Data Quality and its Effects on Market Functions

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Project Overview

Objectives:

The main objective of this research is to investigate how data quality affects market functions of current and future grids:

- develop models and measures of data quality;
- quantify risks of bad and malicious data;
- develop techniques to isolate and mitigate effects of bad and malicious data.

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Summary of results:

- Quantifying impacts of worst analog data on real-time LMP.
- Geometric characterization of real-time LMP.
- Topology error and joint data and topology attacks.
- Robustness of nonlinear state estimation against linear data attack.

Outline

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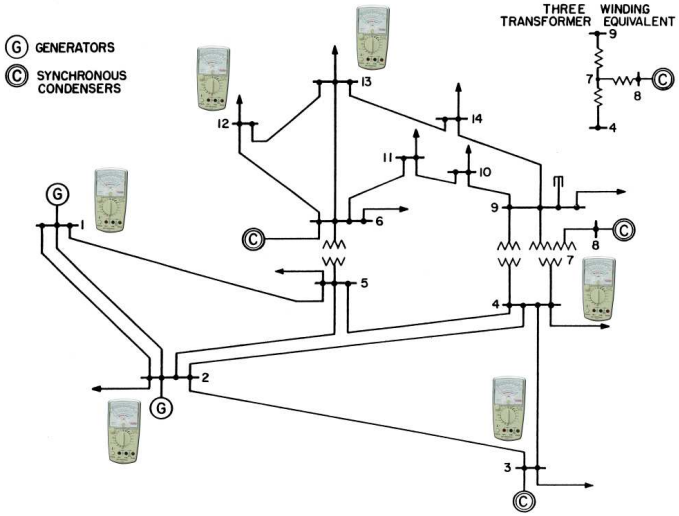
The good, the bad, the malicious, ...



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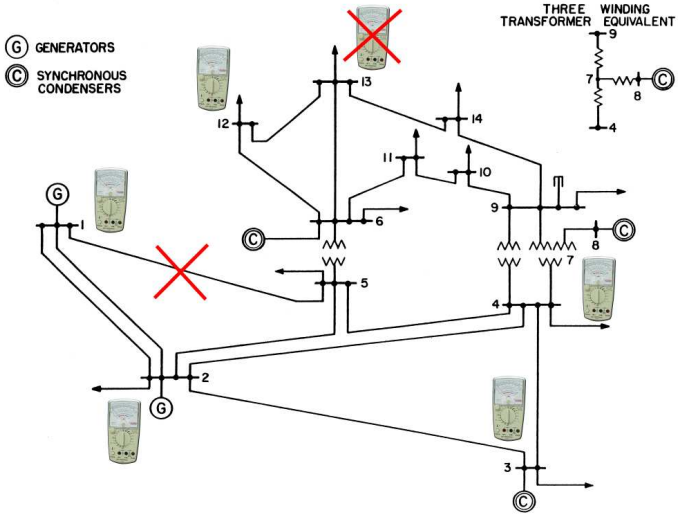

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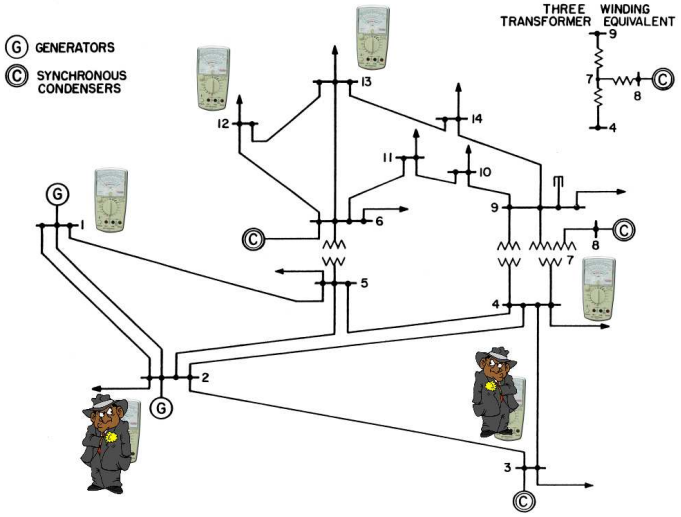
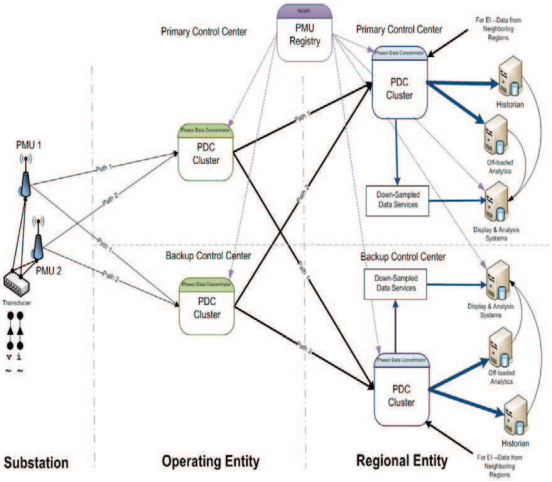
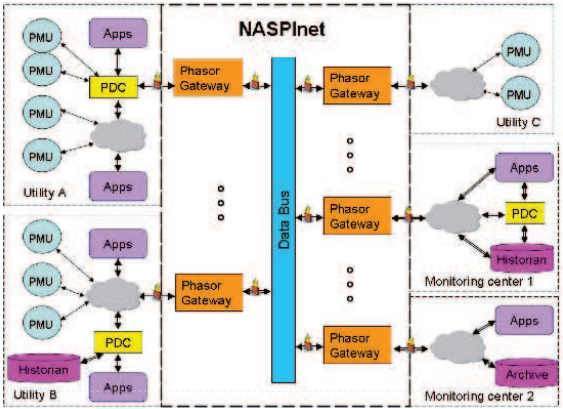
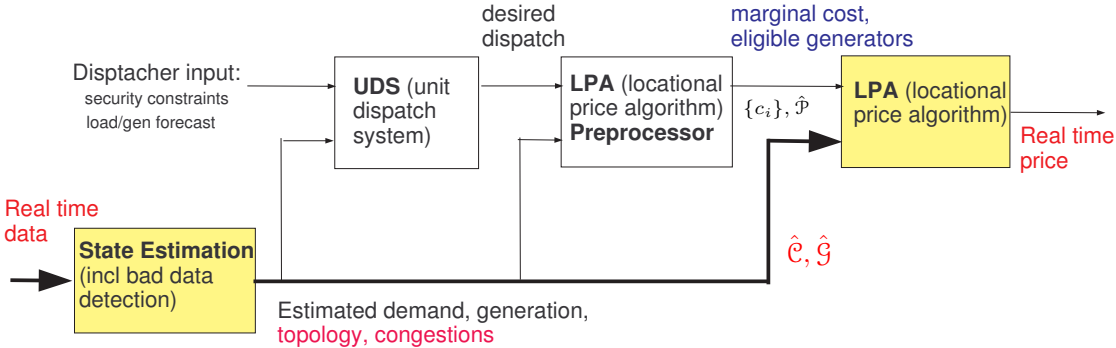


