

Using Smart Meter and PMU Data for Load Inference

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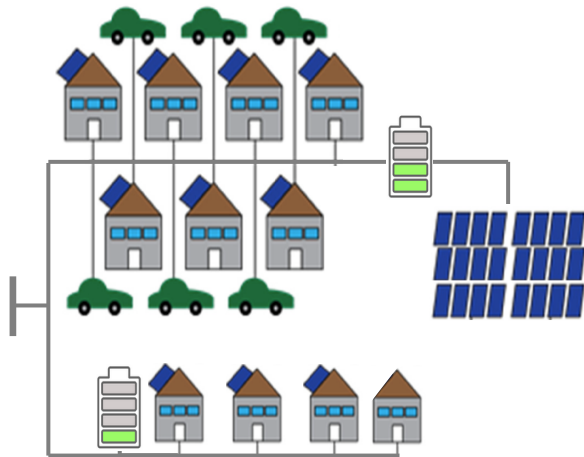
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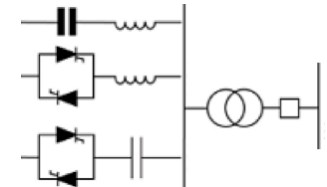
Acknowledgements: 

Learning loads in distribution grids

- Reduced observability due to sheer extent and limited metering infrastructure
- However, load estimates needed for grid optimization, billing, and energy theft detection



- Leverage smart meter data and smart inverters



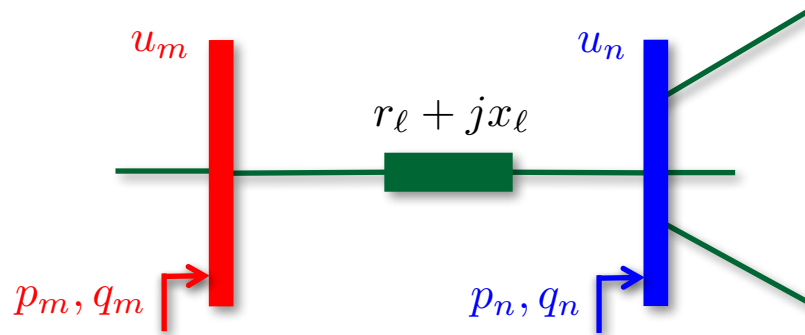
Problem statement and prior work

Load learning: Given readings from a set of metered (controllable) buses \mathcal{M} , recover the system state and hence the power injections at non-metered buses \mathcal{O} .

- Collected readings
 - *passively collected* (smart meter and synchrophasor (PMU) data)
 - *actively collected* through grid probing
- For sufficiently rich (pseudo)measurement sets, solve as D-PSSE [Dzafic-Jabr-Pal et al'13], [Klauber-Zhu'15], [Gomez-Exposito et al'15]
- Linear estimator if grid is equipped with micro-PMUs [A. von Meier'15]
- Meter placement in distribution grids [Lui-Ponci'14]
- Probing transmission grids for estimating oscillation modes [Trudnowski-Pierre'09]
- System identification in DC microgrids [Angjelichinoski-Scaglione '17]

Linearized distribution flow model

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



- Approximate LDF model [Baran-Wu'89], [Bolognani-Dorfler'15], [Deka et al'17]

$$\mathbf{u} \simeq \mathbf{R}\mathbf{p} + \mathbf{X}\mathbf{q}$$

$$\boldsymbol{\theta} \simeq \mathbf{X}\mathbf{p} - \mathbf{R}\mathbf{q}$$

$$\text{nodal voltage phasor } V_n = |V_n|e^{j\theta_n}$$

$$u_n := |V_n|^2 - |V_0|^2$$

- The inverses of (\mathbf{R}, \mathbf{X}) are reduced graph Laplacian matrices

Passive load learning

- Partition data into metered and non-metered buses

$$\begin{bmatrix} \mathbf{u}_M \\ \mathbf{u}_O \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{M,M} & \mathbf{R}_{M,O} \\ \mathbf{R}_{M,O}^\top & \mathbf{R}_{O,O} \end{bmatrix} \begin{bmatrix} \mathbf{p}_M \\ \mathbf{p}_O \end{bmatrix} + \begin{bmatrix} \mathbf{X}_{M,M} & \mathbf{X}_{M,O} \\ \mathbf{X}_{M,O}^\top & \mathbf{X}_{O,O} \end{bmatrix} \begin{bmatrix} \mathbf{q}_M \\ \mathbf{q}_O \end{bmatrix} + \boldsymbol{\eta}$$

