Learning for Monitoring and Control in Power Distribution Grids

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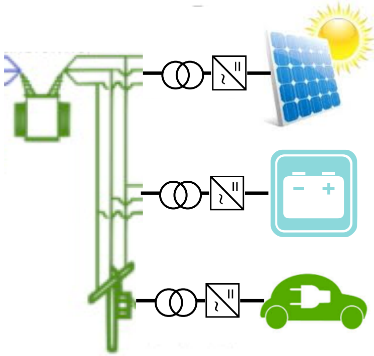
Learning in distribution grids

- Reduced observability due to sheer extent and limited real-time metering

- However, load estimates and topology information needed for grid optimization and control



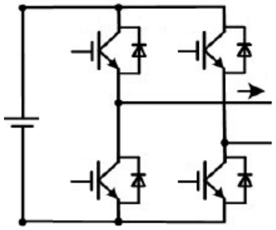
- Smart inverters interfacing new technologies

- Adding a third functionality to smart inverters

1. energy conversion

2. grid control

3. grid monitoring



Inverter Probing for Learning Distribution Grids


Guido Cavraro
[now with NREL]

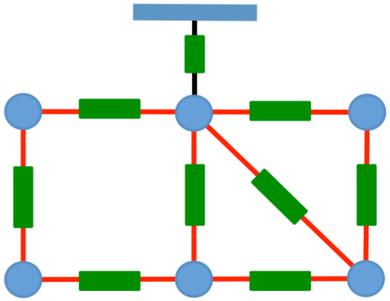

Sid Bhela
[now with
Siemens]


Sina
Taheri


Manish
Singh

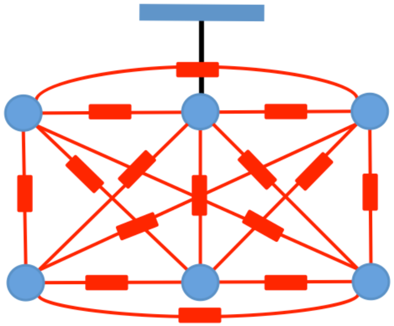

Harsha
Veeramachaneni
Next Era Analytics

Grid topology learning



topology detection

- Given data and existing line infrastructure, find which lines are energized



topology identification

- Given data alone, find grid topology and line impedances

Prior work

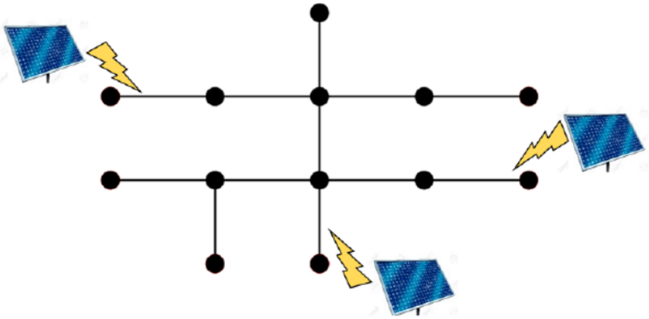
Passive data collection

- Voltage covariance [Bolognani'13], [Deka-Backhaus-Chertkov'15], [Li-Scaglione-Poor'15]
- Graphical models and DNN [Weng-Liao-Rajagopal'17], [Sevlian-Rajagopal'17], [Zhao-Poor'17]
- Micro-PMU data [Ardakanian et al'18]

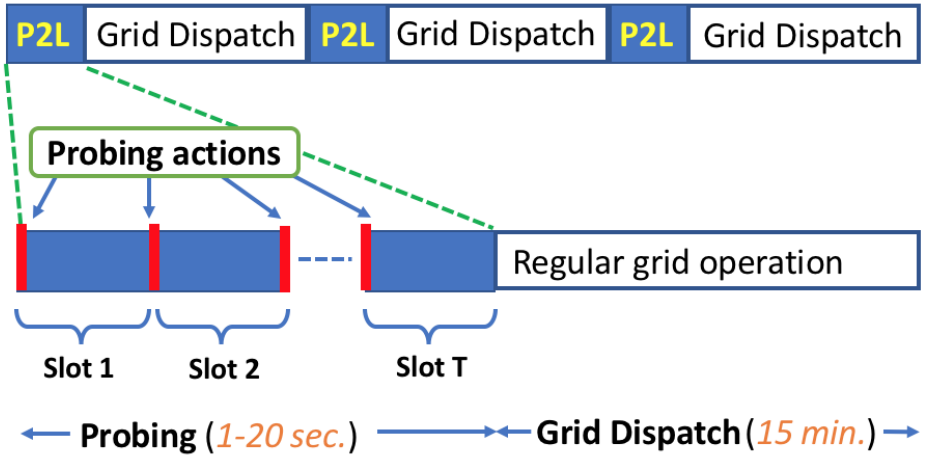
Grid perturbation for active data collection

- Oscillation modes in transmission grid dynamics [Trudnowski-Pierre'09]
- Identification of DC microgrids [Angjelichinoski-Scaglione '16]
- Thevenin impedance for single inverter [Jaksic-Boroyevich-Burgos '17]

Grid probing using inverters

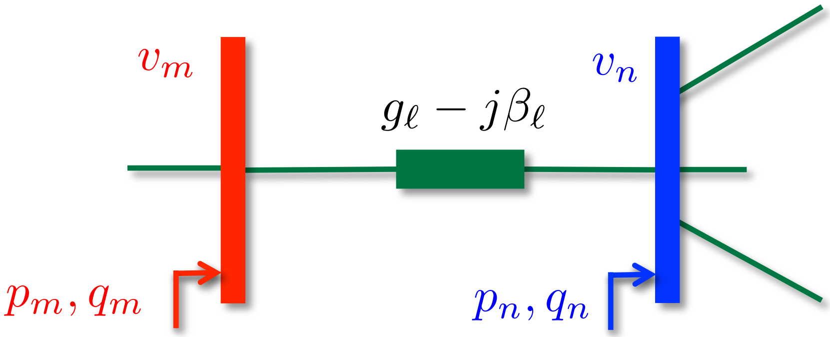


- Perturb power injections at probing buses [how?]
- Collect grid voltage response (magnitudes, phasors)
- Repeat over T probing actions spaced 1-2′ apart



Approximate grid model

- Single-phase *radial* grid with *N+1* nodes and *N* lines



$$\mathbf{a}_\ell = \begin{array}{cl} \begin{bmatrix} \mathbf{0} \\ +1 \\ \mathbf{0} \\ -1 \\ \mathbf{0} \end{bmatrix} & \begin{array}{l} \\ \leftarrow \text{node } m \\ \\ \leftarrow \text{node } n \\ \\ \end{array} \end{array}$$

- Linear distribution flow (LDF) model [Baran-Wu'89], [Deka et al'17]

$$\boxed{\mathbf{v} \simeq \mathbf{R}\mathbf{p} + \mathbf{X}\mathbf{q} + \mathbf{1}_N}$$

inverse graph Laplacian $\mathbf{L} = \mathbf{A}^\top \mathrm{dg}(\mathbf{g})\mathbf{A}$

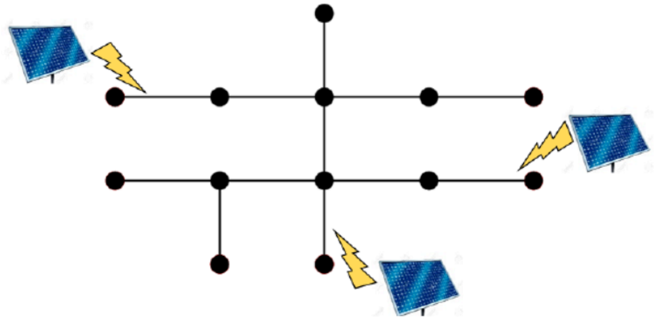
$\mathbf{R} = \mathbf{L}^{-1}$

- Differential quantities $\tilde{\mathbf{v}}_t = \mathbf{R}\tilde{\mathbf{p}}_t + \mathbf{X}\tilde{\mathbf{q}}_t + \mathbf{n}_t$

$\tilde{\mathbf{p}}_t := \mathbf{p}_t - \mathbf{p}_{t-1}$

$\left\{ \begin{array}{l} \text{1. modeling error} \\ \text{2. metering noise} \\ \text{3. unmodeled (load) variations} \end{array} \right.$

Probing for topology identification



- Active power probing $(\tilde{\mathbf{q}}_t = \mathbf{0})$

$$\tilde{\mathbf{p}}_t = \begin{bmatrix} \tilde{\mathbf{p}}_{t,\mathcal{M}} \\ \tilde{\mathbf{p}}_{t,\mathcal{O}} \end{bmatrix} = \begin{bmatrix} \text{known} \\ \mathbf{0} \end{bmatrix} \begin{matrix} \textit{probed buses } \mathcal{M} \\ \textit{unchanged loads } \mathcal{O} \end{matrix}$$

- Probe grid over $T \geq |\mathcal{M}|$ periods and ignore noise

$$\tilde{\mathbf{v}}_t = \mathbf{R}\tilde{\mathbf{p}}_t + \mathbf{X}\tilde{\mathbf{q}}_t + \mathbf{n}_t \Longrightarrow \tilde{\mathbf{V}} = \mathbf{R}\tilde{\mathbf{P}} = \mathbf{R}\begin{bmatrix} \tilde{\mathbf{P}}_{\mathcal{M}} \\ \mathbf{0} \end{bmatrix}$$

