\hat{i}\theta_b})}{(R_{ab} - \hat{i}X_{ab})}$$

- First order expansion: LinDist Flow

$$\theta = H_{1/X}^{-1} P - H_{1/R}^{-1} Q,$$
$$V = H_{1/R}^{-1} P + H_{1/X}^{-1} Q$$

- $H_{1/R} = M^T R^{-1} M$

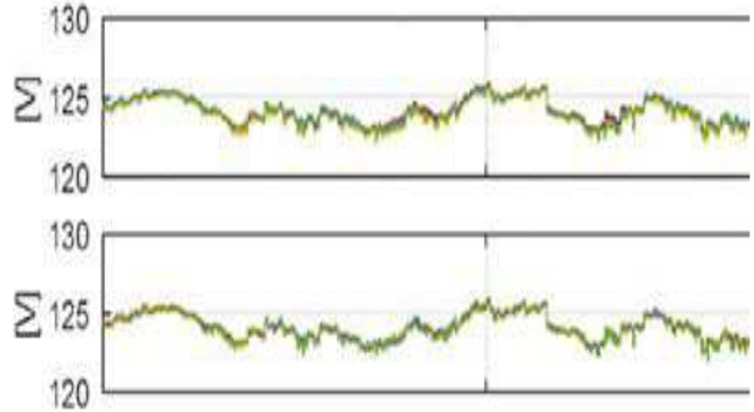
wt. Laplacian matrix



End-user data

- Time-stamped voltage magnitudes (V)

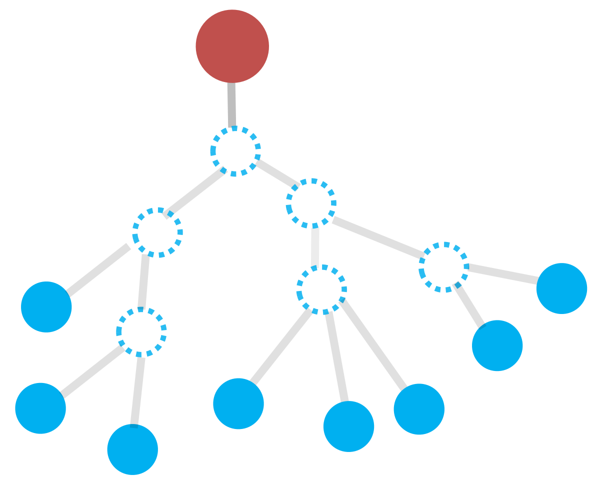
$$\mu_V = \mathbb{E}[V]$$
$$\Omega_V = \mathbb{E}[V - \mu_V][V - \mu_V]^T$$



- Time-stamped nodal active & reactive injections (P &Q)

$$\mu_P, \ \Omega_P, \ \mu_Q, \ \Omega_Q, \ \Omega_{PQ}$$

- Cross-covariances: Ω_{VP}, Ω_{VQ}



Learning with *end-users*

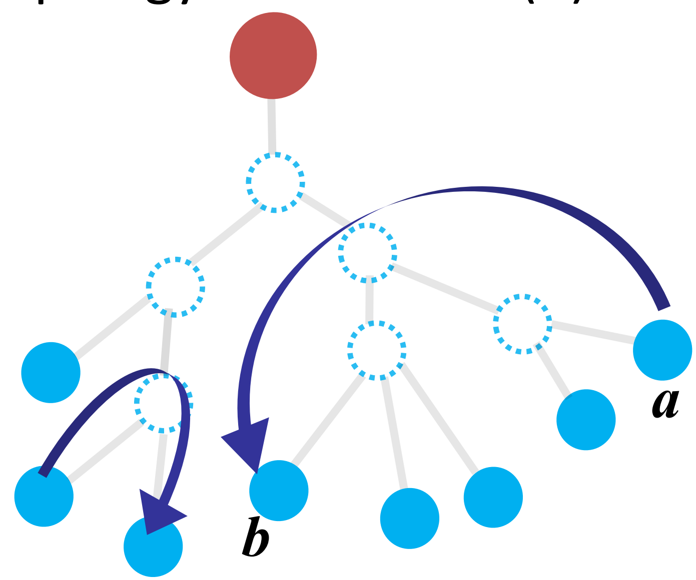
- Data: Time-series Nodal voltages and injection samples at leaves
- Algorithm:

➢ Compute *effective impedances* between leaf pairs

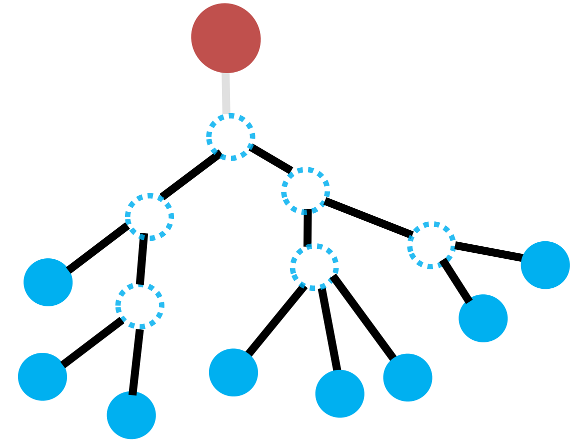
$$R_{eff}(a,b) = H^{-1}_{1/R}(a,a) + H^{-1}_{1/R}(b,b) - 2H^{-1}_{1/R}(a,b)$$