- Model for smart meter data

$$\mathbf{u}_M - \mathbf{R}_{M,M}\mathbf{p}_M - \mathbf{X}_{M,M}\mathbf{q}_M = [\mathbf{R}_{M,O} \quad \mathbf{X}_{M,O}] \begin{bmatrix} \mathbf{p}_O \\ \mathbf{q}_O \end{bmatrix} + \boldsymbol{\eta}_M$$

- Model for synchrophasor data

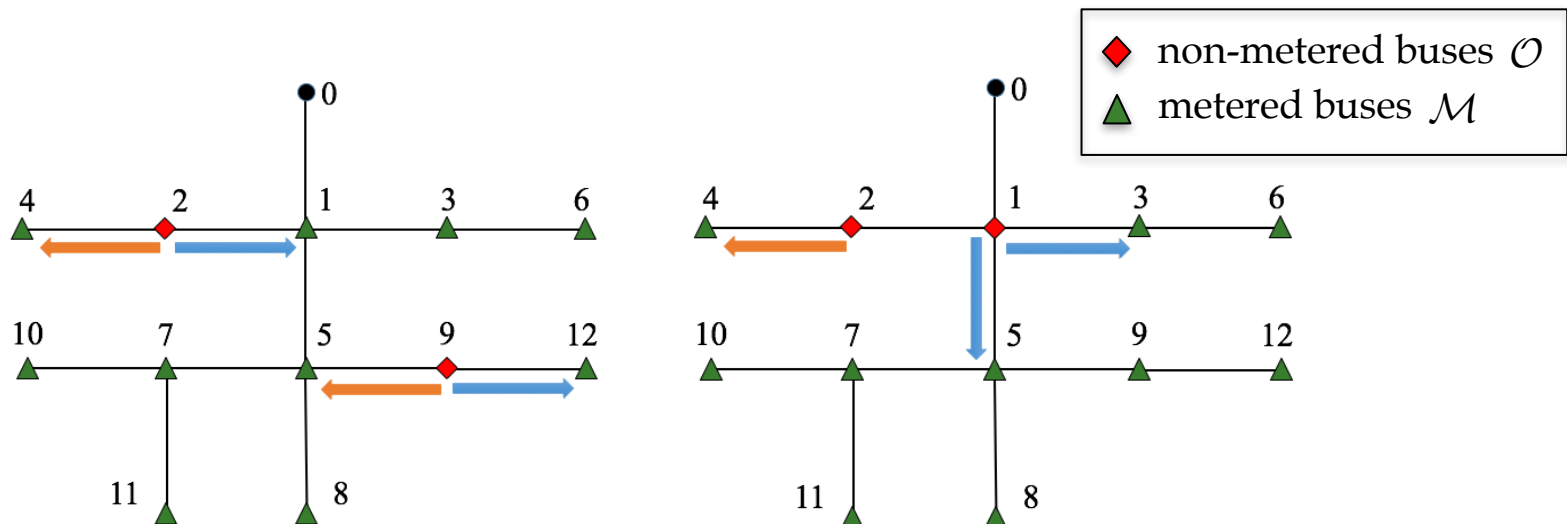
$$\begin{bmatrix} \mathbf{u}_M - \mathbf{R}_{M,M}\mathbf{p}_M - \mathbf{X}_{M,M}\mathbf{q}_M \\ \boldsymbol{\theta}_M - \mathbf{X}_{M,M}\mathbf{p}_M + \mathbf{R}_{M,M}\mathbf{q}_M \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{M,O} & \mathbf{X}_{M,O} \\ \mathbf{X}_{M,O} & -\mathbf{R}_{M,O} \end{bmatrix} \begin{bmatrix} \mathbf{p}_O \\ \mathbf{q}_O \end{bmatrix} + \boldsymbol{\epsilon}_M$$

- Non-metered injections can be uniquely recovered via least-squares if regression matrices are full column-rank

Identifiability with passive load learning

Proposition 1: Given smart meter data on $\mathcal{M} = \mathcal{M}_1 \cup \mathcal{M}_2$, the injections at \mathcal{O} are identifiable if every bus in \mathcal{O} is connected to unique buses in \mathcal{M}_1 and \mathcal{M}_2 .