... and it is a cyber-physical system



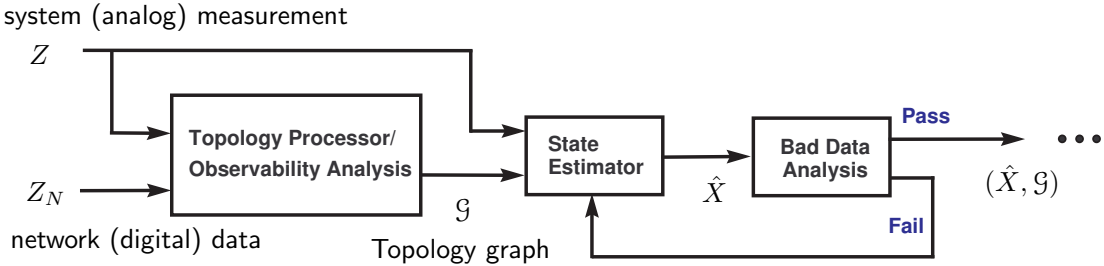


Data in real-time market operation*

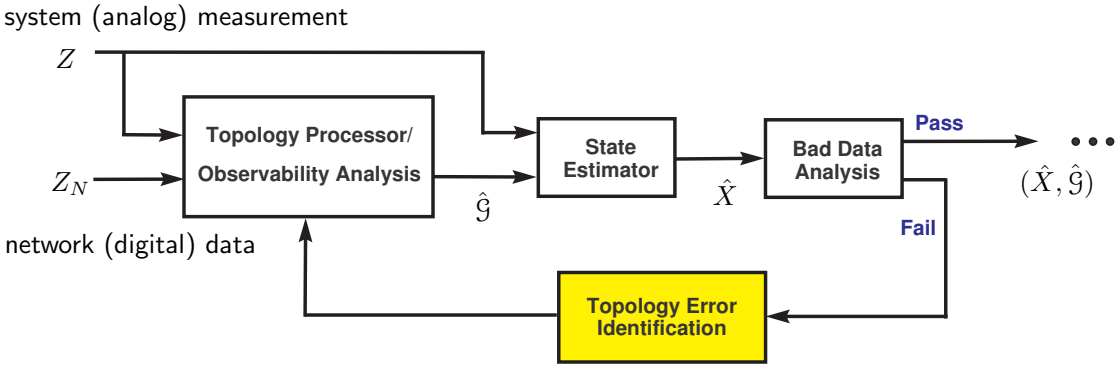


*A. Ott, IEEE TPS, May 2003.

Standard state estimation: schematics



Generalized state estimation: schematics



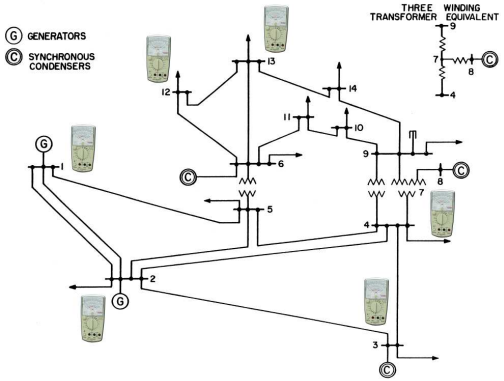
Power system state estimation: model

Static state space model:

$$\begin{aligned} Z_N &= X_N + W_N, X_N \leftrightarrow \mathcal{G} = (\mathcal{V}, \mathcal{E}) \\ Z &= h(X, \mathcal{G}) + W \end{aligned}$$

where

- X: system state (voltage phasors).
- X_N: network state (breaker/switch states).
- Z, Z_N: system and network measurements
- W, W_N: measurement errors.



State estimation: algorithm

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- The weighted least squares (WLS) estimator:

$$Z_N \to \hat{\mathcal{G}}, \hat{X}_{\mathsf{WLS}}(z) = \arg\min_x (z - h(x; \hat{\mathcal{G}}))^\intercal \Sigma_W^{-1} (z - h(x; \hat{\mathcal{G}})).$$

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- The generalized weighted least squares (GWLS) estimator:

$$(\hat{X}_{\text{GWLS}}, \hat{\mathcal{G}}_{\text{GWLS}}) = \arg\min_{(x,\mathcal{G})} \left\{ (z - h(x; \mathcal{G}))^\intercal \Sigma_W^{-1} (z - h(x; \mathcal{G})) \right\}$$

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- The generalized state estimator (Monticelli-Wu) is a practical approach involving bad data detection and heuristic searches.