❖ Key: Effective resistances are additive on trees

➢ ***Recursive Grouping Algo*** (Wilsky) to learn topology & distances (d) from known effective impedances



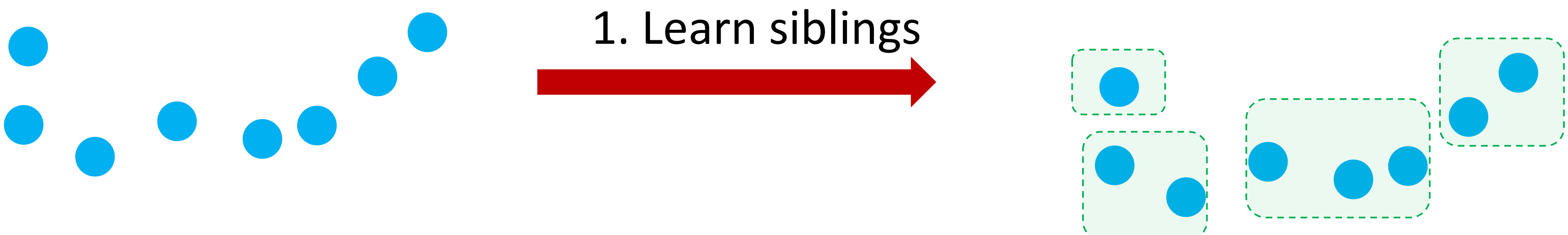
Recursive Grouping Algo



1. a, b are leaf nodes with common parent iff
$d(a,c) - d(b,c) = d(a,c') - d(b,c')$ for all $c, c' \neq a, b$

2. a is a leaf node and b is its parent iff

$d(a,c) - d(b,c) = d(a,b)$ for all $c \neq a, b$



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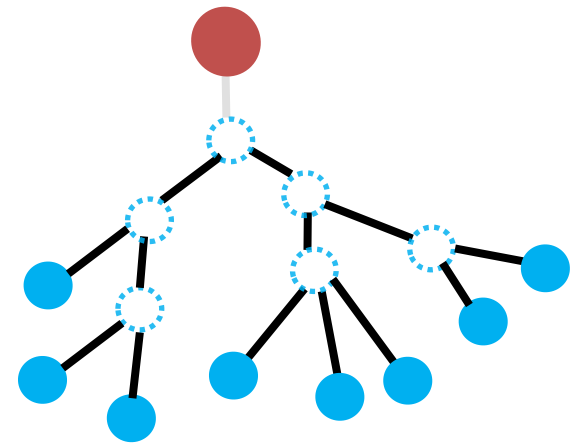
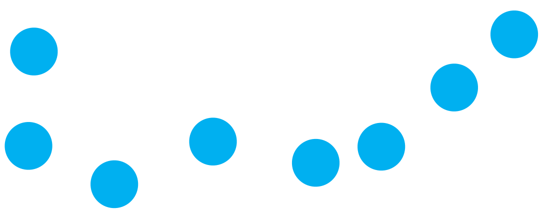
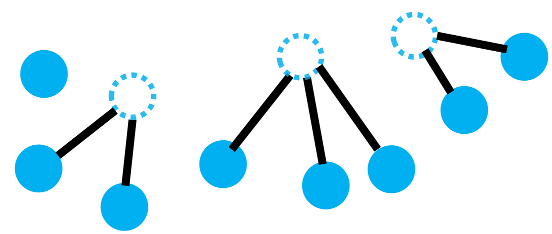




2. Introduce parents

3. Update distance



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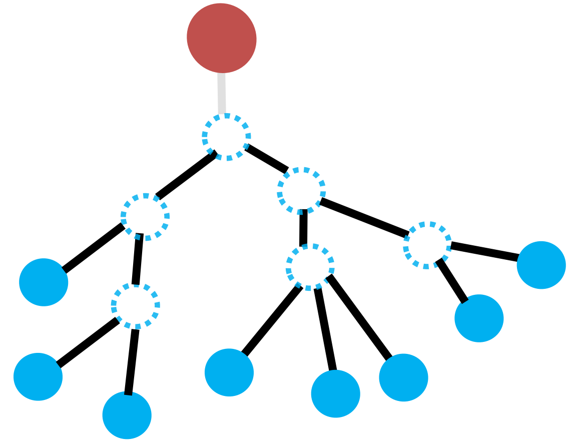