Proposition 2: Given PMU data on \mathcal{M} , the injections at \mathcal{O} are identifiable if every bus in \mathcal{O} is connected to a unique bus in \mathcal{M} .



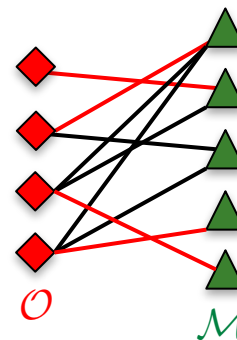
Key ideas

- Partition reduced (resistive) Laplacian $\mathbf{L} := \mathbf{R}^{-1} = \begin{bmatrix} \mathbf{L}_{\mathcal{M},\mathcal{M}} & \mathbf{L}_{\mathcal{M},\mathcal{O}} \\ \mathbf{L}_{\mathcal{M},\mathcal{O}}^\top & \mathbf{L}_{\mathcal{O},\mathcal{O}} \end{bmatrix}$
- Rank of Schur complement $\text{rk}(\mathbf{L}) = \text{rk}(\mathbf{L}_{\mathcal{M},\mathcal{M}}) + \text{rk}(\mathbf{L}_{\mathcal{O},\mathcal{O}} - \mathbf{L}_{\mathcal{M},\mathcal{O}}^\top \mathbf{L}_{\mathcal{M},\mathcal{M}}^{-1} \mathbf{L}_{\mathcal{M},\mathcal{O}})$
- Matrix inversion lemma and Sylvester's inequality

$$\mathbf{R}_{\mathcal{M},\mathcal{O}} = -\mathbf{L}_{\mathcal{M},\mathcal{M}}^{-1} \mathbf{L}_{\mathcal{M},\mathcal{O}} (\mathbf{L}_{\mathcal{O},\mathcal{O}} - \mathbf{L}_{\mathcal{M},\mathcal{O}}^\top \mathbf{L}_{\mathcal{M},\mathcal{M}}^{-1} \mathbf{L}_{\mathcal{M},\mathcal{O}})^{-1}$$

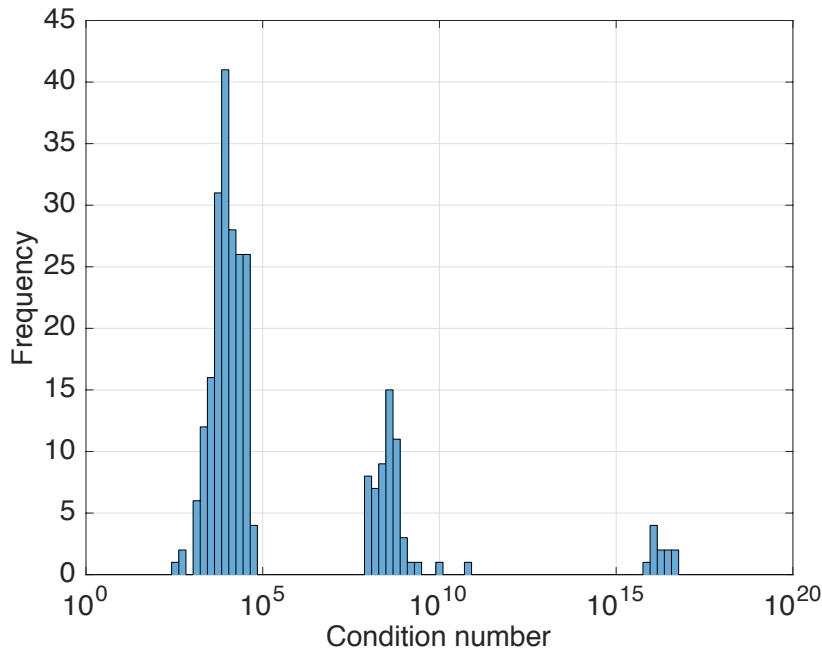
- Matrix $\mathbf{L}_{\mathcal{M},\mathcal{O}}$ is *generically* invertible iff there exists a perfect matching in the bipartite graph defined by its sparsity pattern [Tutte'47]

$$\mathbf{L}_{\mathcal{M},\mathcal{O}} = \begin{bmatrix} 0 & * & * & * \\ * & 0 & * & 0 \\ 0 & * & 0 & * \\ 0 & 0 & 0 & * \\ 0 & 0 & * & 0 \end{bmatrix}$$