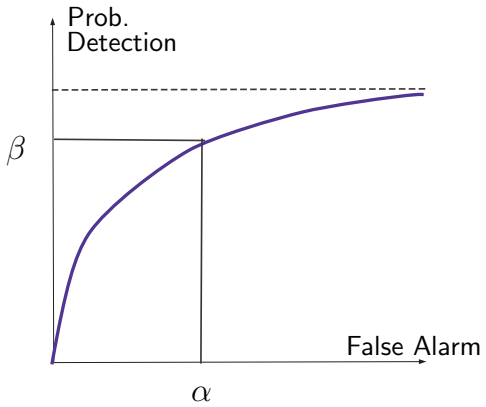
State estimation and bad data detection

- State estimation: Obtain state estimate $\hat{X}$ (and topology graph $\hat{\mathcal{G}}$) using a (generalized) state estimator.
- Bad data detection based on residue error:

$$||z - h(\hat{X}; \hat{\mathcal{G}})||^2_{\Sigma_W^{-1}} \underset{\text{good}}{\overset{\text{bad}}{\gtrless}} \tau$$

where the choice of τ determines the operating point.

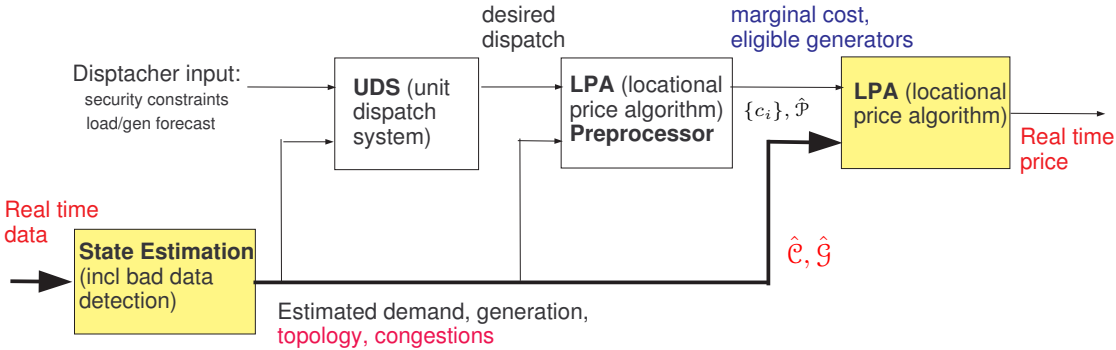
- Bad data identification: If bad data are detected, identify their locations.



Detector operating characteristic

Outline

Real-time LMP†



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Real-time LMP algorithm

- The real time LMP is computed via the incremental DC-OPF:

$$
\begin{array}{lll}
\text{minimize} & \sum_i \hat{c}_i \Delta p_i - \sum_j \hat{c}_j \Delta d_j & \\
\text{subjcet to} & \sum_i \Delta p_i = \sum_j \Delta d_j & (\lambda) \\
& \Delta p_{\min} \le \Delta p_i \le \Delta p_{\max} & i \in \hat{\mathcal{P}}; \\
& \Delta d_{\min} \le \Delta d_i \le \Delta d_{\max} & \\
& \sum S_{ki} \Delta p_i - \sum S_{kj} \Delta d_j \le 0; & k \in \hat{\mathcal{C}} \qquad (\mu_k)
\end{array}
$$

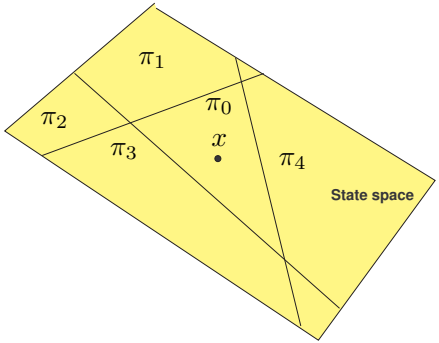
- The LMP at bus i is given by

$$\hat{\pi}_i = \hat{\lambda}^* - \sum_{j \in \hat{\mathcal{C}}} S_{ji} \hat{\mu}_j^*$$

From data to LMP: a geometrical view

- The state space is partitioned by hyperplanes into price regions
  - Each hyperplane corresponds to a congested line:

    congestion on line $i \Leftrightarrow f_i^{\mathsf{T}} x > c_i$



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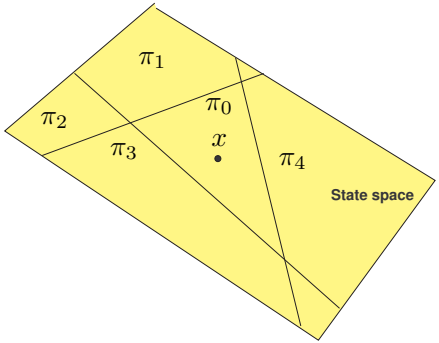

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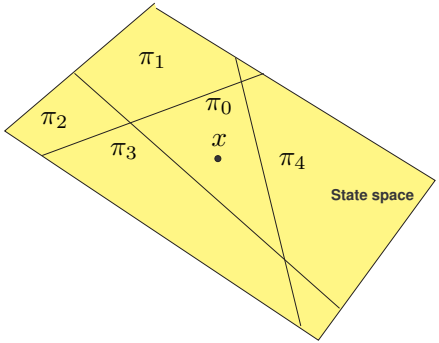
  - The LMP value in each region is determined by shift factors S_{ij}.



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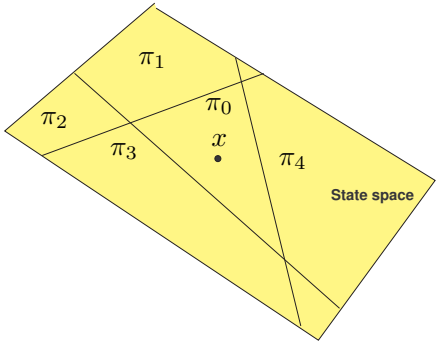
  - The LMP value in each region is determined by shift factors S_{ij}.
  - LMP value in each region is not affected by data!