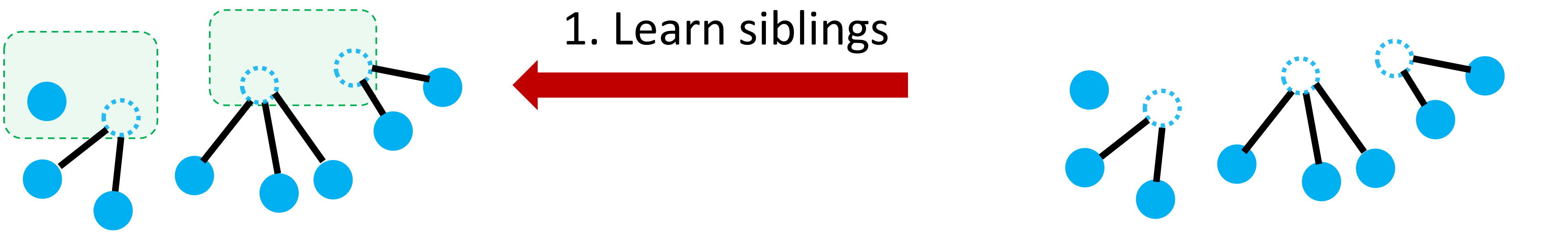

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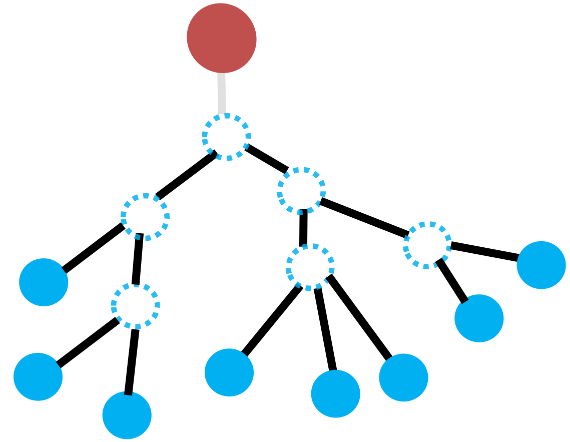

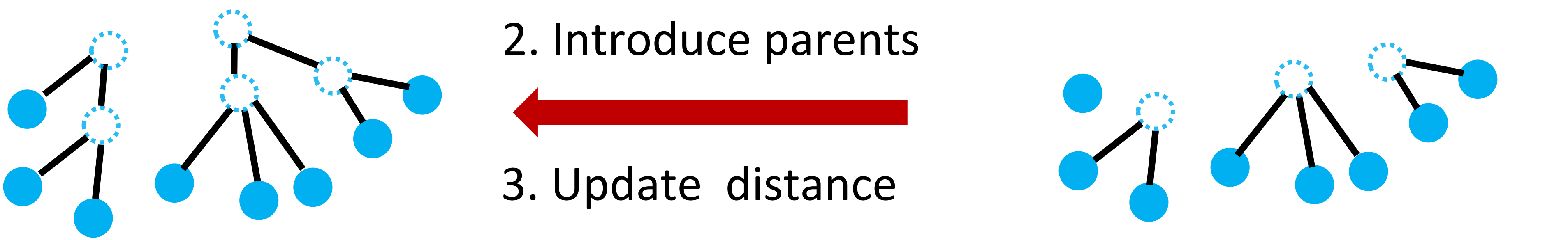

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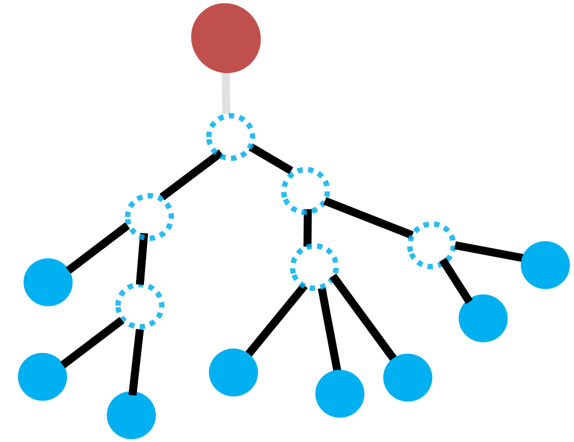
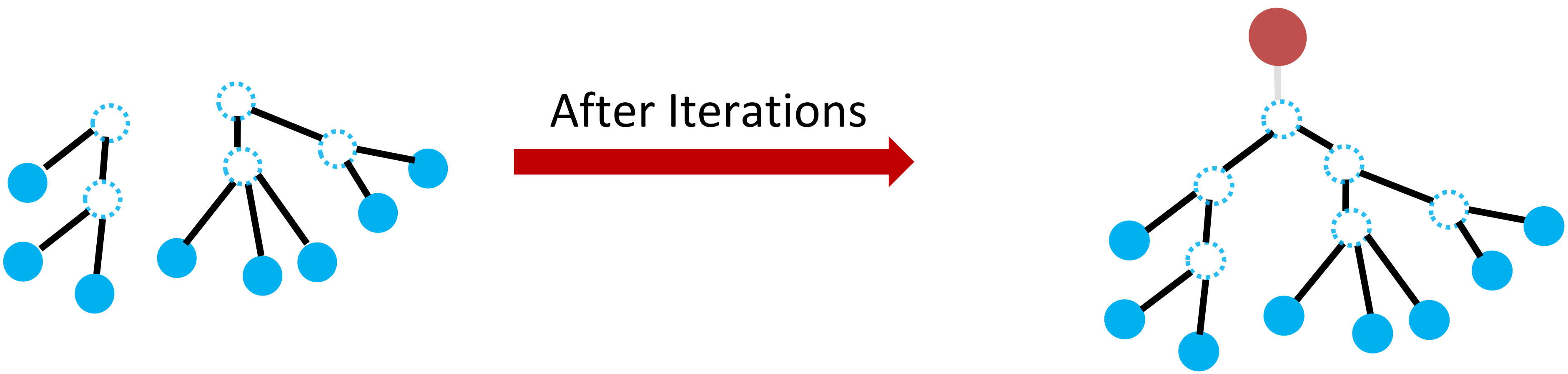




