IRP 4.3: Advanced Monitoring and Controls of the Electrical Distribution Network

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My research topic

Problems

- Large number of buses, but **few measurements available** + **expensive** to install all sensors. Not observable
- **Coupled 3-phases** and **unbalanced loads**. More complex power flow
- Simple load allocation methods based on **estimations produce large inaccuracies**

→ **Not prepared** for Distributed Energy Generation (PVs, EVs, Batteries, etc.)

PhD

Monitoring

1. **Distribution System State Estimation** using sensor information
2. **Optimal Sensor Placement** to maximize network observability

Controls

Controls to ensure stability and optimize operation

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① Two Step State Estimation

Problem statement:

- **State Estimation** = network voltages V estimation using measurements $z = h(V) + noise$:

$$V = \text{argmin}_V (z - h(V))^T \Sigma_{noise}^{-1} (z - h(V))$$

- **Mixed measurements** z: 1. Load estimations (load forecast, installed/contracted capacity)
  2. Real-time measurements (Smart Meter, Phasor Measurement Units)

Two Step State Estimation: split problem (extending Schenato et al., 2014[1]):

Prior Solution

- Solve the **Power Flow** problem using load pseudo-measurements / estimations:

$$V_{prior} = PowerFlow(S_{pseudo})$$

Offline
Iterative
High computational cost

Posterior Update

- Improve prior solution using real-time measurements $z_{RT} = C_{RT}(V) + noise$:

$$V_{post} = V_{prior} + K\left(z_{RT} - C_{RT}(V_{prior})\right)$$

- Optimal Bayesian gain K w.r.t. trace of estimation covariance: $K = \text{argmin tr}(\Sigma_{post})$

Real-time / Online
No iterations
Low computational cost

[1] L. Schenato, G. Barchi, D. Macii, R. Arghandeh, K. Poolla, and A. Von Meier, "Bayesian linear state estimation using smart meters and pmus measurements in distribution grids," in 2014 IEEE International Conference on Smart Grid Communications (SmartGridComm).

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② Optimal sensors: definition

Problem statement:

- **Sensor optimal allocation** = choose optimal number and location of sensors with budget B w.r.t. metric f:

  $$x = \text{argmin}_x \left(f\left(\Sigma_{post}(x)\right)\right) s.t. \sum_i c_i x_i \leq B, x_i \in \{0,1\}$$

  where $x_i = 1\ (0)$ if sensor i is (not) selected and $c_i \geq 0\ \forall i$ is the cost of installing it
- Combinatorial optimization → NP-hard problem

Metrics	f =	Covariance eigenvalues	Convex	Gradient expression	Linear	Super-modular[1]
A-opt.	$\text{tr}(\Sigma_{post})$	Sum	✓	✓		
D-opt.	$\log\left(\det\left(\Sigma_{post}\right)\right)$	Logarithm of product	✓	✓		✓
E-opt.	$\lambda_{max}(\Sigma_{post})$	Maximum	✓			
T-opt.	$-\text{tr}(\Sigma_{post}^{-1})$	? (Fisher Information)	✓	✓	✓	✓

[1] Supermodular set function $f()$: For sets $X \subseteq Y \subseteq \Omega \backslash \{a\}$, then $f(Y \cup \{a\}) - f(Y) \geq f(X \cup \{a\}) - f(X)$

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② Optimal sensors: approximations

Lower bounds

Convex relaxation:

- $x_i \in \{0,1\} \rightarrow x_i \in [0,1]$, convex set

→ Global minimum x_{convex} for convex relaxed problem, but not feasible w.r.t. real problem

Supermodularity minimization:

1. $\tilde{f}_{greedy} = \left(1 - \prod_i \left(1 - \frac{c_i}{B}\right) x_{greedy,i}\right) f\left(x_{greedy}\right)$
2. Select best single sensors till filling budget[1]:

$$\text{argmin}_{i \in \mathcal{B}, i \notin X} f(\{i\})$$

→ Online bound x_{online}

Upper bounds

Feasible solution:

- Select best sensors of x_{convex} till filling budget[1]:

$$\text{argmin}_{i \in \mathcal{B}, i \notin X} x_{convex,i}$$

→ Feasible, yet suboptimal solution $x_{feasible}$

Greedy forward selection:

- Select best incremental sensor till filling budget[1]:

$$\text{argmin}_{i \in \mathcal{B}, i \notin X} \frac{f(X \cup \{i\}) - f(X)}{c_i}$$

→ Greedy feasible suboptimal solution x_{greedy}

$$\max\left(f(x_{convex}), f(x_{online}), \tilde{f}_{greedy}\right) \le f(x_{minimum}) \le \min\left(\mathrm{f}\left(x_{feasible}\right), \mathrm{f}\left(x_{greedy}\right)\right)$$

[1] Where X denotes the selected sensors by each method and $\mathcal{B} = \{i | c_i \le \sum_{j \in X} c_j\}$ is the set of possible sensors satisfying the budget

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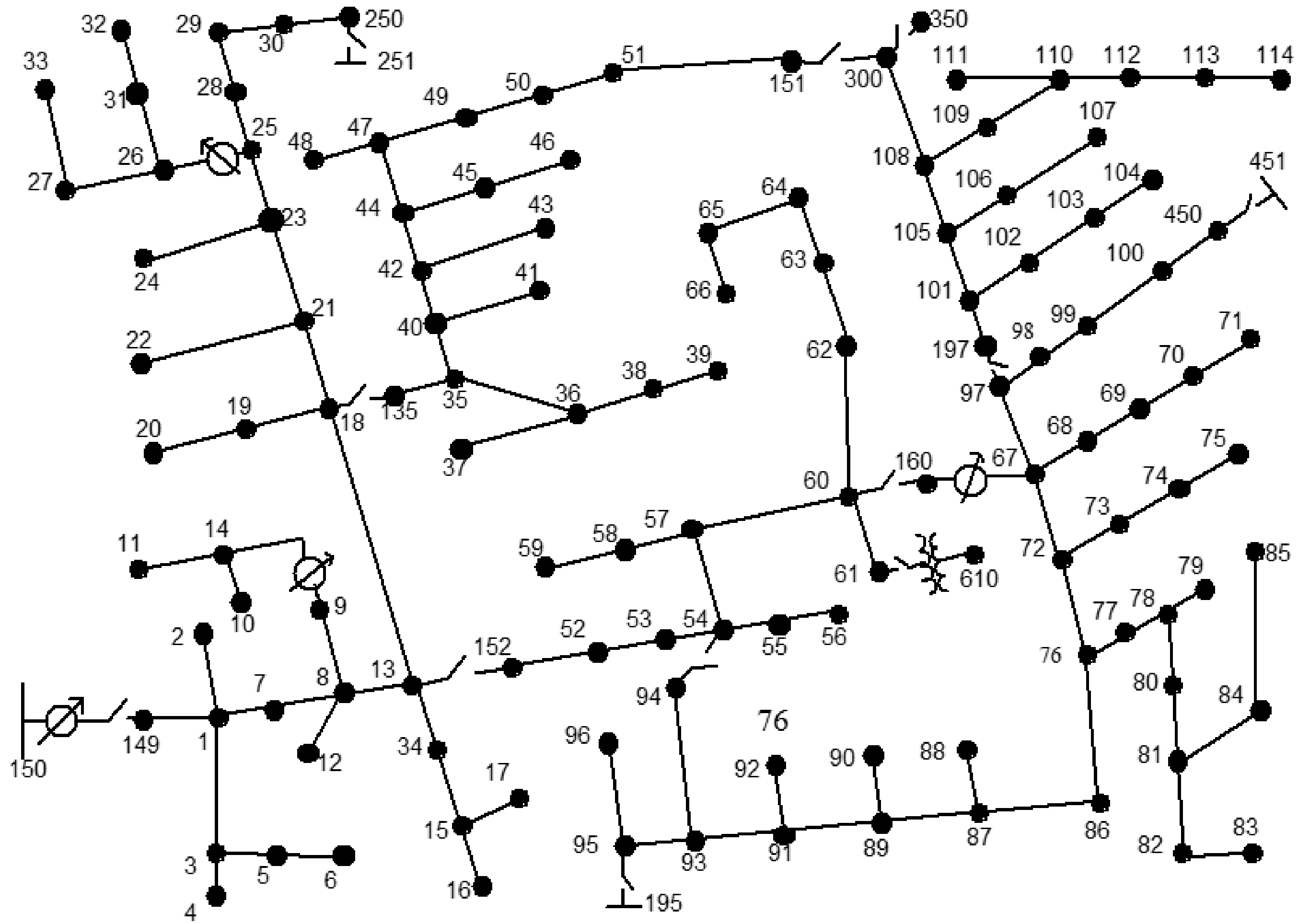
Test Feeder: IEEE 123 Node