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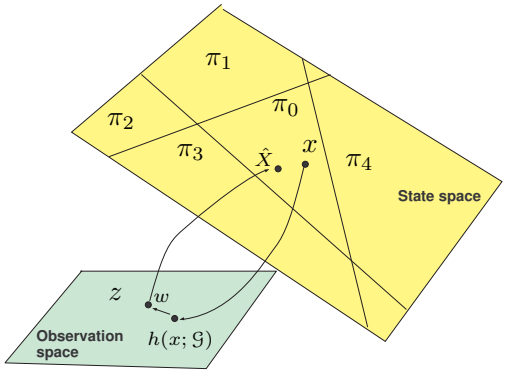
- The state space is partitioned by hyperplanes into price regions
- The real time LMP forms a Markov chain:

$$Z \to \hat{X} \to \pi$$



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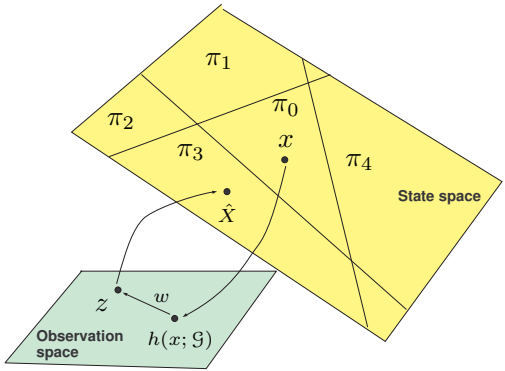

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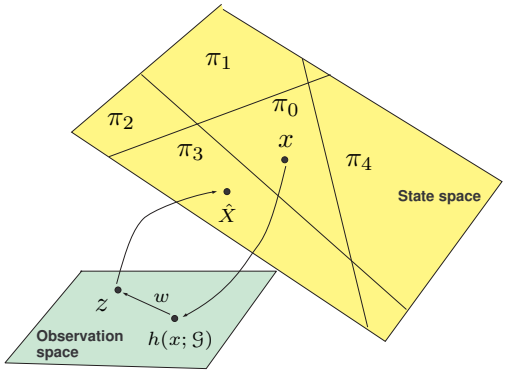
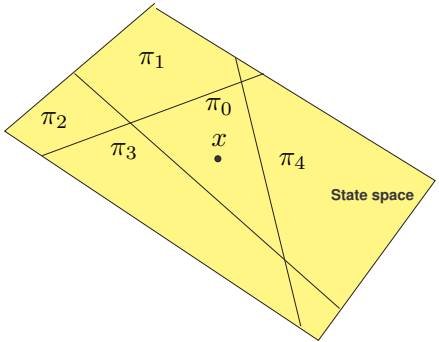
- What happens with topology error?



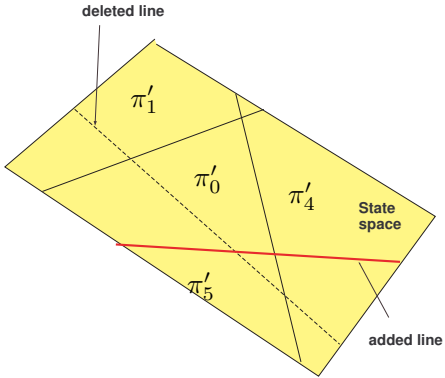
From data to LMP with topology error

- The state space is partitioned by hyperplanes into price regions, and each region corresponds to a congestion pattern.



From data to LMP with topology error

- The state space is partitioned by hyperplanes into price regions, and each region corresponds to a congestion pattern.
- A change in topology may add or delete hyperplanes.



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- The state space is partitioned by hyperplanes into price regions, and each region corresponds to a congestion pattern.
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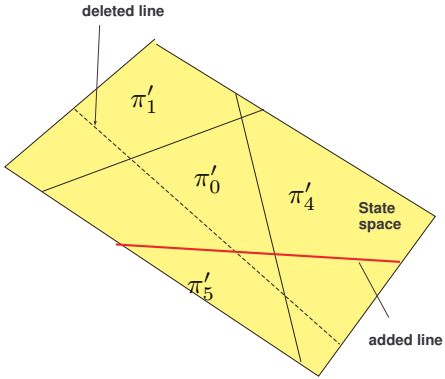
- But LMP values in all regions are function of shift factor S_{ij}.



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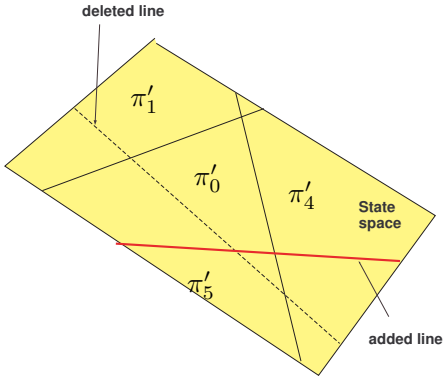


LMPs may all change due to the deletion of a single line!