Estimating effective impedances

- Algorithm:

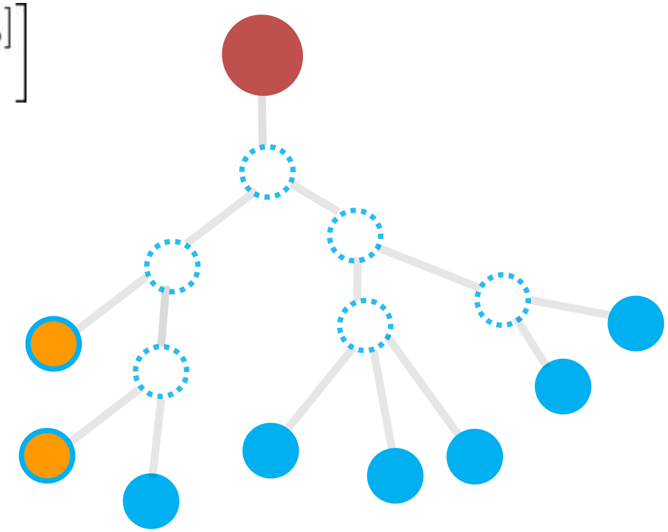
➢ Compute *effective impedances* between leaves

$$R_{eff}(a,b) = H^{-1}_{1/R}(a,a) + H^{-1}_{1/R}(b,b) - 2H^{-1}_{1/R}(a,b)$$

➢ **Uncorrelated** Injections

$$\begin{bmatrix}\mathbb{E}[v_a p_b] & \mathbb{E}[v_a q_b]\end{bmatrix} = \begin{bmatrix}H^{-1}_{1/r}(a,b) & H^{-1}_{1/x}(a,b)\end{bmatrix}\begin{bmatrix}\mathbb{E}[p_b^2] & \mathbb{E}[p_b q_b] \\ \mathbb{E}[q_b p_b] & \mathbb{E}[q_b^2]\end{bmatrix}$$

– Two equations with 2 unknowns



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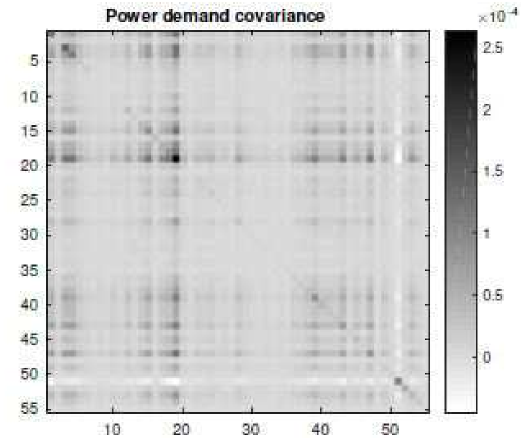

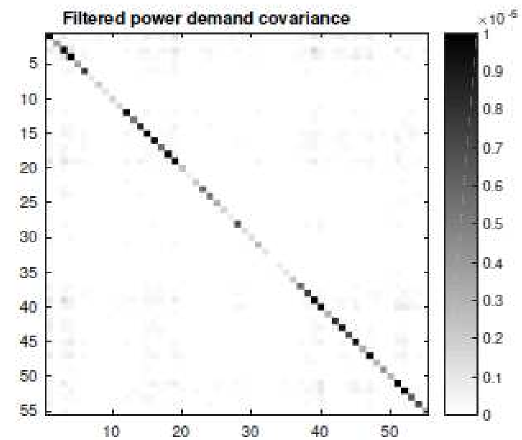

DiSc data set, Aalborg Univ

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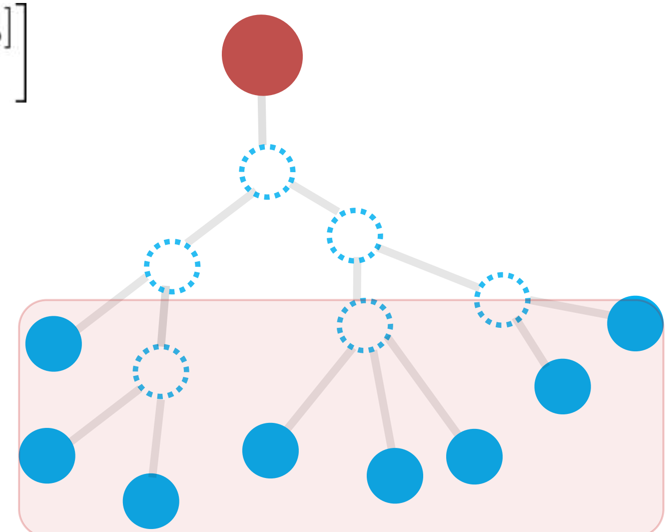
➢ **Correlated** Injections