- Perfect matching as max-flow problem; analysis holds for radial multiphase too

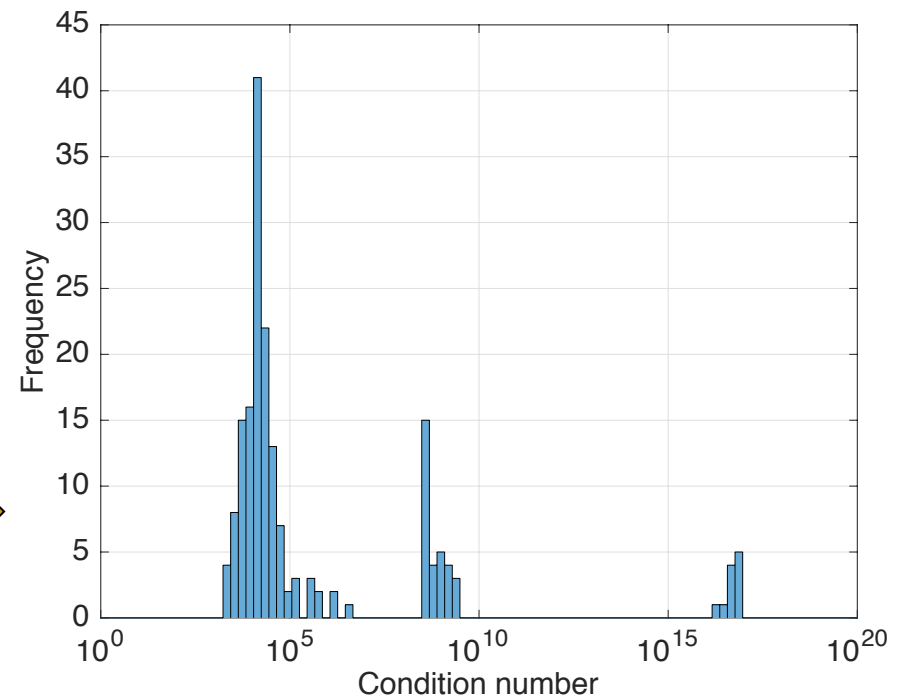
Identifiable setups with smart meter data



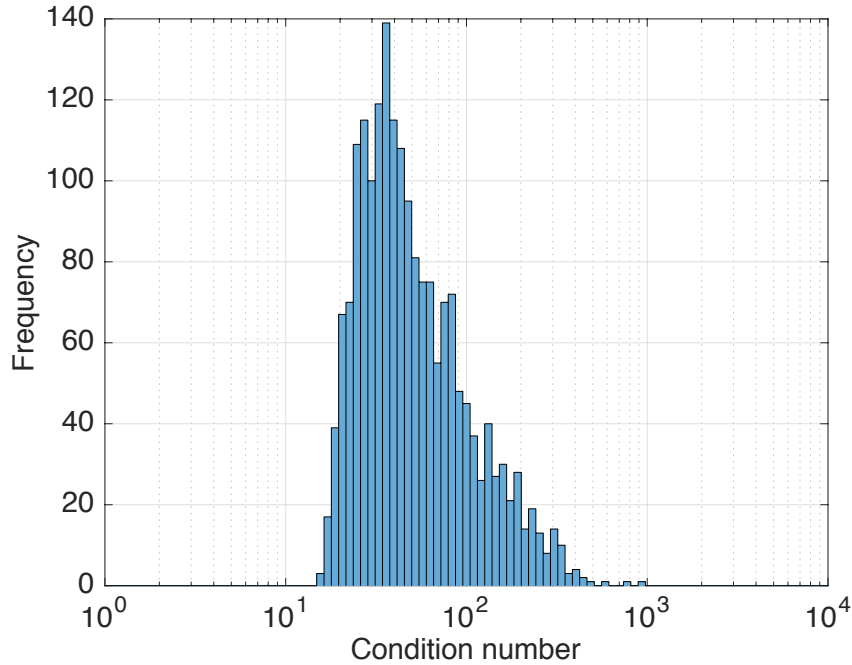
*IEEE 123-bus network with $|\mathcal{O}| = 10$
and 10 added lines (meshed)*