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_{\mathcal{M},\mathcal{M}} & \mathbf{R}^{\top}_{\mathcal{O},\mathcal{M}} \\ \mathbf{R}_{\mathcal{O},\mathcal{M}} & \mathbf{R}_{\mathcal{O},\mathcal{O}} \end{bmatrix}$$

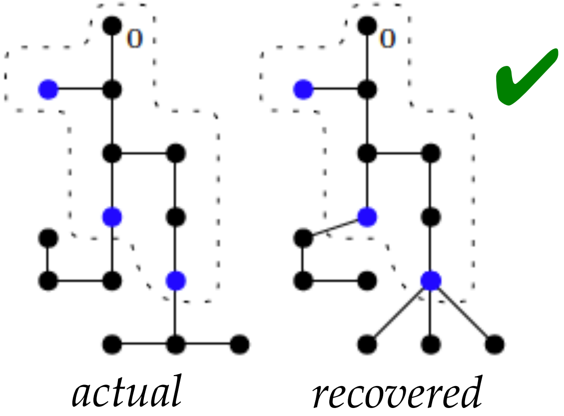
matrix partition

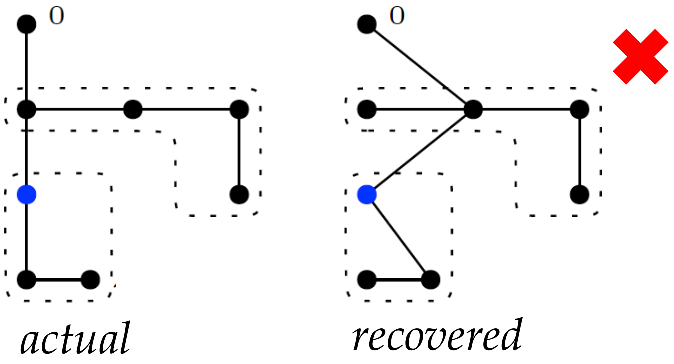
- *Complete data:* voltages collected at all buses, recover $\mathbf{R}_{\mathcal{M}} = \begin{bmatrix} \mathbf{R}_{\mathcal{M},\mathcal{M}} \\ \mathbf{R}_{\mathcal{O},\mathcal{M}} \end{bmatrix}$

- *Partial data:* voltages collected only at probing buses, recover $\mathbf{R}_{\mathcal{M},\mathcal{M}}$

Topology identifiability

Theorem 1 (Complete data): *Remove the descendants of probed buses. If you get a tree with all its leaves probed, this tree can be identified.*



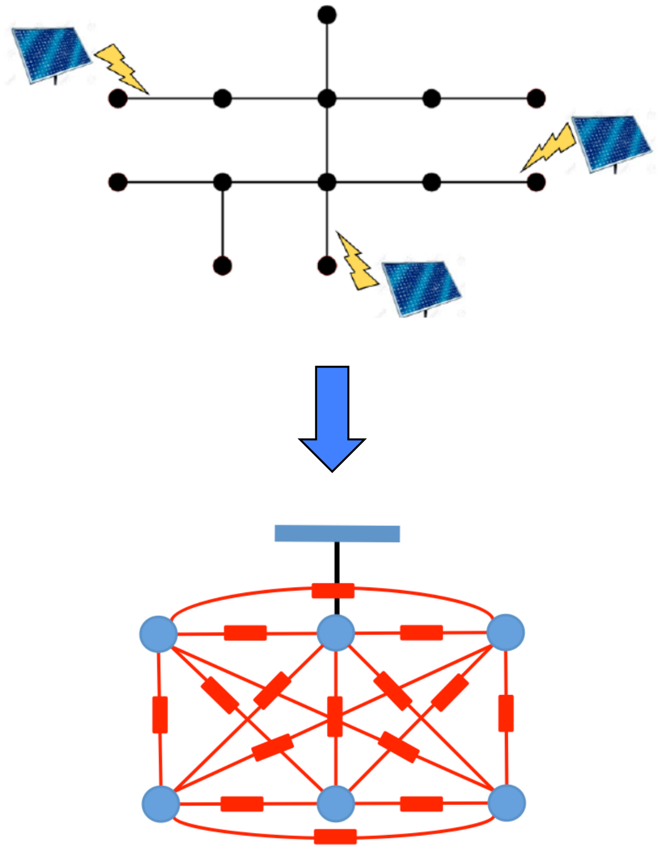


Corollary: *If all leaf buses are probed, the entire grid topology can be identified.*

Theorem 2 (Partial data): *If all leaf nodes are probed, a reduced grid can be identified.*

- Rich literature on recovering graphs; parallel results [Park-Deka-Chertkov'17]

From probing data to topology identification

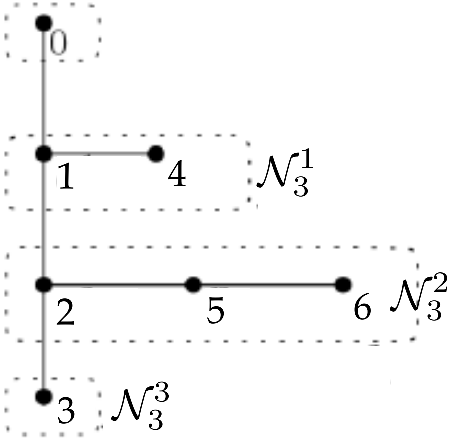


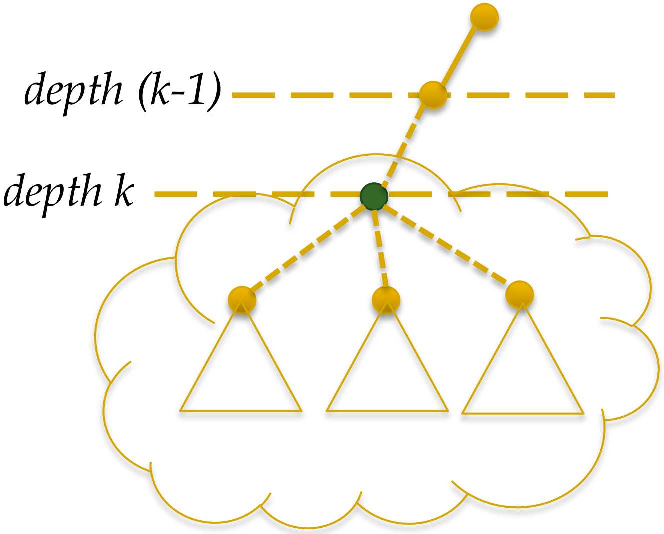
- *Graph algorithms*
- *Convex relaxation*
- *Mixed-integer linear program (MILP) approach*

Root and Branch (R&B) algorithm

- Group entries of m-th column of $\mathbf{R}_{\mathcal{M}}$
- Buses grouped together comprise a *level set* $\mathcal{N}_m^k$

$$\mathbf{R}_{:,3} = \begin{bmatrix} 1 \\ 3 \\ 6 \\ 1 \\ 3 \\ 3 \end{bmatrix}$$





Recursive graph algorithm

S1) Find k-depth root as intersection of $\{\mathcal{N}_m^k\}$

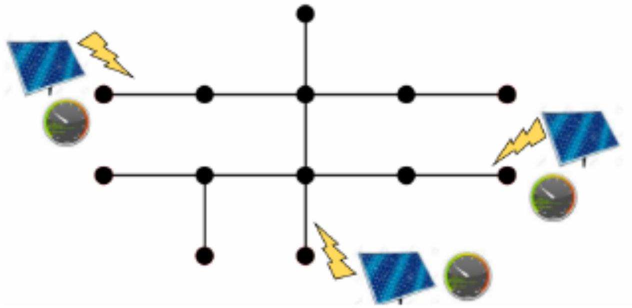
S2) Connect k- to *(k-1)*-depth root with resistance

S3) Group buses with identical $\mathcal{N}_m^k$ and recurse

G. Cavraro and V. Kekatos, “Graph Algorithms for Topology Identification using Power Grid Probing,” *IEEE Control Systems Letters*, October 2018.

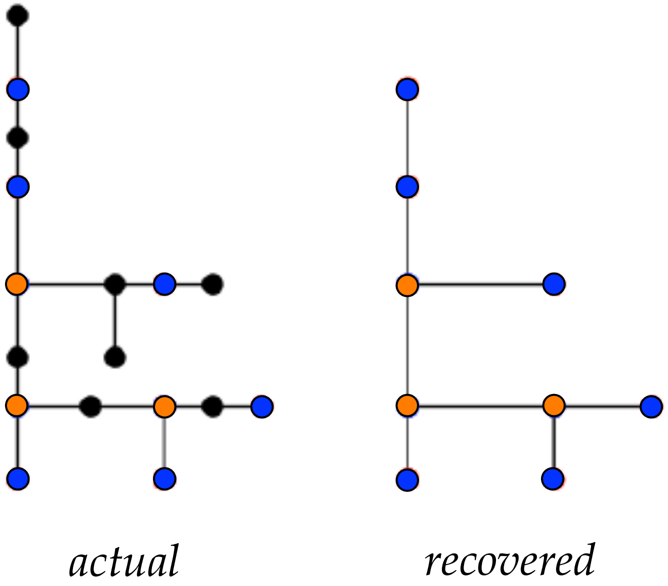
R&B with partial voltage data

- What if voltages are collected only at $\mathcal{M}$?