$$\begin{bmatrix}\mathbb{E}[v_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[v_{\mathcal{L}} q_{\mathcal{L}}^T]\end{bmatrix} = \begin{bmatrix}H^{-1}_{1/r}(\mathcal{L},\mathcal{L}) & H^{-1}_{1/x}(\mathcal{L},\mathcal{L})\end{bmatrix}\begin{bmatrix}\mathbb{E}[p_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[p_{\mathcal{L}} q_{\mathcal{L}}^T] \\ \mathbb{E}[q_{\mathcal{L}} p_{\mathcal{L}}^T] & \mathbb{E}[q_{\mathcal{L}} q_{\mathcal{L}}^T]\end{bmatrix}$$

- Equations as many as number of leaves
- but can be solved as inverse covariance is sparse



Sample Complexity

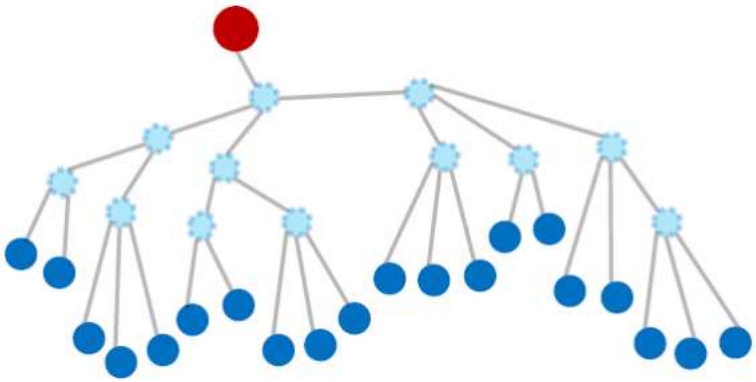
Uncorrelated :

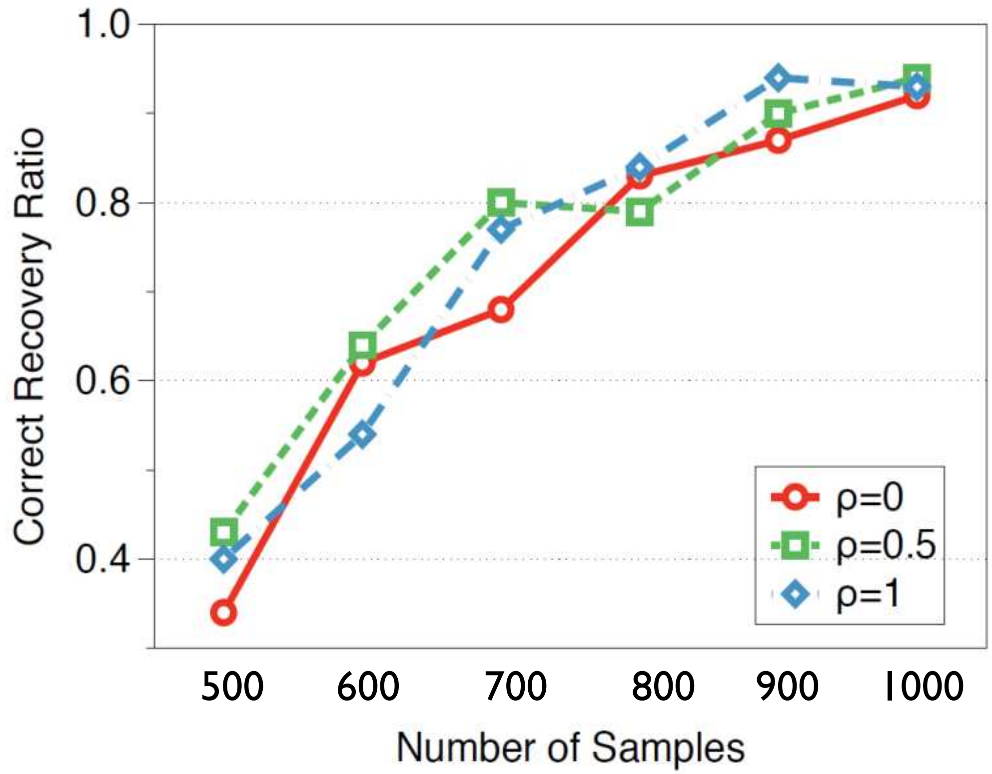
For a grid with constant depth and sub-Gaussian complex power injections, $O(|V| \log(|V|/\eta))$ samples recovers the true topology with probability $1 - \eta$.