IEEE 123-bus network with $|\mathcal{O}| = 4$

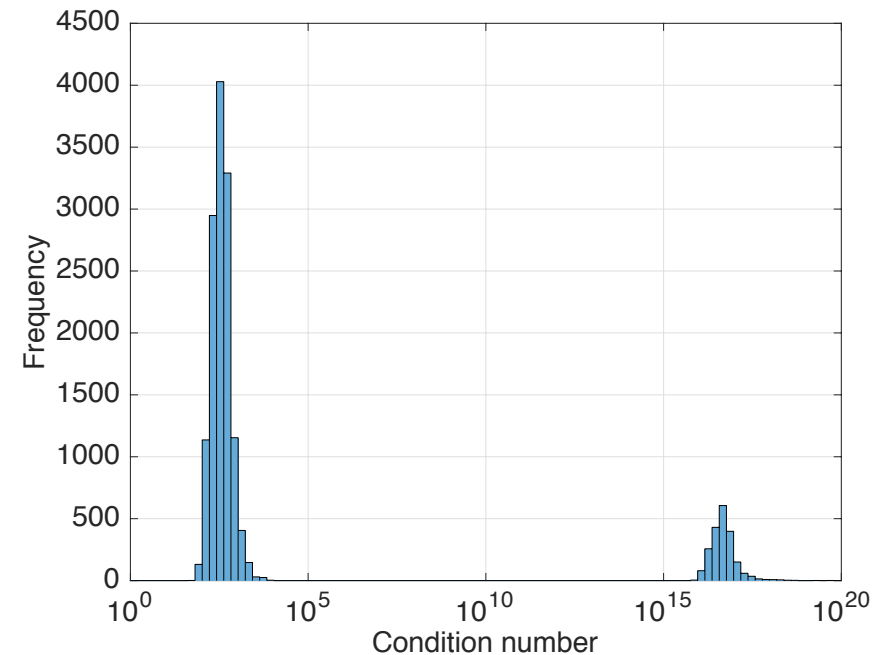


Identifiable setups with PMUs



IEEE 123-bus network with $|\mathcal{O}| = 4$

IEEE 123-bus network with $|\mathcal{O}| = 10$



Similar results for weakly meshed networks

Load learning through grid probing

Time $t = 1$: Record data $\{u_n^1, p_n^1, q_n^1\}_{n \in \mathcal{M}}$
associated with state \mathbf{v}_1

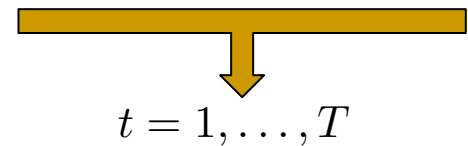
Time $t = 2$

- Probe *nonlinear physical system* by perturbing power injections at controllable buses [how?]
- Record data $\{u_n^2, p_n^2, q_n^2\}_{n \in \mathcal{M}}$ associated with state $\mathbf{v}_2 \neq \mathbf{v}_1$

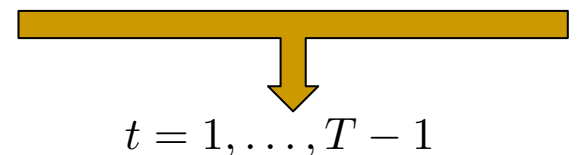
Repeat say every second for $t = 1, \dots, T$
each separated by say 5 secs, over 5 mins

- Exploit the fact that $\{p_n^t, q_n^t\}_{n \in \mathcal{O}}$ remain *invariant* during probing

$$\begin{aligned} p_n(\mathbf{v}_t) &= \hat{p}_n^t & \forall n \in \mathcal{M} \\ q_n(\mathbf{v}_t) &= \hat{q}_n^t & \forall n \in \mathcal{M} \\ u_n(\mathbf{v}_t) &= \hat{u}_n^t & \forall n \in \mathcal{M} \end{aligned}$$