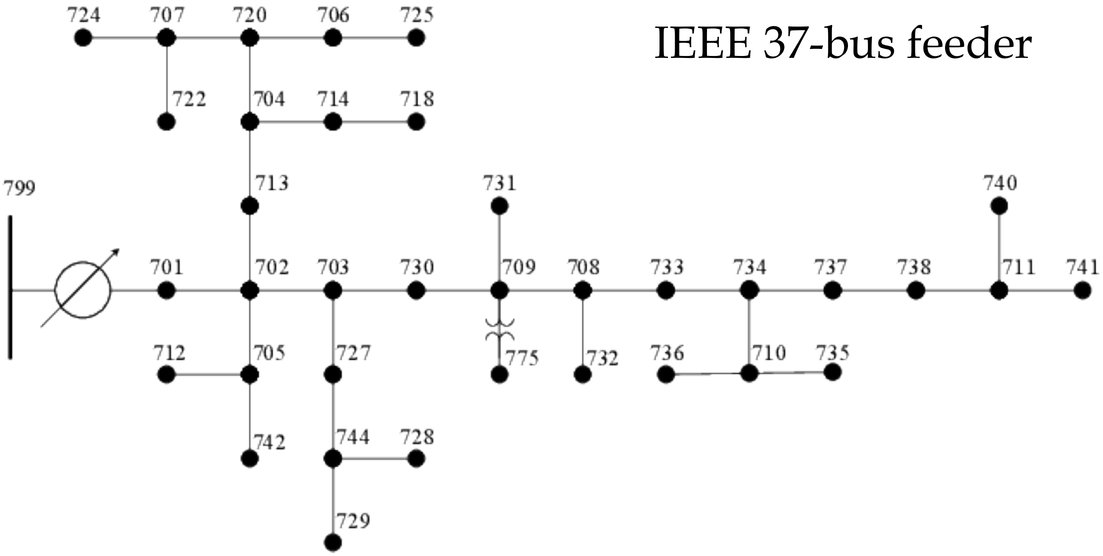
$$\tilde{\mathbf{V}}_{\mathcal{M}} = \mathbf{R}_{\mathcal{M}\mathcal{M}}\tilde{\mathbf{P}}_{\mathcal{M}} \quad \text{where} \quad \mathbf{R} = \begin{bmatrix} \mathbf{R}_{\mathcal{M},\mathcal{M}} & \mathbf{R}_{\mathcal{M},\mathcal{O}} \\ \mathbf{R}_{\mathcal{O},\mathcal{M}} & \mathbf{R}_{\mathcal{O},\mathcal{O}} \end{bmatrix}$$

- Level sets of probing nodes are *partially observed*



- Modified R&B recovers a ***reduced grid***
  - ✓ radial grid
  - ✓ recovers non-metered buses having two children each one with a probed descendant
  - ✓ correct pair-wise path resistances

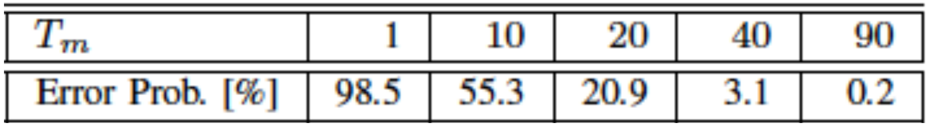
Numerical tests



IEEE 37-bus feeder

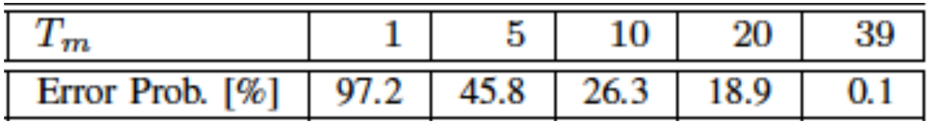
Probability of Erroneous Topology

Complete voltage data



T_m	1	10	20	40	90
Error Prob. [%]	98.5	55.3	20.9	3.1	0.2

Partial voltage data



T_m	1	5	10	20	39
Error Prob. [%]	97.2	45.8	26.3	18.9	0.1

- Each inverter is probed T_m times to average out noise

Convex relaxation heuristic

- Graph algorithms rely on noiseless estimates of $\mathbf{R}_{\mathcal{M}}$ $(\mathbf{R}_{\mathcal{M},\mathcal{M}})$
- For complete voltage data, invert probing data model

$$\tilde{\mathbf{V}} = \mathbf{R}\tilde{\mathbf{P}} + \mathbf{N} \xrightarrow{\mathbf{L} = \mathbf{R}^{-1}} \tilde{\mathbf{P}} = \mathbf{L}\tilde{\mathbf{V}} + \mathbf{E}$$

- Topology identification via data fitting

$$\begin{aligned} \min_{\mathbf{L}} \quad & \|\tilde{\mathbf{P}} - \mathbf{L}\tilde{\mathbf{V}}\|_F^2 \\ \text{s.to} \quad & \mathbf{L} \succ \mathbf{0} \\ & L_{m,n} \leq 0, \quad \forall m \neq n \\ & \|\mathbf{L}\|_{0,\text{off}} = 2N \end{aligned} \xrightarrow{\textit{convex relaxation}} \begin{aligned} \min_{\mathbf{L}} \quad & \|\tilde{\mathbf{P}} - \mathbf{L}\tilde{\mathbf{V}}\|_F^2 + \lambda\|\mathbf{L}\|_1 - \mu \log|\mathbf{L}| \\ \text{s.to} \quad & \mathbf{L} \succeq \mathbf{0} \\ & L_{m,n} \leq 0, \quad \forall m \neq n \end{aligned}$$

- Recover tree through heuristics (e.g., minimum spanning tree)

G. Cavraro and V. Kekatos, "Inverter Probing for Power Distribution Network Topology Processing," *IEEE Trans. on Control of Network Systems*, Sep. 2019.

Topology detection vs. identification

- Similar formulation if Laplacian is parameterized in terms of lines

$$L(\mathbf{b}) = \sum_{\ell \in \mathcal{L}} \frac{b_\ell}{r_\ell} \mathbf{a}_\ell \mathbf{a}_\ell^\top \qquad \text{where} \quad b_\ell = \begin{cases} 1 & , \text{ line } \ell \text{ is energized} \\ 0 & , \text{ otherwise} \end{cases}$$

- Topology detection through data fitting

$$\begin{aligned} \min_{\mathbf{b}} \quad & \|\tilde{\mathbf{P}} - \mathbf{L}(\mathbf{b})\tilde{\mathbf{V}}\|_F^2 \\ \text{s.to} \quad & \mathbf{b} \in \{0,1\}^{\bar{L}} \\ & \mathbf{b}^\top \mathbf{1} = N \\ & \mathbf{L}(\mathbf{b}) \succ \mathbf{0} \end{aligned} \quad \xrightarrow{\textit{convex relaxation}} \quad \begin{aligned} \min_{\mathbf{b}} \quad & \|\tilde{\mathbf{P}} - \mathbf{L}(\mathbf{b})\tilde{\mathbf{V}}\|_F^2 - \mu \log |\mathbf{L}(\mathbf{b})| \\ \text{s.to} \quad & \mathbf{b} \in [0,1]^{\bar{L}} \\ & \mathbf{b}^\top \mathbf{1} = N \end{aligned}$$

- Related formulations with covariance matrices for smart meter data analytics

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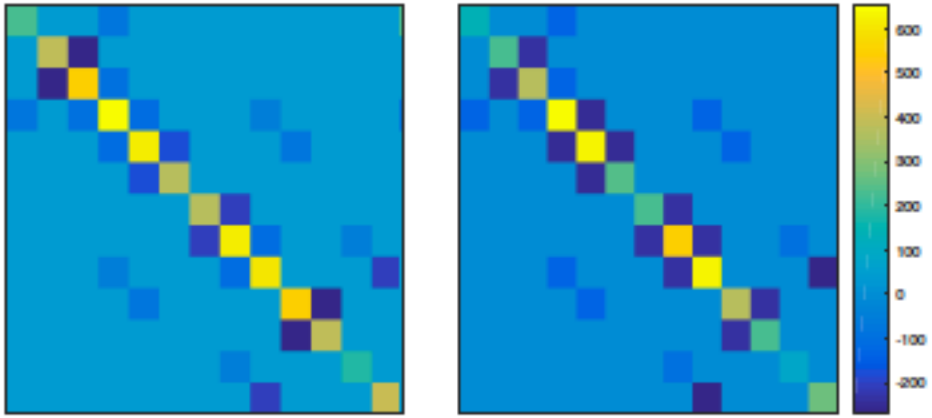
G. Cavraro, V. Kekatos, and H. Veeramachaneni ”Voltage analytics for power distribution network topology verification," *IEEE Trans. on Smart Grid*, Jan. 2019.