Outline

Data quality models

We consider a simple perturbation model

$$\begin{aligned} Z &= h(X;\mathcal{G}) + \Delta + W, \quad \Delta \in \mathcal{A} \\ Z_N &= X_N + \Delta_N, \quad \Delta_N \in \mathcal{A}_N \end{aligned}$$

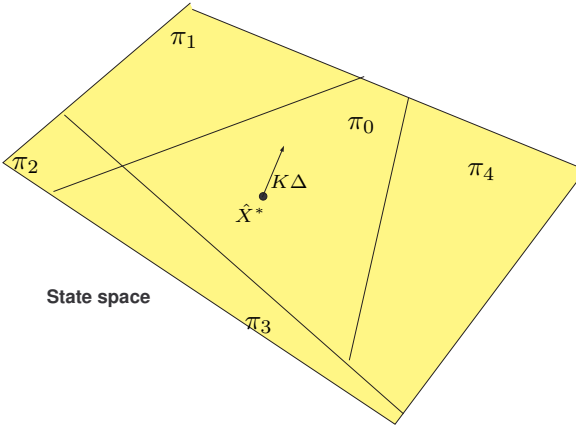
where $\mathcal{A}, \mathcal{A}_N$ characterize the nature of the perturbation.

- Some examples:
  1. Static perturbation: $\mathcal{A} = \{a : \|a\|_0 \leq T\}$, $\mathcal{A}_N = \{\text{single line change}\}$.
  2. Data dependent perturbation: $\Delta = Q(Z) \in \mathcal{A}$.
  3. Dynamic perturbation: $\Delta_t = Q(Z_t, Z_{t-1}, \cdots)$.
- We focus on the worst case analysis for (1-2).

Data attack: constructing the worst data

- Under the DC model, $z = Hx + \Delta + w$, the bad data Δ moves the WLS estimate

$$\hat{X}^* \to \hat{X}_{\text{WLS}} = Kz = \hat{X}^* + K\Delta$$



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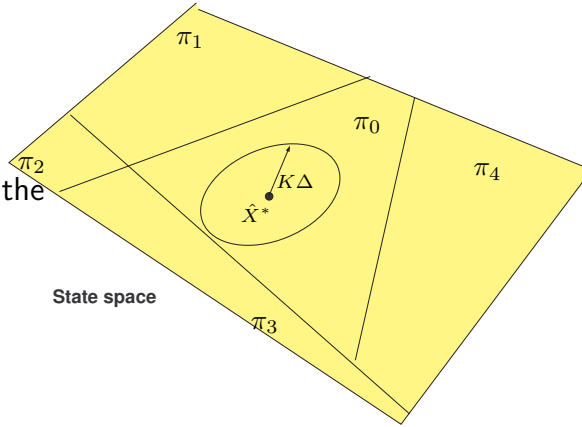
- Thus Δ are not detectable if $\hat{X}_{\text{WLS}}$ passes the bad data test,

$$\|z - H\hat{X}_{\text{WLS}}\|^2_{\Sigma_W^{-1}} \quad \leq \quad \tau$$



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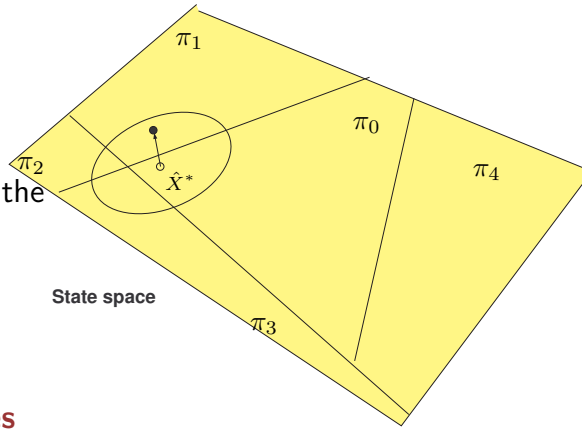


- **LMP change is possible only for states near boundaries!**

Joint topology and data attack

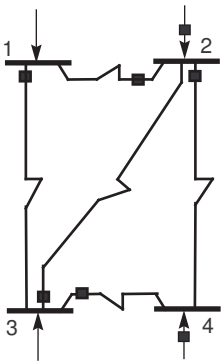
- Under the actual topology,

$$\begin{aligned} z_N &= x_N \leftrightarrow \mathcal{G} = (\mathcal{V}, \mathcal{E}) \\ z &= Mf = MYA^{\mathsf{T}}x + w, \end{aligned}$$

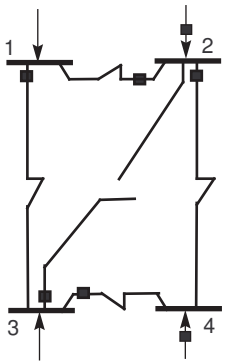
  where Y is the admittance matrix, A^{T} the reduced branch-to-node incidence matrix.

- Under the bad data perturbed topology $z_N \to \bar{\mathcal{G}} = (\bar{\mathcal{V}}, \bar{\mathcal{E}})$,

$$\begin{aligned} \bar{z}_N &= x_N + \Delta_N \\ \bar{z} &= M\bar{f} = MY\bar{A}^{\mathsf{T}}\bar{x} + w \end{aligned}$$



Actual topology



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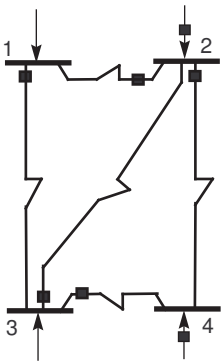

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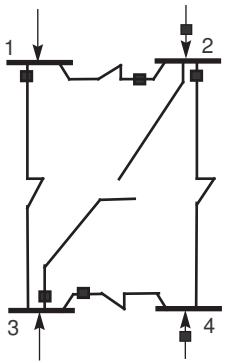


Bad data perturbed topology

- Find undetectable bad and sparse data such that $\bar{z} = z + \Delta$ and $\bar{z}_N = z_N + \Delta_N$.