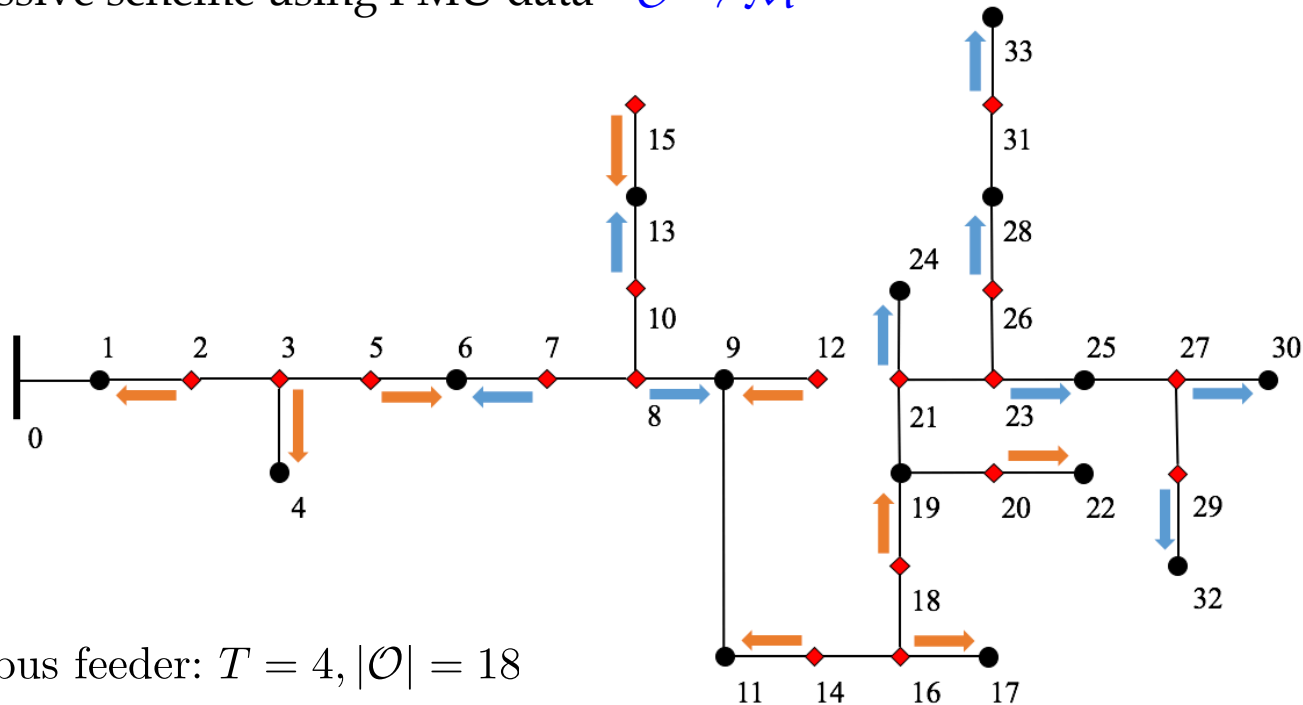
$$\begin{aligned} p_n(\mathbf{v}_t) &= p_n(\mathbf{v}_{t+1}) & \forall n \in \mathcal{O} \\ q_n(\mathbf{v}_t) &= q_n(\mathbf{v}_{t+1}) & \forall n \in \mathcal{O} \end{aligned}$$