Numerical tests

- Resistive Laplacian matrix for *IEEE 13-bus feeder*



actual *recovered*

- Identification/detection results for *IEEE 37-bus feeder*

AVERAGE NUMBER OF LINE STATUS ERRORS FOR THE 37-BUS FEEDER

	$T = 1$	$T = 2$	$T = 5$	$T = 10$
Identification task of (22)	5.07	3.92	3.73	2.69
Verification task of (32)	0.32	0.21	0.08	0.01

Exact model fitting

- Recall grid Laplacian $\mathbf{L} = \mathbf{A}^\top \mathrm{dg}(\mathbf{g})\mathbf{A}$

  topology *line conductances*

- Vectorize probing data model

  $$\tilde{\mathbf{P}} = \mathbf{L}\tilde{\mathbf{V}} + \mathbf{E} \quad \Longrightarrow \quad \mathbf{p} = \mathbf{H}\mathbf{g} + \mathbf{e} \quad \text{where} \quad \mathbf{H} = \tilde{\mathbf{V}}^\top \mathbf{A}^\top \star \mathbf{A}^\top$$

  Khatri-Rao product

- Pretending topology $\mathbf{A}$ is known, find conductances $\mathbf{g}$ through LS fit

- Optimal $\mathbf{g}_{LS}$ provides LS fit error $f(\mathbf{A}) = -\mathbf{p}^\top \mathbf{H}\left(\mathbf{H}^\top \mathbf{H}\right)^{-1} \mathbf{H}^\top \mathbf{p}$

- Find topology $\mathbf{A}$ attaining smallest LS fit $f(\mathbf{A})$

S. Taheri, G. Cavraro, and V. Kekatos, 'An MILP Approach for Distribution Grid Topology Identification using Inverter Probing,' *IEEE PowerTech*, Milan, Italy, June 2019.

Topology identification

selection matrix

- Select from candidate lines $\mathbf{A} = \mathbf{S}\bar{\mathbf{A}}$ $\quad \mathbf{S}\mathbf{S}^\top = \mathbf{I}_N, \quad \mathbf{S}^\top\mathbf{S} = \mathrm{dg}(\mathbf{b})$
- Reformulate LS fit $f(\mathbf{b}) = \bar{\mathbf{p}}^\top \mathrm{dg}(\mathbf{b})\bar{\mathbf{p}} + \bar{\mathbf{p}}^\top \mathrm{dg}(\mathbf{b}) \underbrace{\left(\mathbf{C} - \mathrm{dg}(\mathbf{b})\right)^{-1} \mathrm{dg}(\mathbf{b})\bar{\mathbf{p}}}_{\mathbf{z}}$
- Solve problem

$$\begin{aligned}
\min_{\mathbf{z},\mathbf{b}\in\{0,1\}^{\bar{L}\times 1}} \quad & f'(\mathbf{b},\mathbf{z}) = \bar{\mathbf{p}}^\top \mathrm{dg}(\mathbf{b})\bar{\mathbf{p}} + \bar{\mathbf{p}}^\top \mathrm{dg}(\mathbf{b})\mathbf{z} \\
\text{s.to} \quad & (\mathbf{C} - \mathrm{dg}(\mathbf{b}))\mathbf{z} = \mathrm{dg}(\mathbf{b})\bar{\mathbf{p}} \\
& \mathbf{1}_{\bar{L}}^\top \mathbf{b} = N \\
& \left|\bar{\mathbf{A}}\right|^\top \mathbf{b} \geq \mathbf{1}_{N+1}
\end{aligned}$$

every bus connected to at least one line

- Products handled by *McCormick linearization* to yield MILP
- *Caveat:* If $(\mathbf{C} - \mathrm{dg}(\mathbf{b}^*))$ is *singular*, the relaxation is *not exact!*

Ensuring connectivity

Lemma: Matrix $(\mathbf{C} - \mathrm{dg}(\mathbf{b}^*))$ is invertible iff $\mathbf{A} = \mathbf{S}\bar{\mathbf{A}}$ yields a connected grid

- *Key question:* How to guarantee a connected topology?

- Introduce optimization vector of *virtual* line flows $\mathbf{f} \in \mathbb{R}^L$

add these constraints to previous formulation

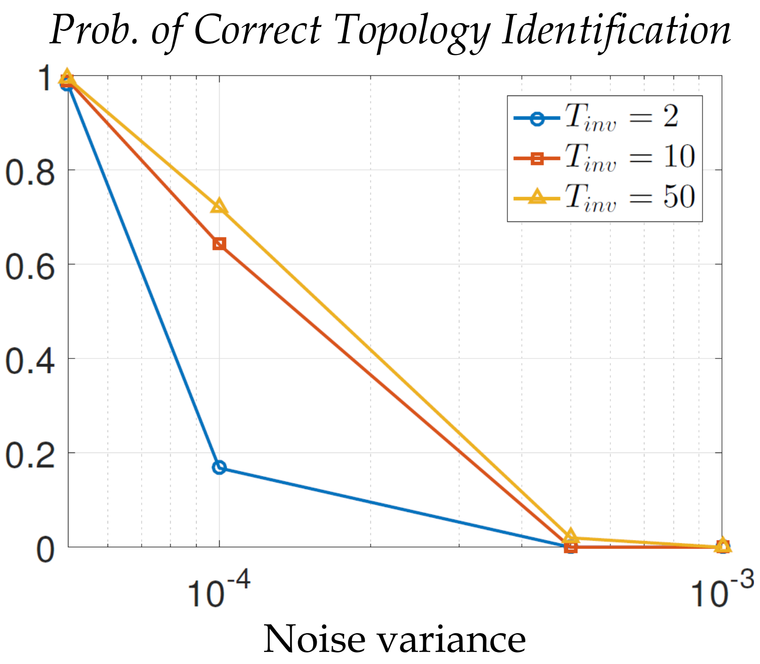
$$\bar{\mathbf{A}}^\top \mathbf{f} = \mathbf{1}$$
$$-N\mathbf{b} \leq \mathbf{f} \leq N\mathbf{b}$$

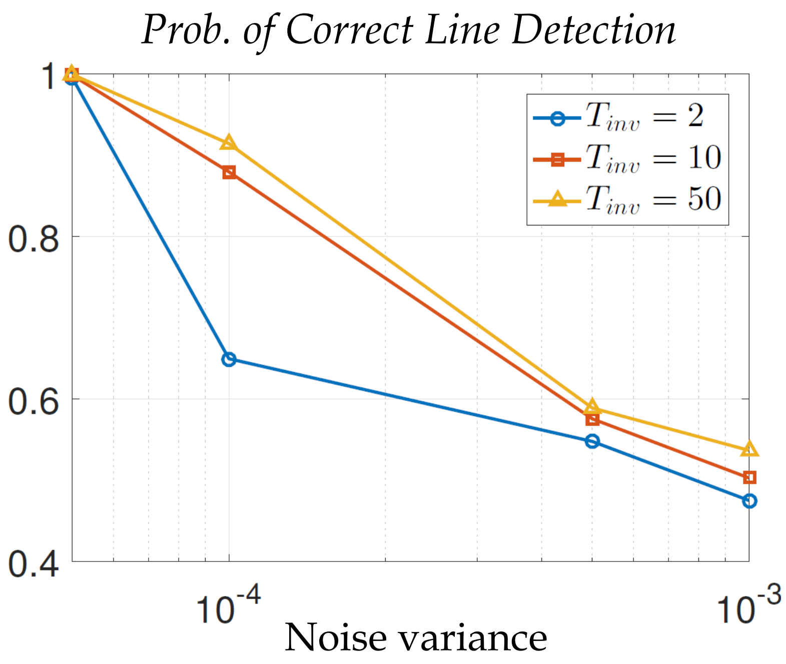
- *Intuition:* find topology that can deliver *1 pu* injected at each bus and *N pu* received by substation

- Comparison to formulation of [Lei-Chen-Song-Hou'19]

Singh, Kekatos, Taheri, Schneider, and Liu, 'Enforcing Radiality constraints for DER-aided power distribution grid reconfiguration,' *in Proc. PSCC*, June 2020, Porto, Portugal.

Numerical tests


Prob. of Correct Topology Identification

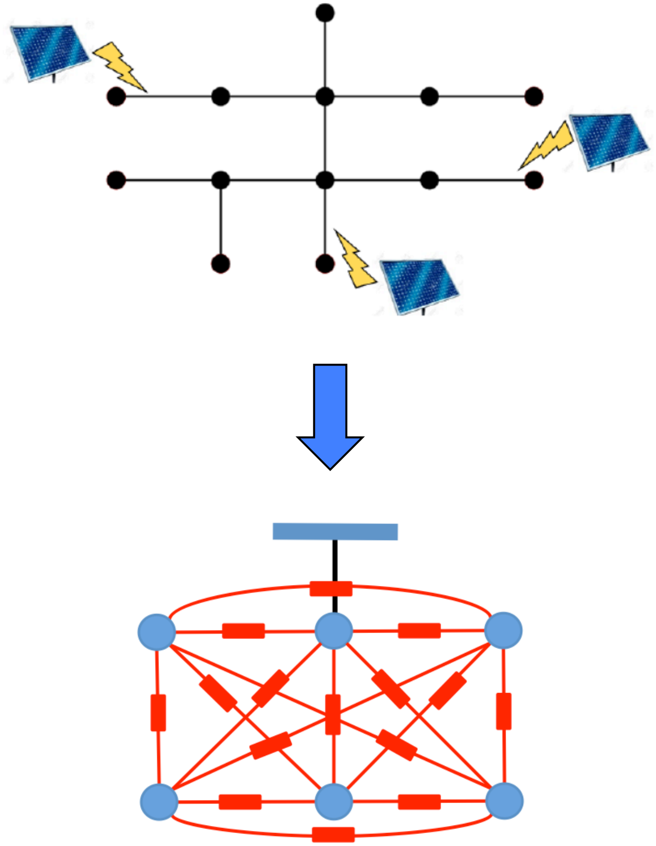

Prob. of Correct Line Detection

- Each inverter probed T times to average out noise

RUNNING TIME FOR MILPS [SEC]