Single branch topology change

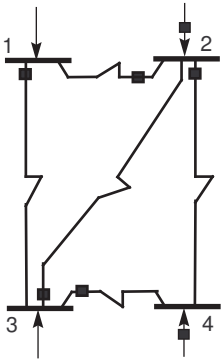
- Fix the state the same in both (noiseless) systems

$$\begin{aligned} z &= MYA^{\mathsf{T}}x \quad \xrightarrow{\Delta} \quad \bar{z} = MY\bar{A}^{\mathsf{T}}\bar{x} \\ \Delta &= \bar{z} - z = MY(\bar{A} - A)^{\mathsf{T}}x \end{aligned}$$

- If $\mathcal{G}$ differ from $\bar{\mathcal{G}}$ by only one branch, then

$$\Delta z = \rho_i m_i$$

where ρ_i is the power flow on the ith branch, and m_i is a column of M. And it is sparse!



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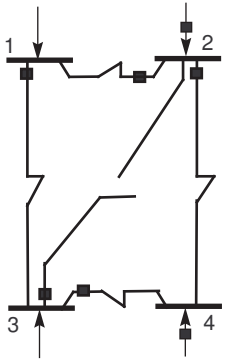


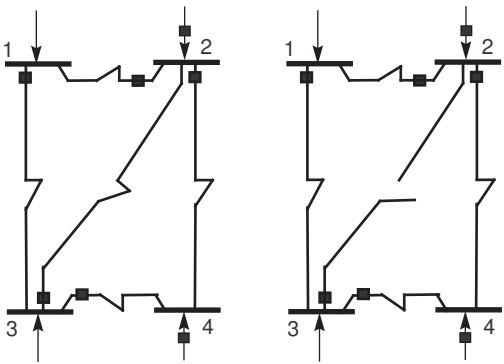
Bad data perturbed topology

Single branch topology change

- By jointly change the system (analog) and network (digital) data

$$z \to \bar{z} = z + \Delta z, \quad \mathcal{G} \to \bar{\mathcal{G}}$$

the bad data is not detectable.



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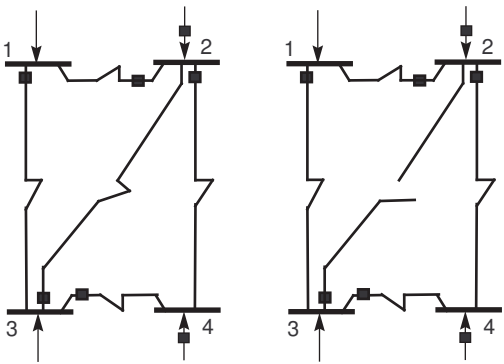
- In general, a set of lines can be added or deleted by

$$\Delta z = \sum_i \rho_i m_i$$



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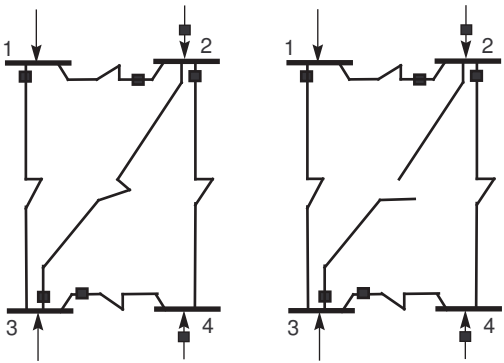
$$z \to \bar{z} = z + \Delta z, \quad \mathcal{G} \to \bar{\mathcal{G}}$$

  the bad data is not detectable.

- In general, a set of lines can be added or deleted by

$$\Delta z = \sum_i \rho_i m_i$$

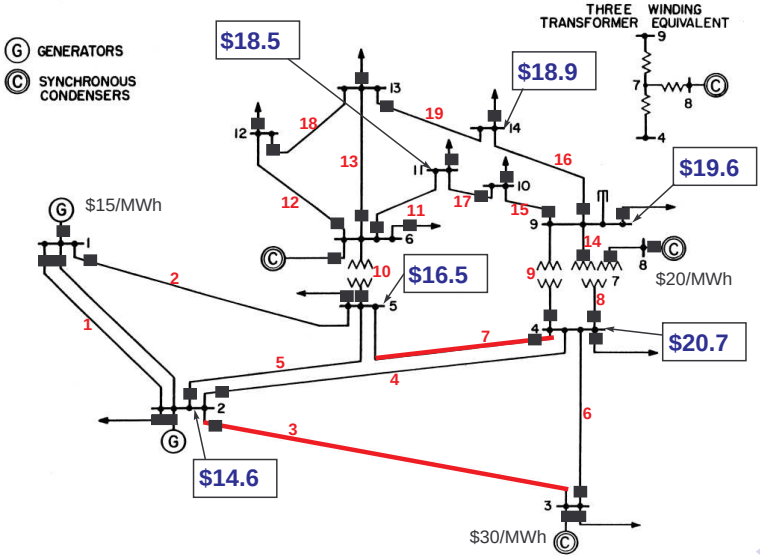
- Intuition: redistribute flow of the altered branches.