Identifiability through grid probing

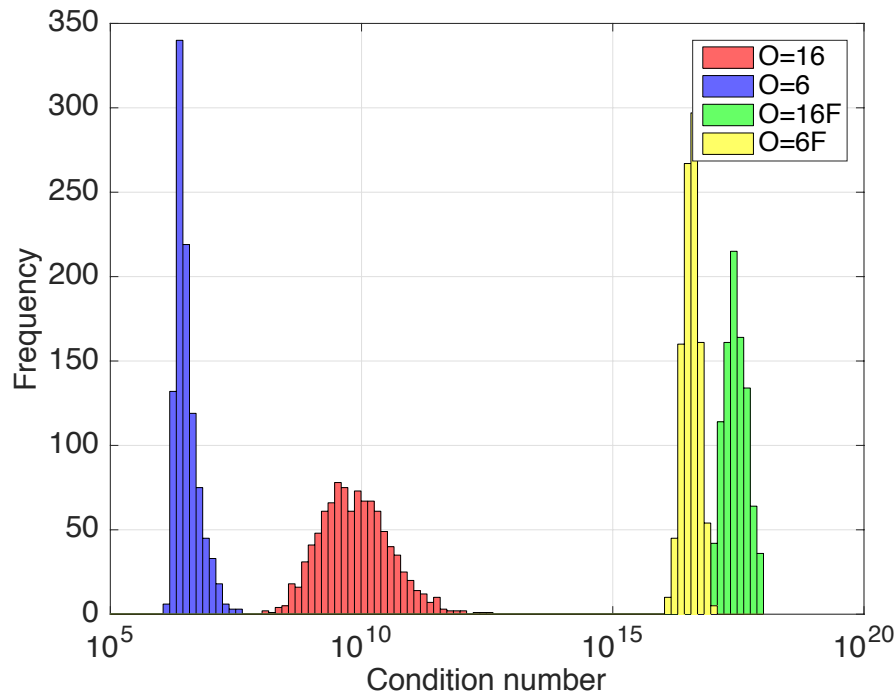
Theorem: If \mathcal{O} can be partitioned into $T/2$ subsets such that each can be matched to \mathcal{M} , then the states $\{\mathbf{v}_t\}_{t=1}^T$ and the injections at \mathcal{O} are locally identifiable.

- $T = 1$: passive scheme with smart meter data
- $T = 2$: passive scheme using PMU data $\mathcal{O} \rightarrow \mathcal{M}$



IEEE 34-bus feeder: $T = 4$, $|\mathcal{O}| = 18$

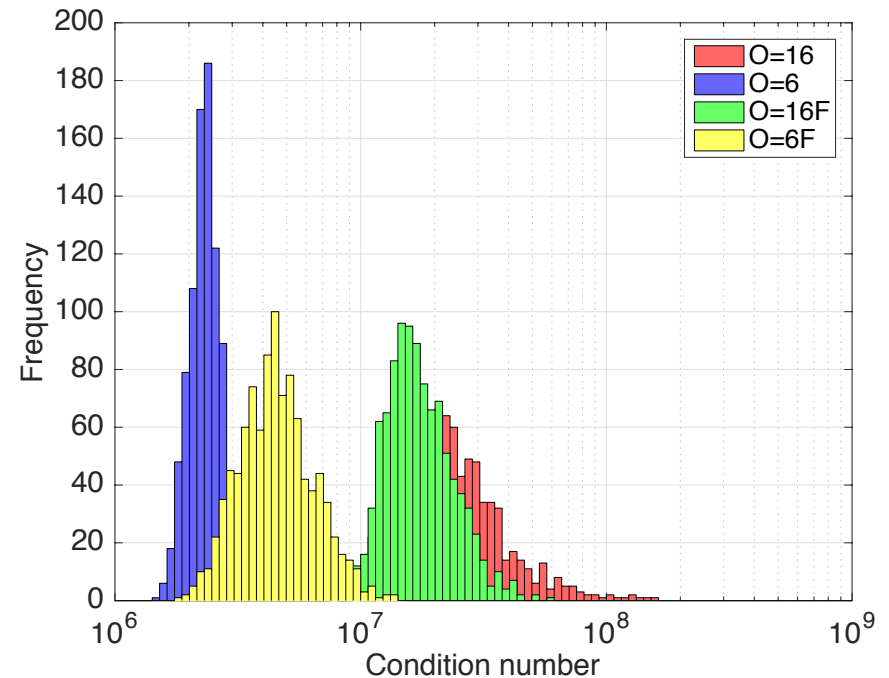
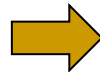
Numerical tests (Jacobian condition numbers)