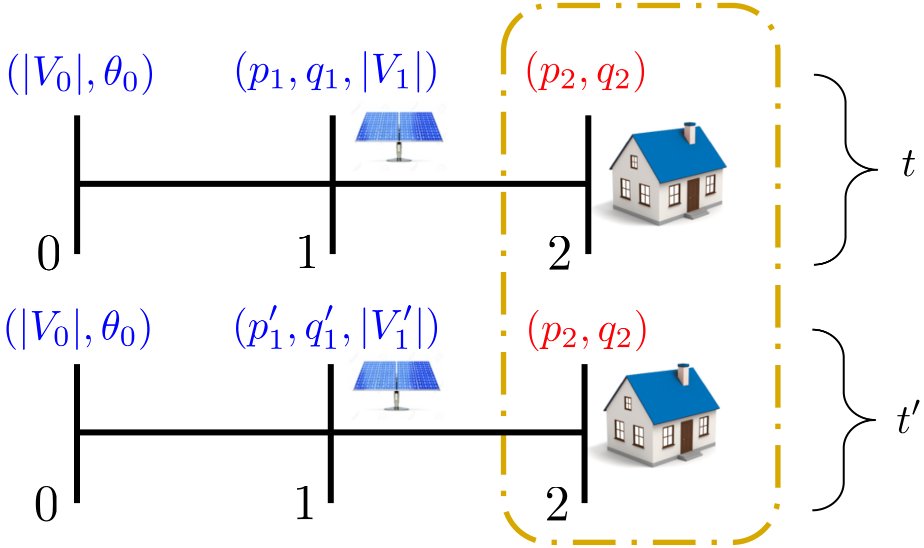
# of candidate lines $\bar{L}$	24	36	48
MILP formulation	1	27	200

Topology identification algorithms



- *Graph algorithms*
  - complete or partial voltage data
  - exact for noiseless data
- *Convex relaxation*
  - complete voltage data
  - noisy data but heuristic
- *Mixed-integer linear program (MILP) approach*
  - complete voltage data
  - computationally more demanding yet exact

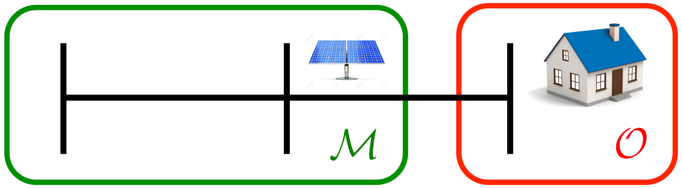
Probing for learning loads



S. Bhela, V. Kekatos, and S. Veeramachaneni, "Enhancing Observability in Distribution Grids using Smart Meter Data," *IEEE Trans. on Smart Grid*, Nov. 2018.

Coupled power flow (CPF) problem

Problem statement: *Given inverter data on metered buses* $\mathcal{M}$ *and assuming time-invariant injections at buses* $\mathcal{O}$*, find states* $\{\mathbf{v}_t\}_{t=1}^{T}$ *and non-metered loads on* $\mathcal{O}$



probing (metered) buses   non-metered buses

$$\left.\begin{aligned} p_n(\mathbf{v}_t) &= \hat{p}_n^t \quad \forall n \in \mathcal{M} \\ q_n(\mathbf{v}_t) &= \hat{q}_n^t \quad \forall n \in \mathcal{M} \\ u_n(\mathbf{v}_t) &= \hat{u}_n^t \quad \forall n \in \mathcal{M} \end{aligned}\right\} 3MT \qquad \left.\begin{aligned} p_n(\mathbf{v}_t) &= p_n(\mathbf{v}_{t+1}) \quad \forall n \in \mathcal{O} \\ q_n(\mathbf{v}_t) &= q_n(\mathbf{v}_{t+1}) \quad \forall n \in \mathcal{O} \end{aligned}\right\} 2O(T-1)$$

- Counting equations and unknowns yields $|\mathcal{M}| \geq \dfrac{2|\mathcal{O}|}{T}$

Q1) Can non-metered loads be recovered by probing T slots?

Q2) How to optimally design probing actions?

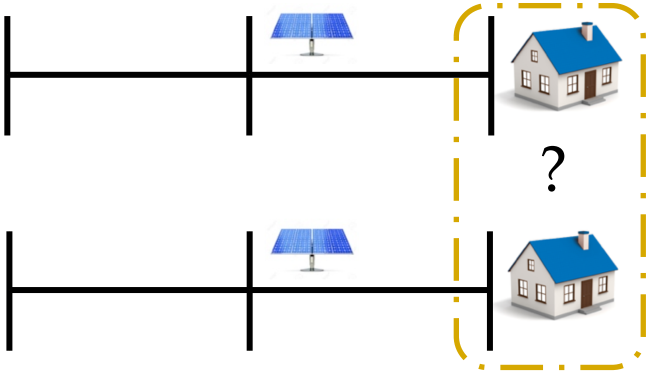
Q3) How to solve the CPF problem?

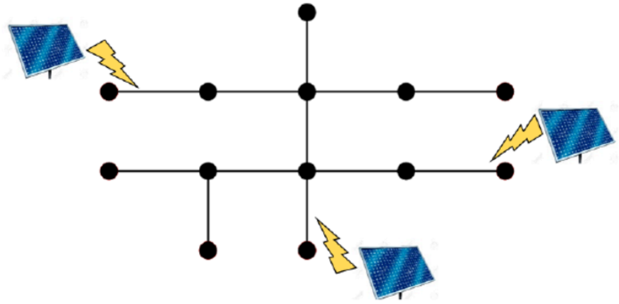
S. Bhela, V. Kekatos, and S. Veeramachaneni, "Smart Inverter Grid Probing for Learning Loads: Parts I & II", *IEEE Trans. on Power Systems*, Sep 2019.

Conclusions

Take-home: *Inverter probing as active data collection paradigm for grid learning*

- ☑ identifiability
- ☑ topology ID algorithms
- ☑ probing for load learning





- ☐ multiphase configurations
- ☐ partial and noisy data
- ☐ ‘probing’ by regulators/capacitors

Kernel-Based Learning for Smart Inverter Control


Mana Jalali


Aditie Garg
[now with EPRI]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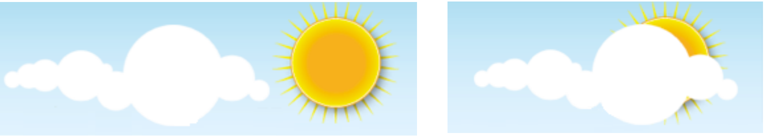
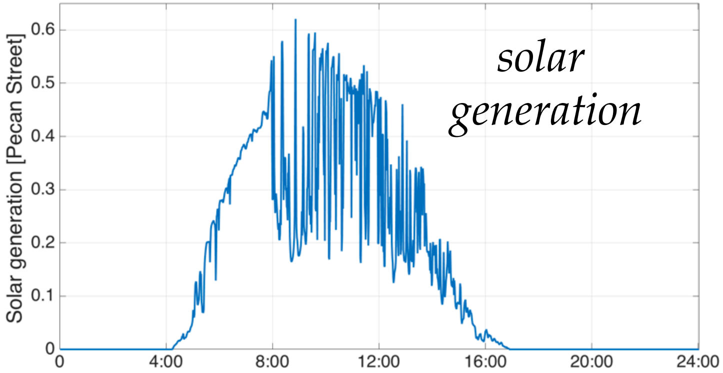
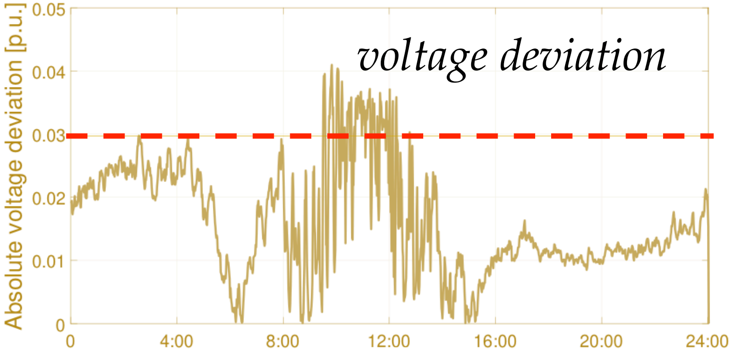
Un. of Texas San Antonio


Deep Deka
Los Alamos National Lab

Motivation







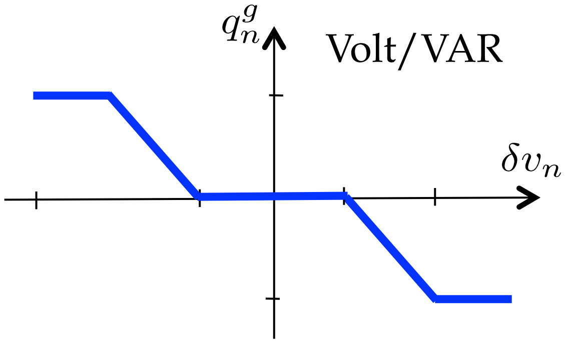
- Voltage fluctuations due to renewables

- Inefficiency of voltage control devices

- Reactive power control with inverters

Finding reactive power setpoints

- Local control curves [Turitsyn'11], [Kekatos-Zhang-Giannakis'15], [IEEE 1547]