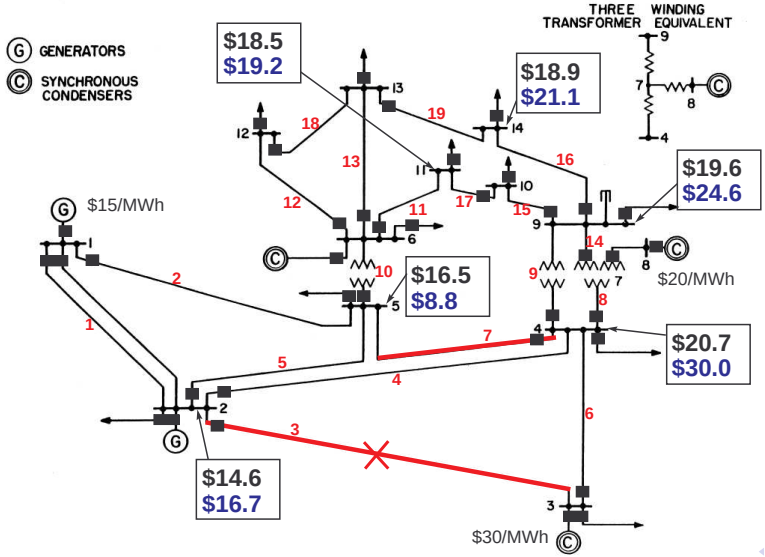
Actual topology

Bad data perturbed topology

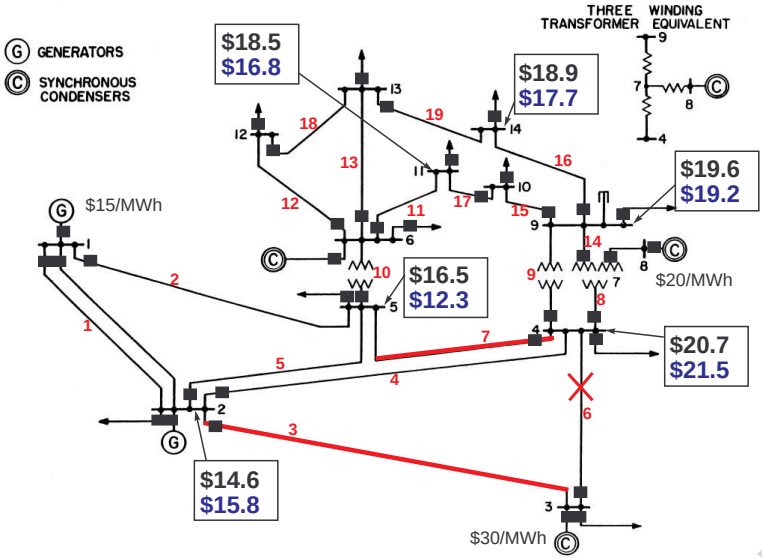
Example: IEEE 14-bus network



Single branch change: IEEE 14-bus network



Example: IEEE 14-bus network



Single branch change: IEEE 14-bus network

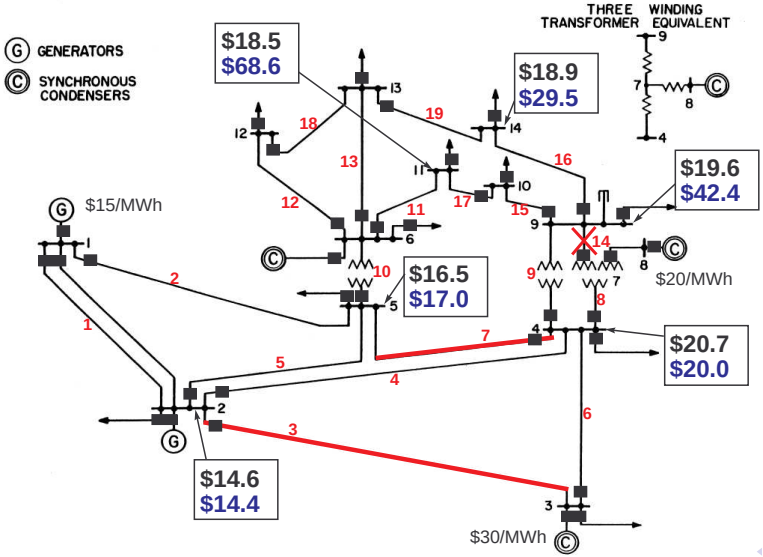
Line 6 removed

	line 3	line 7	line 11
2	0.00	0.07	-0.00
3	-1.00	0.07	-0.00
4	0.00	0.58	-0.02
5	0.00	-0.24	0.01
6	0.00	0.01	0.18
7	0.00	0.45	-0.12
8	0.00	0.45	-0.12
9	0.00	0.37	-0.17
10	0.00	0.31	-0.28
11	0.00	0.16	-0.54
12	0.00	0.03	0.16
13	0.00	0.06	0.13
14	0.00	0.24	-0.04

No attack

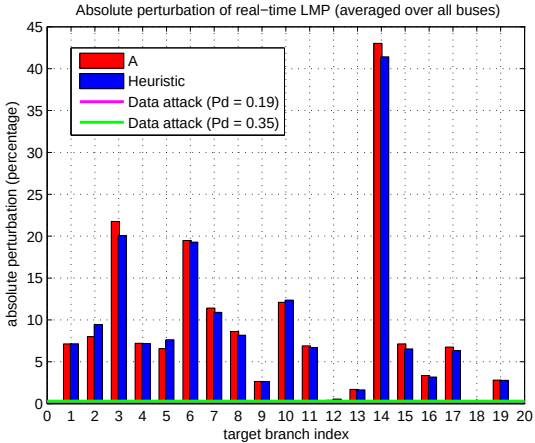
	line 3	line 7	line 11
2	0.03	0.08	0.00
3	-0.55	0.30	-0.01
4	-0.15	0.51	-0.02
5	-0.10	-0.30	0.01
6	-0.12	-0.05	0.19
7	-0.14	0.37	-0.11
8	-0.14	0.37	-0.11
9	-0.14	0.30	-0.17
10	-0.13	0.24	-0.28
11	-0.13	0.10	-0.54
12	-0.12	-0.03	0.16
13	-0.12	0.00	0.13
14	-0.13	0.17	-0.04