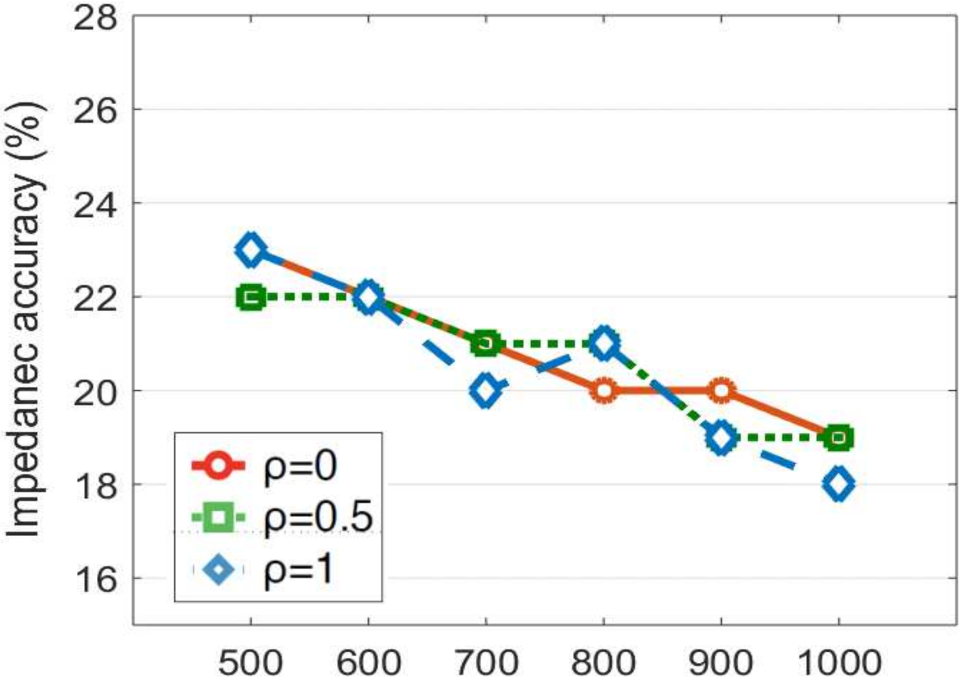
Correlated :

$O(|V|^2 \log(|V|/\eta))$ samples recovers the true topology with probability $1 - \eta$.

Simulations: IEEE 33 bus graphs (Matpower samples)

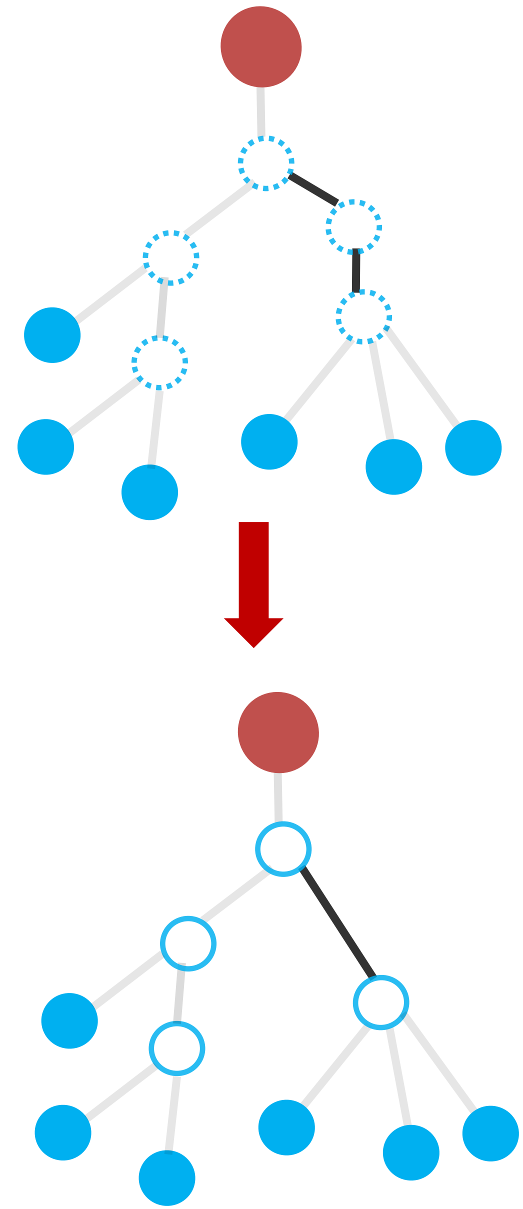






Extensions

- If intermediate node has degree 2, node ignored but impedance stays intact.
- Needs 50% observability (else Kron reduction)
- Can be modified for dynamic measurements/three-phase topology etc.