✓ no cyber cost
✗ suboptimal

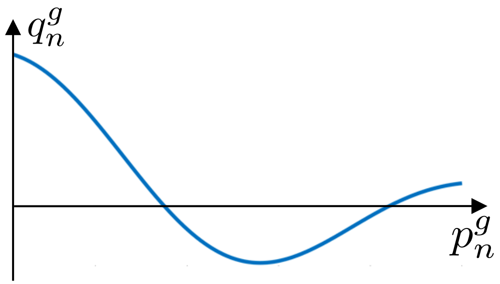
- Centralized OPF [Lavaei-Low'14], [Farivar-Low'15]

✓ optimal
✗ cyber, obsolete

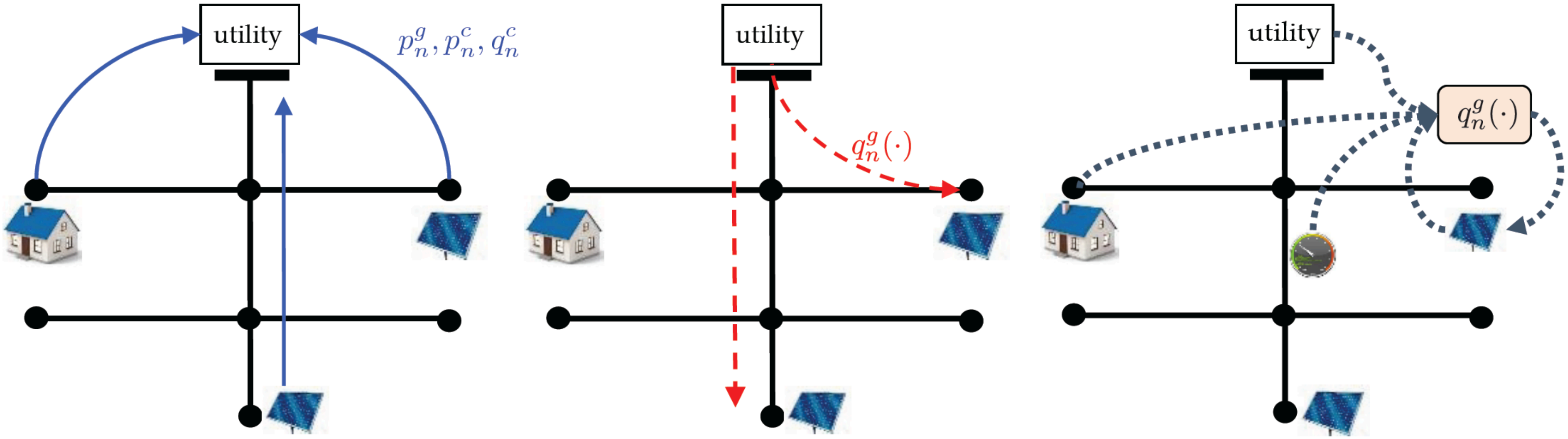
- Decentralized OPF
  [Dallanese-Dhople-Giannakis'15], [Peng-Low'16]

✓ cyber
✗ iterations

- Customize control curves on a quasi-stationary basis



Designing control rules



Data collection
[30-min basis]

Design inverter rules
[30-min basis]

Real-time operation
[5-sec basis]

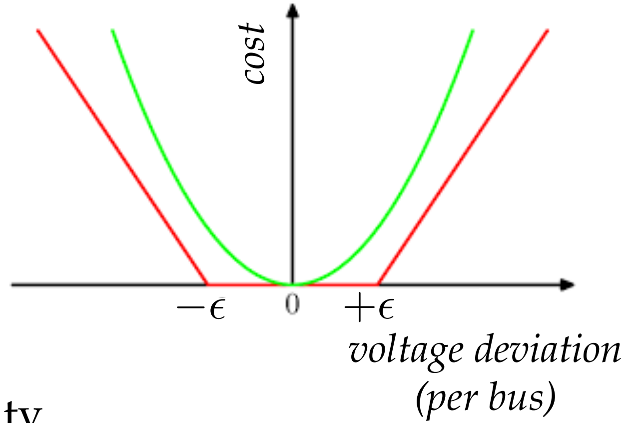
- Control rules as *linear* policies
  - Chance-constrained [Ayyagari-Gatsis-Taha'17]
  - Robust approaches [Jabr'18]; [Lin-Bitar'18]
  - Closed-loop approach [Baker, Bernstein, Dall'Annese, Zhao'18]
  - OPF-then-Fit [Dobbe-Callaway'18], [Karagiannopoulos-Hug'18]

Control rules do not have to be linear!

Problem formulation

- Approximate grid model $$\begin{aligned}\tilde{\mathbf{v}} &\simeq \mathbf{R}(\mathbf{p}^g - \mathbf{p}^c) + \mathbf{X}(\mathbf{q}^g - \mathbf{q}^c) \\ &= \mathbf{X}\mathbf{q}^g + \mathbf{y}\end{aligned}$$

- Options for voltage deviation penalties



- least-squares $\Delta_s(\mathbf{q}^g) = \|\mathbf{X}\mathbf{q}^g + \mathbf{y}\|_2^2$

- epsilon-insensitive $\Delta_\epsilon(\mathbf{q}^g) = \sum_{n=1}^{N} [\mathbf{e}_n^\top (\mathbf{X}\mathbf{q}^g + \mathbf{y})]_\epsilon$

- Inverter setpoints to minimize voltage deviation penalty

$$\boxed{\begin{aligned}\min_{\mathbf{q}^g} \quad & \Delta(\mathbf{q}^g;\mathbf{y}) \\ \text{s.to} \quad & -\bar{\mathbf{q}}^g \leq \mathbf{q}^g \leq \bar{\mathbf{q}}^g\end{aligned}}$$

OPF

- Inverter setpoints as policies $q_n^g(\mathbf{z}_n) = f_n(\mathbf{z}_n)$

- remote and local inputs $\mathbf{z}_n = [p_n^g - p_n^c \quad \bar{q}_n^g \quad q_n^c]^\top$

Kernel-based learning

- Given data $\{(x_t \in \mathcal{X}, z_t \in \mathbb{R})\}_{t=1}^{T}$, and kernel function $K : \mathcal{X} \times \mathcal{X} \to \mathbb{R}$

$$f^* = \arg \min_{f \in \mathcal{H}_{\mathcal{K}}} \sum_{t=1}^{T} (z_t - f(x_t))^2 + \mu \|f\|_{\mathcal{K}}$$

where $\mathcal{H}_{\mathcal{K}} := \left\{ f(x) = \sum_t K(x, x_t) a_t \right\}$

- *Representer's Theorem:* Minimizing function depends only on training data

$$\boxed{f^*(x) = \sum_{t=1}^{T} K(x, x_t) a_t^*}$$

- Functional minimization as vector optimization

$$\arg \min_{\mathbf{a}} \ \|\mathbf{z} - \mathbf{K}\mathbf{a}\|_2^2 + \mu \sqrt{\mathbf{a}^\top \mathbf{K}\mathbf{a}}$$

Hastie, Tibshirani, Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer, 2009.

Least-squares inverter control

- Control rule design as function fitting using T scenario data

$$\begin{aligned} \min \quad & \sum_{t=1}^{T} \Delta(\mathbf{q}_t^g; \mathbf{y}_t) + \mu \sum_{n=1}^{N} \|q_n^g\|_{\mathcal{K}_n} \\ \text{s.to} \quad & |q_{n,t}^g| \leq \bar{q}_{n,t}^g \quad \forall n, t \end{aligned}$$

- Jointly learning inverter functions can be solved as QP or SOCP

$$q_{n,t}^g(\mathbf{z}_n) = \sum_{t=1}^{T} K(\mathbf{z}_n, \mathbf{z}_{n,t}) a_{n,t}^*$$

← *rule described by* $\{\mathbf{z}_{n,t}, a_{n,t}^*\}_{t=1}^{T}$

- Increasing μ unselects some inverters from reactive control *(spatial sparsity)*

- Policy output heuristically projected within feasible range

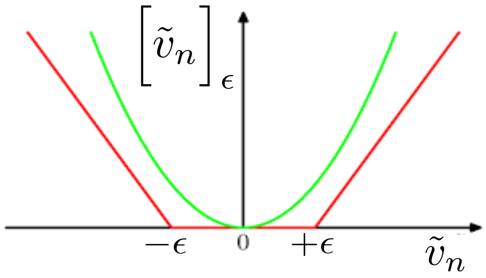
A. Garg, M. Jalali, V. Kekatos, and N. Gatsis, 'Kernel-Based Learning for Smart Inverter Control,' *in Proc. GlobalSIP*, Anaheim, CA, Nov. 2018.