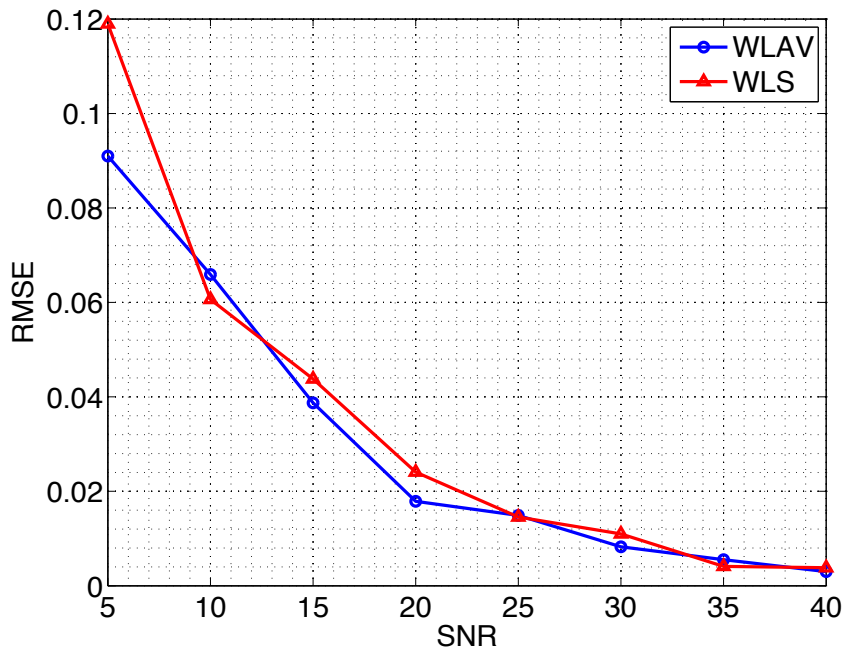
← *condition numbers of CPF
Jacobians for random states*

IEEE 34-bus feeder: $T = 2$

IEEE 34-bus feeder: $T = 4$

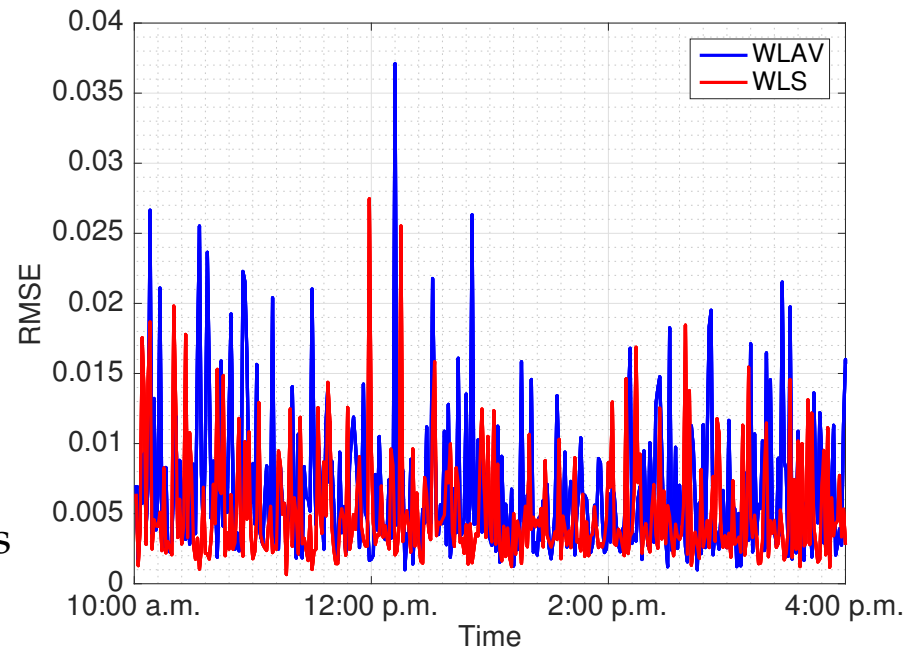


Numerical tests with synthetic and real data



■ State RMSE for CPSSE ($T = 2$)

- Actual load/solar data (Pecan St.)
- RMSE on system state over one day
- Probing by changing pf in smart inverters



Conclusions

Passive injection learning

- Identifiability for single-phase radial grids smart meter and PMU data
- Simple LS solver using LDF model
- No time coupling; timescale depends on data

Active injection learning

- Inverter data collected via intentional probing
- Identifiability for possibly meshed and polyphase grids
- Improvements with increasing T
- Optimal probing design? PMU data? Line flow data?
- Probing for topology identification?

Thank You!