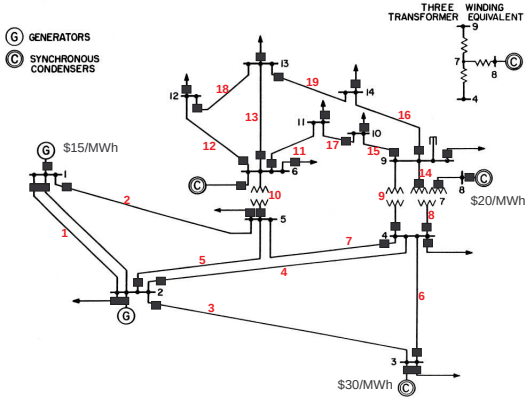
Example: IEEE 14-bus network



Example: data attack vs. topology attack

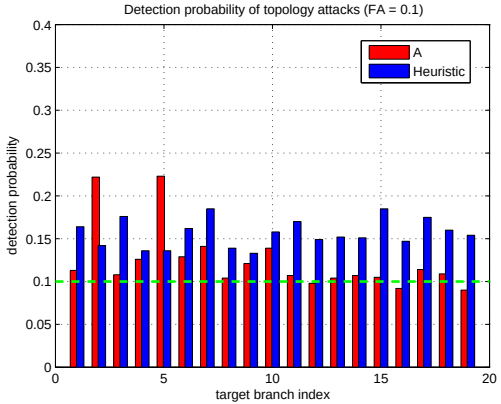
- Real-time LMP perturbation.

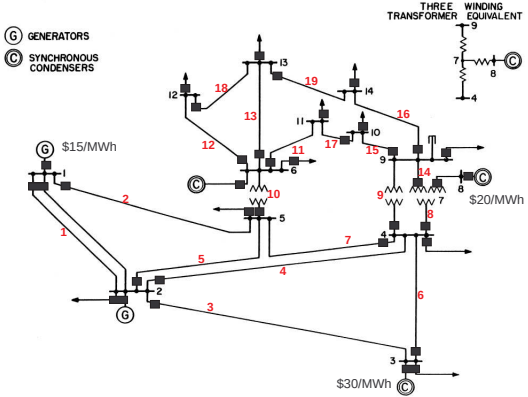




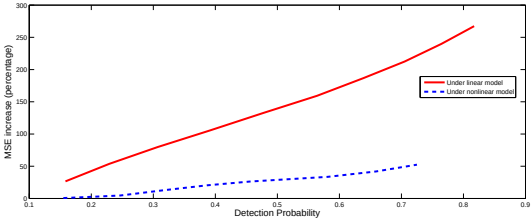
Detectability

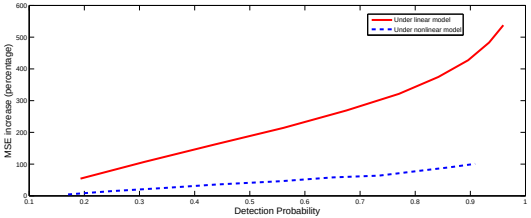
- FA of residual test is 0.1. AC model/ AC state estimator.
- Detection probability:

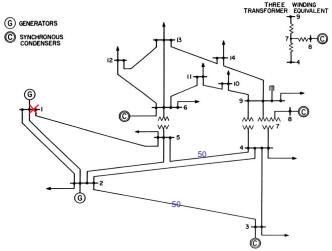


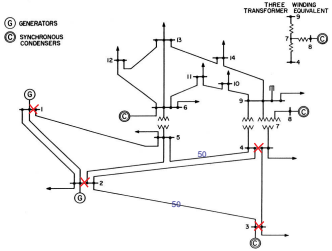


Robustness of nonlinear state estimation: MSE

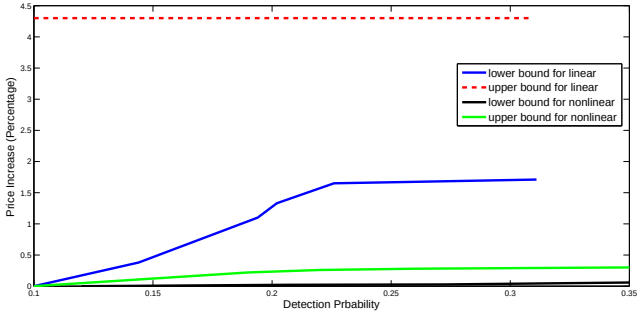


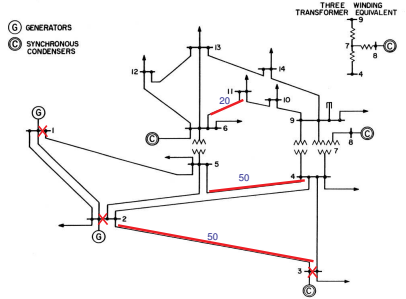




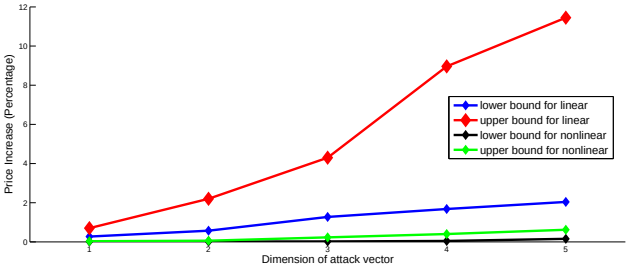


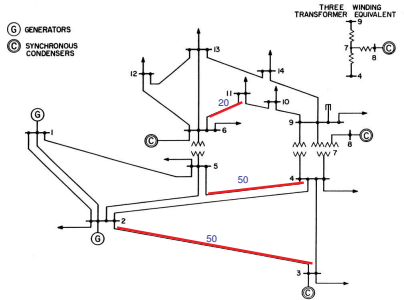
Robustness of nonlinear state estimation: LMP





Robustness of nonlinear state estimation: LMP





Project summary and future work

Project summary

1. Developed system and network and data quality models.
2. Obtained geometric characterization of real-time LMP.
3. Showed that bad analog and bad topology data affect LMP differently.
4. Constructed a simple undetectable joint topology and data attack.
5. Evaluated the effectiveness of worst data constructed from DC model.

Future work

- Optimal use of local information to construct joint data and topology attacks.
- Impacts of data on unit dispatch system (UDS) and LPA preprocessing.
- Dynamic models and more sophisticated bad data detection.