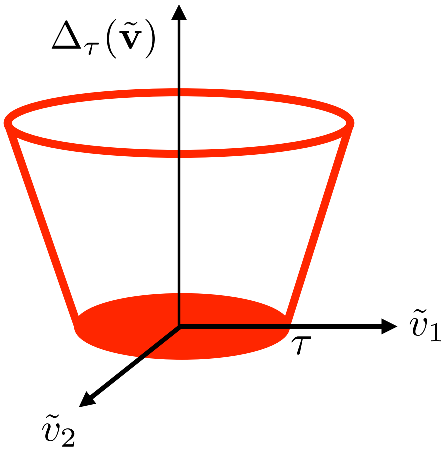
Support vector inverter control

***Lemma*:** Voltage deviation penalties and *sparsity across scenarios*

$$\Delta_\epsilon(\mathbf{q}^g) = \sum_{n=1}^{N} \left[\tilde{v}_n\right]_\epsilon \; : \quad \text{if} \quad \|\tilde{\mathbf{v}}_t\|_\infty > \epsilon, \; \text{then} \quad a_{n,t} \neq 0 \;\; \forall n$$

$$\Delta_\tau(\mathbf{q}^g) = \left[\|\tilde{\mathbf{v}}\|_2\right]_\tau \; : \quad \text{if} \quad \|\tilde{\mathbf{v}}_t\|_2 \leq \tau, \; \text{then} \quad a_{n,t} = 0 \;\; \forall n \;\; \text{with} \;\; |q^g_{n,t}| < \bar{q}^g_{n,t}$$

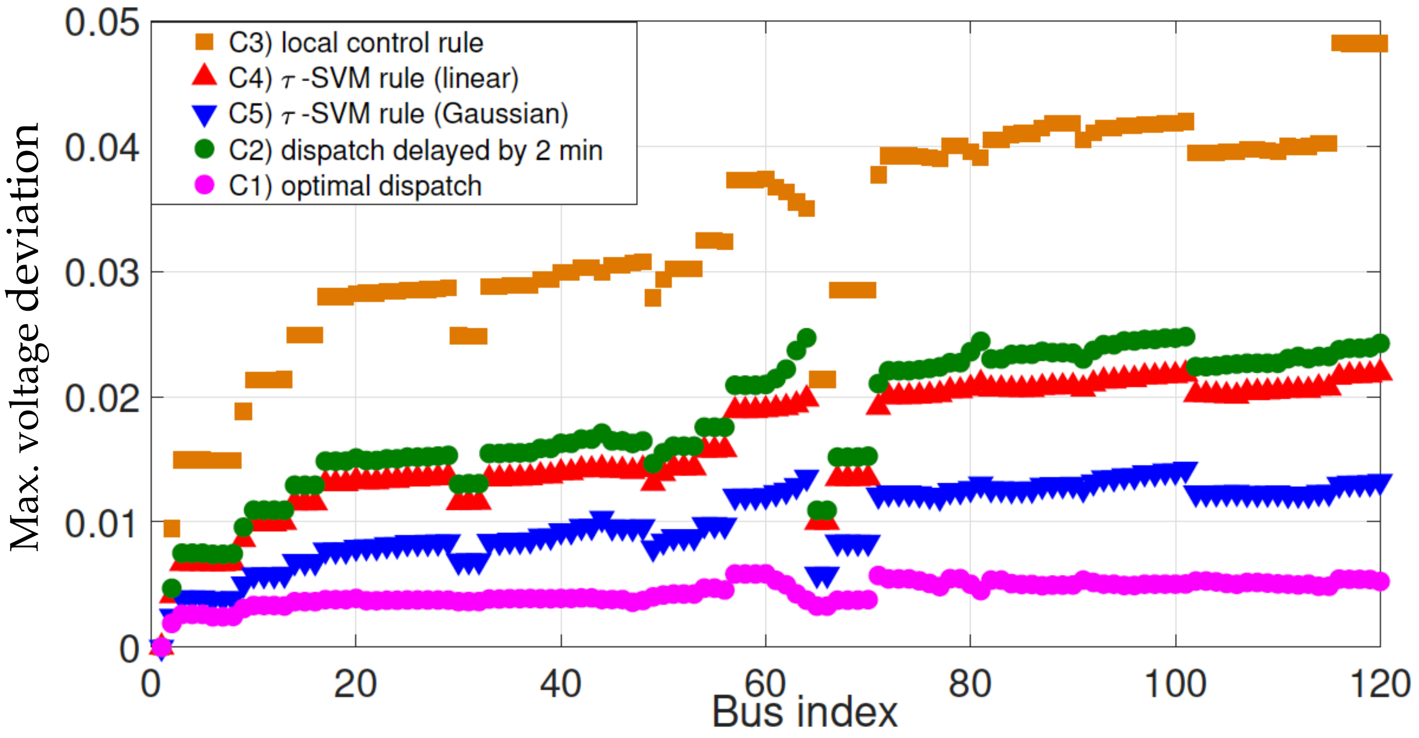




- Different from SVMs, *block* voltage penalties yield *support feeder scenarios*

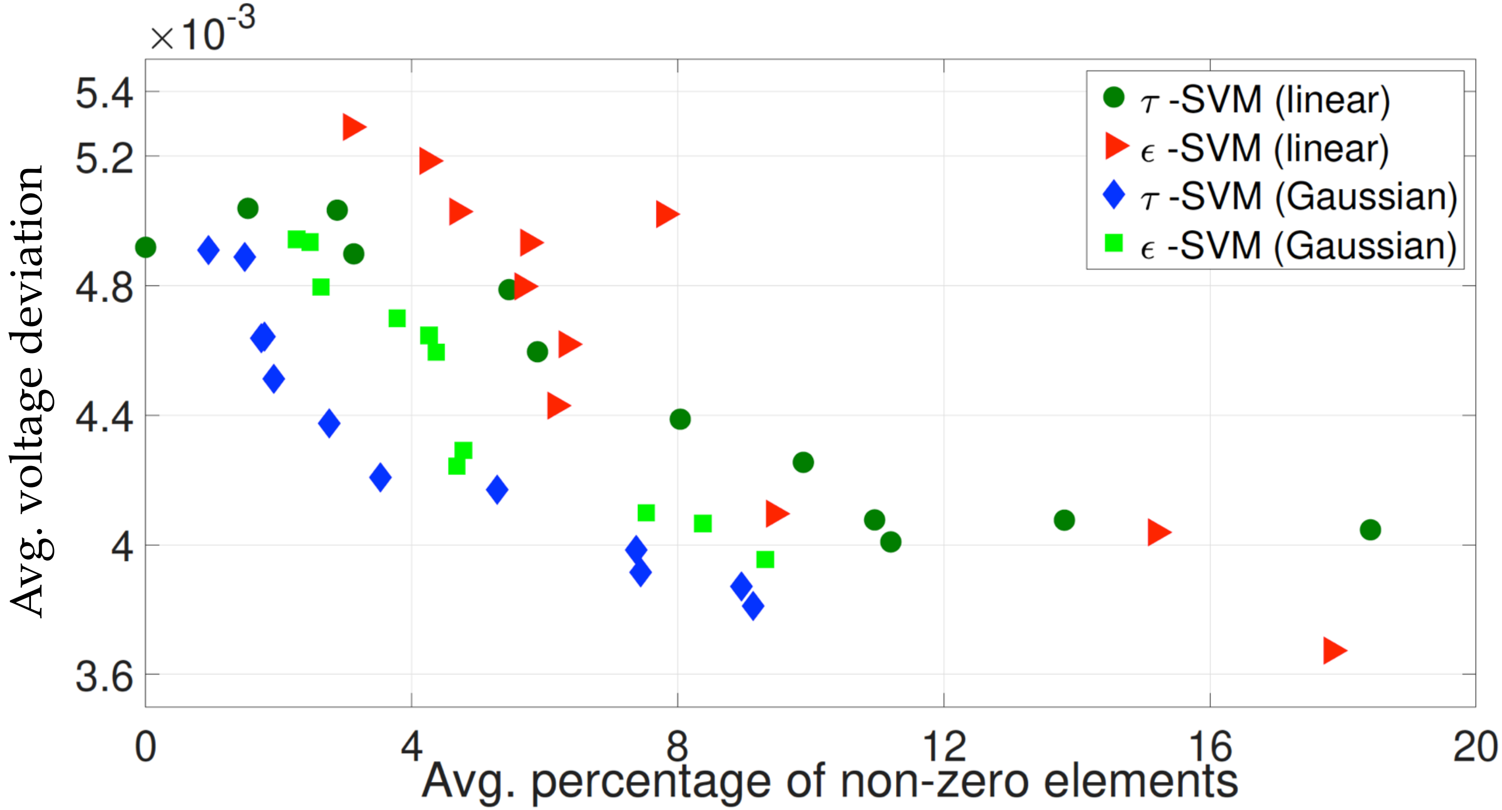
M. Jalali, V. Kekatos, N. Gatsis, and D. Deka, "Designing Reactive Power Control Rules for Smart Inverters using Support Vector Machines," *IEEE Trans. on Smart Grid*, (early access)

Numerical tests

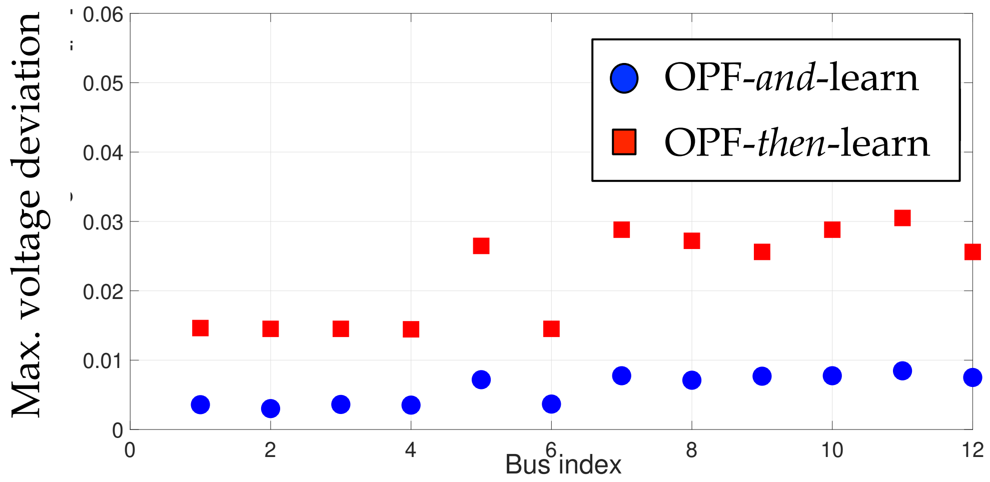


- Pecan Street data (8am-8pm) on IEEE 123-bus feeder (1-phase)
- 50% solar penetration with 1.1 inverter oversizing
- Train for T=30 one-min data; validate on next 30 one-min data