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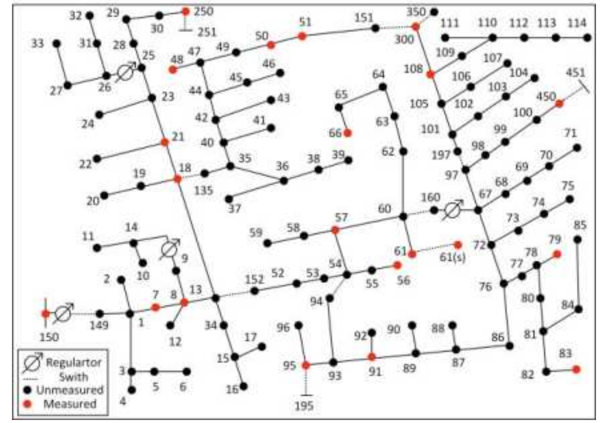
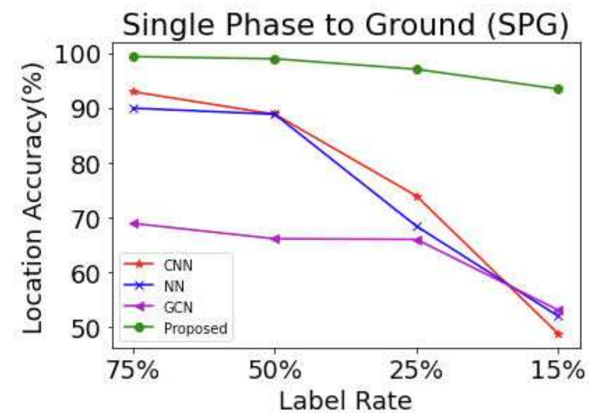


Limitations

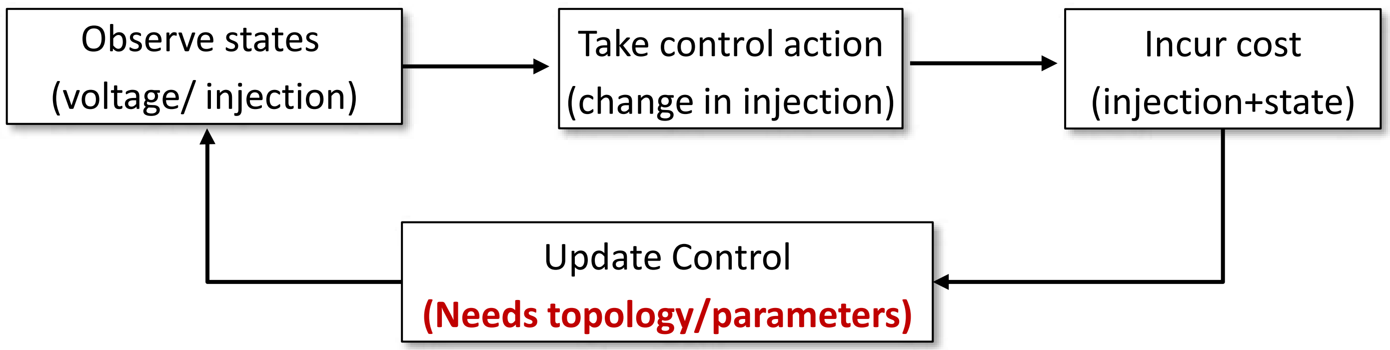
- If extremely low observability (~15%), approximate topology
- Not good for faults
  - Signatures are non-linear
  - Neural network based methods work great



W. Li, D. Deka, *PPGN: Physics-Preserved Graph Networks for Real-Time Fault Location in Distribution Systems with Limited Observation and Labels,* HICSS, 2023

Current Work

- Topology Learning inside control loop and impact on performance for voltage control.



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Learning with End-Users in Distribution Grids: Topology and Parameter Estimation

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†Theoretical Division, Los Alamos National Laboratory, Los Alamos, New Mexico, USA
‡ Quantum Electromagnetics Group, National Institute of Standards and Technology, Boulder, Colorado, USA
§ Dept. of Mathematics, University of Arizona, Tucson, Arizona, USA

***Abstract*—Efficient operation of distribution grids in the smart-grid era is hindered by the limited presence of real-time nodal and line meters. In particular, this prevents the easy estimation of grid topology and associated line parameters that are necessary for control and optimization efforts in the grid. This paper studies the problems of topology and parameter estimation in radial balanced distribution grids where measurements are restricted to only the leaf nodes and all intermediate nodes are unobserved/hidden. To this end, we propose two exact learning algorithms that use balanced voltage and injection measured only at the end-users. The first algorithm requires time-stamped voltage samples, statistics of nodal power injections and permissible line impedances to recover the true topology. The second and improved algorithm requires only time-stamped voltage and complex power samples to recover both the true topology and impedances without any additional input (e.g., number of grid nodes, statistics of injections at hidden nodes, permissible line impedances). We prove the correctness of both learning algorithms for grids where unobserved buses/nodes have a degree greater than three and discuss extensions to regimes where that assumption doesn't hold. Further, we present computational and, more importantly, the sample complexity of our proposed algorithm for joint topology and impedance estimation. We illustrate the performance of the designed algorithms through numerical experiments on the IEEE and custom power distribution models.**