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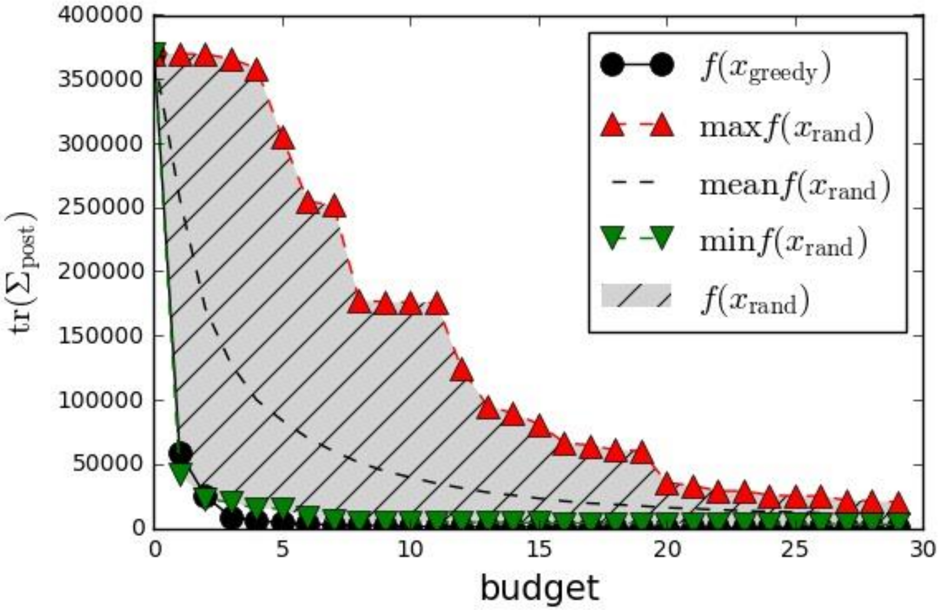
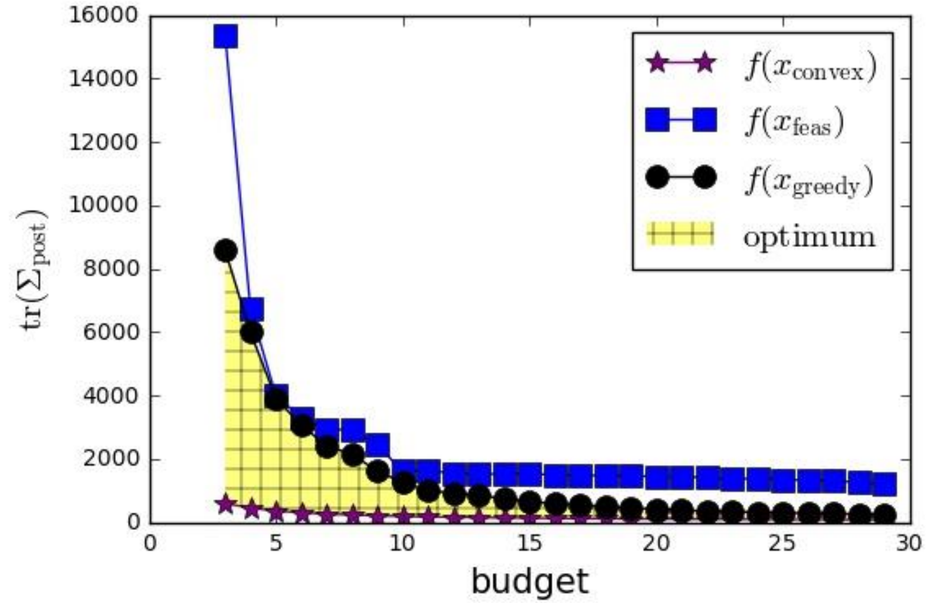
Results for A-opt.

Greedy vs Random Placement (100 samples)



Bounds & possible optimum



- Randomized selection might be far from optimum
- Convex relaxation bound is too optimistic for small number of sensors, but useful for many sensors

→Greedy solution is sufficiently good for large number of sensors

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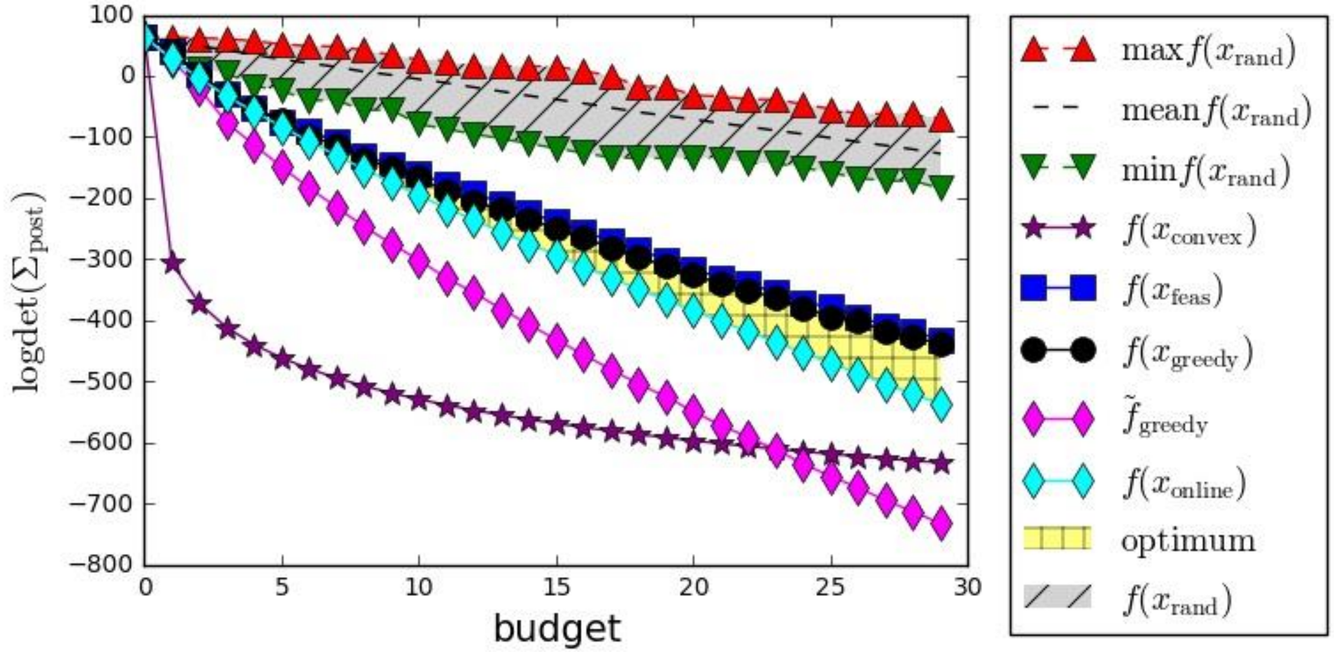
Results for D-opt.



- Randomized selection is far from optimum
- Convex relaxation bound is too optimistic for small number of sensors, but useful for many sensors
- Tight bound area for actual minimum combining all bounds

→Greedy solution is sufficiently good

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