Performance vs. sparsity

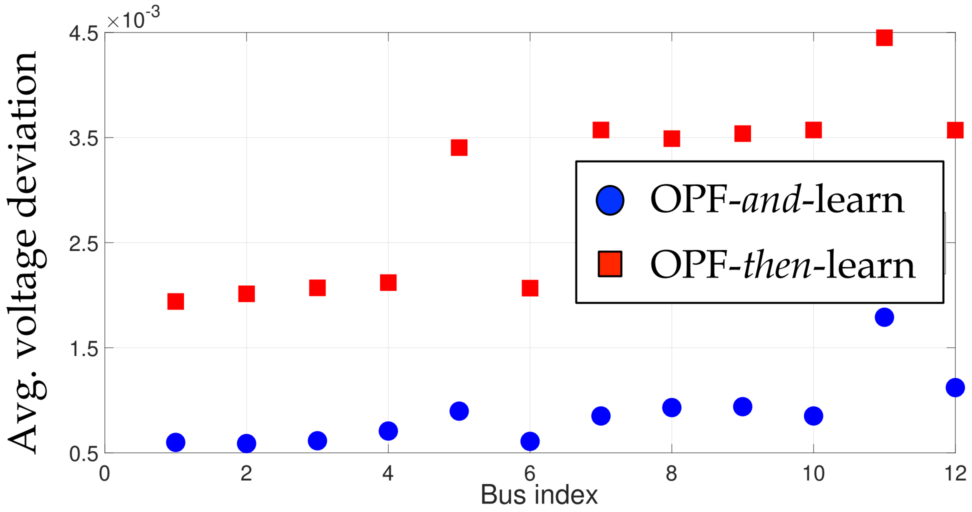


OPF-then-learn vs. OPF-and-learn



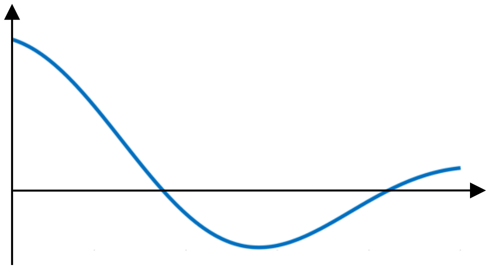
- *OPF-then-learn*: 2-step approach
  - solve multiple OPFs
  - fit input-minimizer pairs

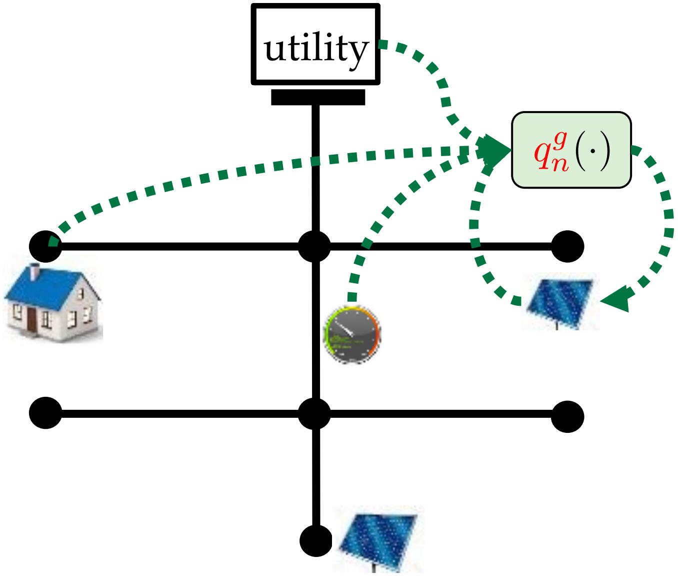
- Linear rules on IEEE 13-bus grid



Conclusions

- ☑ learning non-linear inverter rules
- ☑ data-based feeder-wide designs
- ☑ SVM costs for communication savings





- ☐ closed-loop control
- ☐ remote input and kernel selection
- ☐ constrained kernel learning
- ☐ DNN-based rules

Thank you!

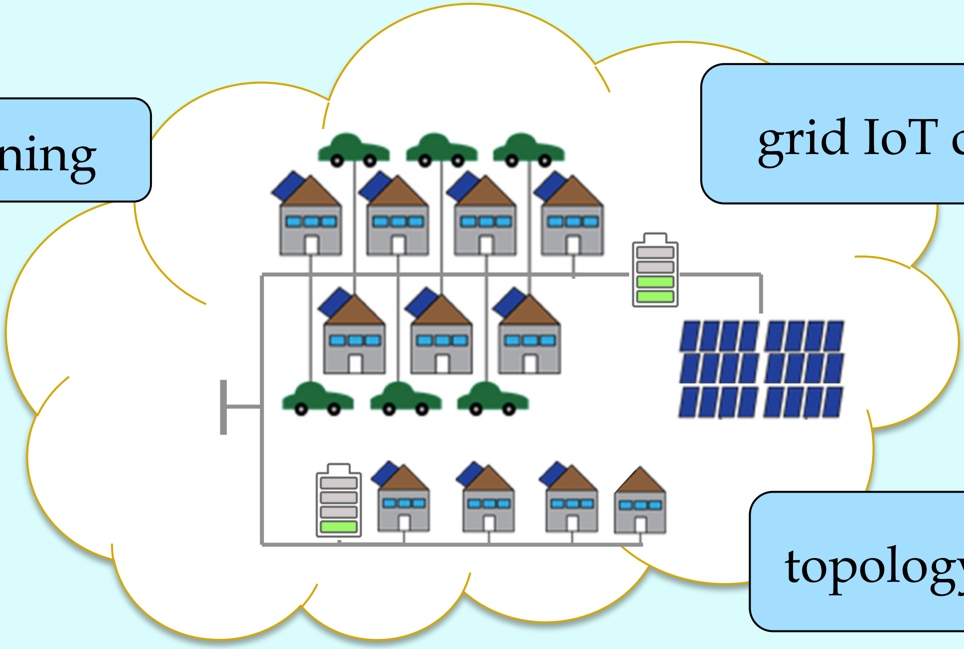
Grid IoT data analytics

Tools

inverter probing

machine learning for grid control

Problems



load learning

grid IoT control

topology learning

Thank You!

Related publications

- G. Cavraro and V. Kekatos, "Inverter Probing for Power Distribution Network Topology Processing," *IEEE Trans. on Control of Network Systems*, Sep 2019.
- G. Cavraro and V. Kekatos, "Graph Algorithms for Topology Identification using Power Grid Probing," *IEEE Control Systems Letters*, Oct 2018.
- G. Cavraro, A. Bernstein, V. Kekatos, and Y. Zhang, "Real-Time Identifiability of Power Distribution Network Topologies with Limited Monitoring," *IEEE Control Systems Letters*, Apr 2020.
- G. Cavraro, V. Kekatos, and S. Veeramachaneni, "Voltage Analytics for Power Distribution Network Topology Verification," *IEEE Trans. on Smart Grid*, Jan. 2019.
- S. Taheri, V. Kekatos, and G. Cavraro, "An MILP Approach for Distribution Grid Topology Identification using Inverter Probing," *IEEE PES PowerTech*, Milan, Italy, June 2019.
- M. K. Singh, V. Kekatos, S. Taheri, K. P. Schneider, and C.-C. Liu, "Enforcing Radiality Constraints for DER-Aided Power Distribution Grid Reconfiguration," *in Proc. PSCC*, Porto, Portugal, June 2020.
- S. Bhela, V. Kekatos, and S. Veeramachaneni, "Smart Inverter Grid Probing for Learning Loads: Part I -- Identifiability Analysis," *IEEE Trans. on Power Systems*, Sep 2019.
- S. Bhela, V. Kekatos, and S. Veeramachaneni, "Smart Inverter Grid Probing for Learning Loads: Part II -- Probing Injection Design," *IEEE Trans. on Power Systems*, Sep 2019.
- S. Bhela, V. Kekatos, and S. Veeramachaneni, "Enhancing Observability in Distribution Grids using Smart Meter Data," *IEEE Trans. on Smart Grid*, Nov 2018.
- M. Jalali, V. Kekatos, N. Gatsis, and D. Deka, "Designing Reactive Power Control Rules for Smart Inverters using Support Vector Machines," IEEE Trans. on Smart Grid, (early access).
- A. Garg, M. Jalali, V. Kekatos, and N. Gatsis, "Kernel-Based Learning for Smart Inverter Control," *in Proc. IEEE GlobalSIP*, Anaheim, CA, Nov. 2018.