***Index Terms*—Distribution networks, Missing data, Power flows, Sample complexity, Topology and Impedance estimation**

state estimation in the grid, in particular of the current radial topology of current operational lines, and their impedances. In addition, real or near real-time estimation of the distribution grid topology and corresponding line impedances is not straightforward due to the limited availability of real-time measurement devices, unlike in high voltage transmission grids. In recent years, Phasor Measurement Unit (PMU) technology and its alternatives (e.g., micro-PMUs [1], FNETs [2]) have become available in distribution grids, but their presence is not ubiquitous [3]. Among others, the presence of underground lines in urban areas makes meter placement, direct estimation, and calibration of parameters challenging. Thus, there is a greater need to develop efficient algorithms that can provably estimate topology and line parameters under sparse meter presence and infrequent calibration of line parameters. More importantly, new loads such as smart air-conditioners or electric vehicles connected to the grid at the end-user level have the ability to measure and communicate nodal voltages and injections. In this work, we consider such scenarios and analyze the topology and parameter estimation problem in grids where only leaf nodes measurements of the grids are available.

A. Prior Work

IEEE TRANSACTIONS ON SMART GRID, VOL. 15, NO. 1, JANUARY 2024 999

Learning Distribution Grid Topologies: A Tutorial

Deepjyoti Deka, *Senior Member, IEEE*, Vassilis Kekatos, *Senior Member, IEEE*, and Guido Cavraro, *Member, IEEE*

***Abstract*—Unveiling feeder topologies from data is of paramount importance to advance situational awareness and proper utilization of smart resources in power distribution grids. This tutorial summarizes, contrasts, and establishes useful links between recent works on topology identification and detection schemes that have been proposed for power distribution grids. The primary focus is to highlight methods that overcome the limited availability of measurement devices in distribution grids, while enhancing topology estimates using conservation laws of power-flow physics and structural properties of feeders. Grid data from phasor measurement units or smart meters can be collected either passively in the traditional way, or actively, upon actuating grid resources and measuring the feeder's voltage response. Analytical claims on feeder identifiability and detectability are reviewed under disparate meter placement scenarios. Such topology learning claims can be attained exactly or approximately so via algorithmic solutions with various levels of computational complexity, ranging from least-squares fits to convex optimization problems, and from polynomial-time searches over graphs to mixed-integer programs. Although the emphasis is on radial single-phase feeders, extensions to meshed and/or multiphase circuits are sometimes possible and discussed. This tutorial aspires to provide researchers and engineers with knowledge of the current state-of-the-art in tractable distribution grid learning and insights into future directions of work.**

***Index Terms*—Smart inverters, smart meter data, radial graph, recursive grouping, active sensing, voltage covariances, graph Laplacian matrix, linear distribution flow model.**

I. Introduction

DISTRIBUTION grids constitute the final tier in the delivery of electricity to end-users. To ease protection and voltage control, most distribution grids are operated in a radial (tree-like) topology, which can be modified by chang- the growth of behind-the-meter distributed energy resources (DERs) and smart loads (e.g., air-conditioners, storage devices, electric vehicles) have brought distribution grids to the forefront of smart grid advancement [85]. Industrial and academic research on smart distribution grids has advocated the participation of distribution grid resources in wholesale electricity markets and ancillary services (such as demand response, frequency regulation, and transactive energy services [62]). Integrating renewables introduces new challenges for voltage regulation and calls for dispatching DERs without violating physical and operational grid ratings. This necessitates knowing the correct feeder models. Moreover, situational awareness requires accurate distribution grid state estimation (DSSE) [26], in which the operational topology is a critical component. Topology estimates are also important for ensuring the dynamic stability of inverter-interfaced DERs.

However, distribution utilities often have only partial knowledge of their primary and/or secondary networks and the associated line impedances. Similarly, even if the utility knows the line infrastructure and line impedances, it may not have information on which lines are currently energized. This is owing to the fact that distribution grids are frequently reconfigured for maintenance; load balancing; to improve voltage profiles, minimize losses, or alleviate faults; or rashly, while restoring service after extreme weather events. Such changes may not be logged into the distribution management system, and hence, need to be estimated or at least verified. In this context, grid topology learning can be broadly classified into *topology detection* and *topology identification*. In topology detection, the estimator or system operator knows the line infrastructure and their impedances and needs to determine

S. Park, D. Deka, S. Backhaus, M. Chertkov. Learning with end-users in distribution grids: Topology and parameter estimation. IEEE Transactions on Control of Network Systems. 2020.

D. Deka, V. Kekatos, G. Cavraro. Learning distribution grid topologies: A tutorial. IEEE Transactions on Smart Grid. 2023.

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Univ. of Arizona

Scott Backhaus
NIST

Sejun Park
KAIST

Support:

LDRD LABORATORY DIRECTED RESEARCH & DEVELOPMENT

GRID MODERNIZATION INITIATIVE U.S. Department of Energy

Thank You. *Questions!*

Ans: