

PowerUp 2026

Outage Identification from Electricity Market Data: Quickest Change Detection Approach

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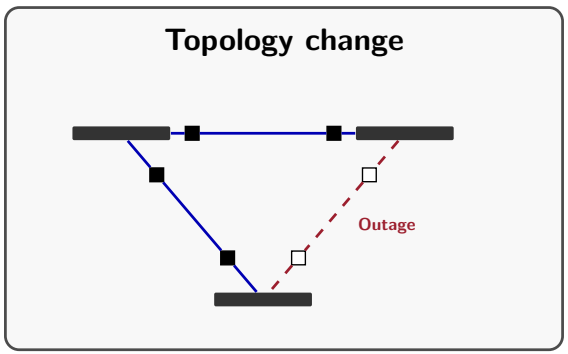
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Why topology information has value?

A market participant may update its **bidding decision** upon receiving new **outage information**.

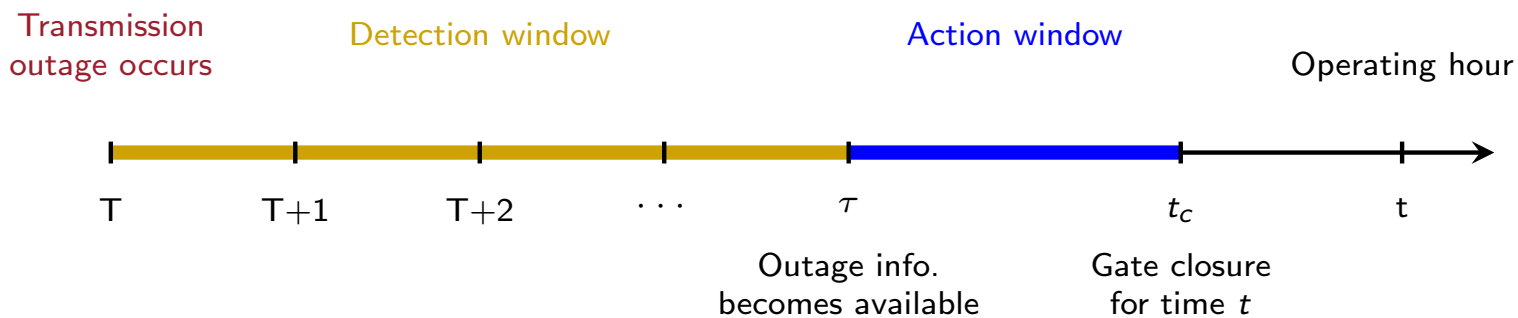


$\mathcal{G}_t$

Bidding decision

$$b_t^\star = \arg \max_{b_t \in \mathcal{B}} \Pi_t(b_t; \mathcal{G}_t)$$

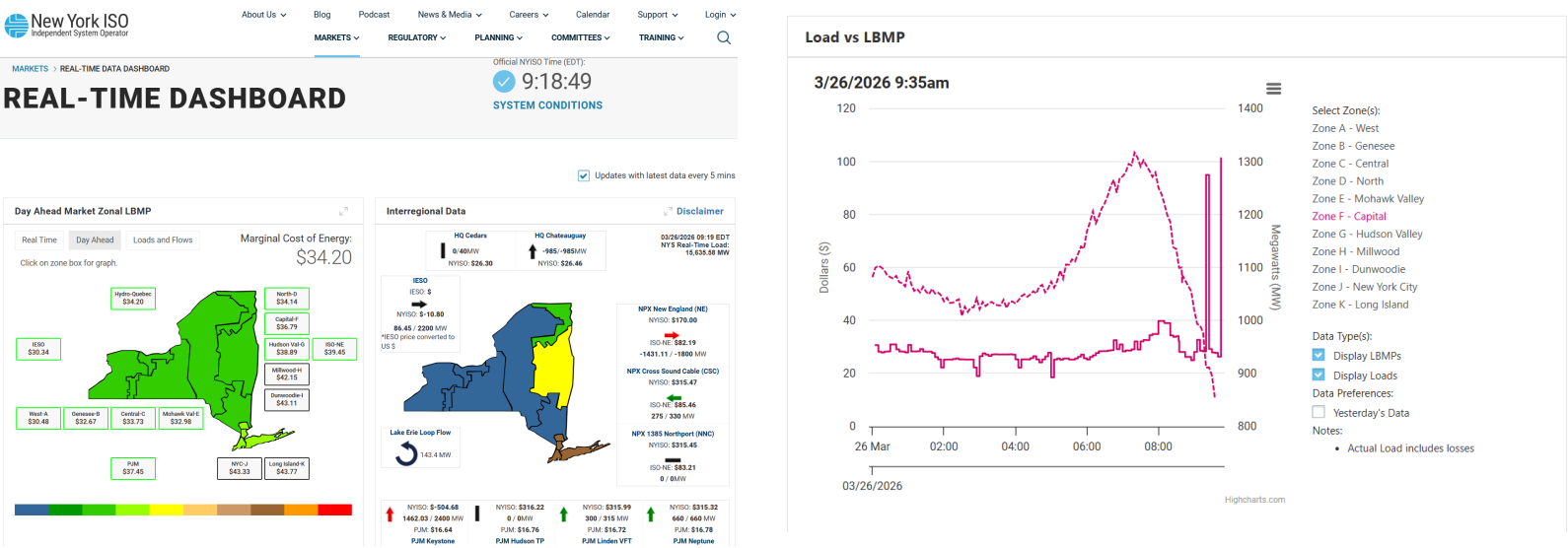
b_t: bidding decision at hour t
$\mathcal{G}_t$: assumed grid topology at hour t
Π_t: profit function at hour t



Takeaway: If the outage information becomes available before t_c, the market participant can update the next market decision.

How are unplanned outages communicated?

- Physical measurements (e.g., PMUs) enabling direct detection are not accessible to market participants.
- System operator reports may be delayed, aggregated, or access-restricted.
- **Opportunity:** Public market data enable independent outage detection.



NYISO Dashboard

Image source: NYISO (https://www.nyiso.com/).

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Research Question

How to design a sequential detector that identifies outages using publicly available stream of market data?

From Outage Signatures to Sequential Detection

Key Insight: From Physical Outages to Market Signals

A topology change induces a measurable and persistent distributional shift in LMPs, which can be exploited as a statistical signal for outage detection.

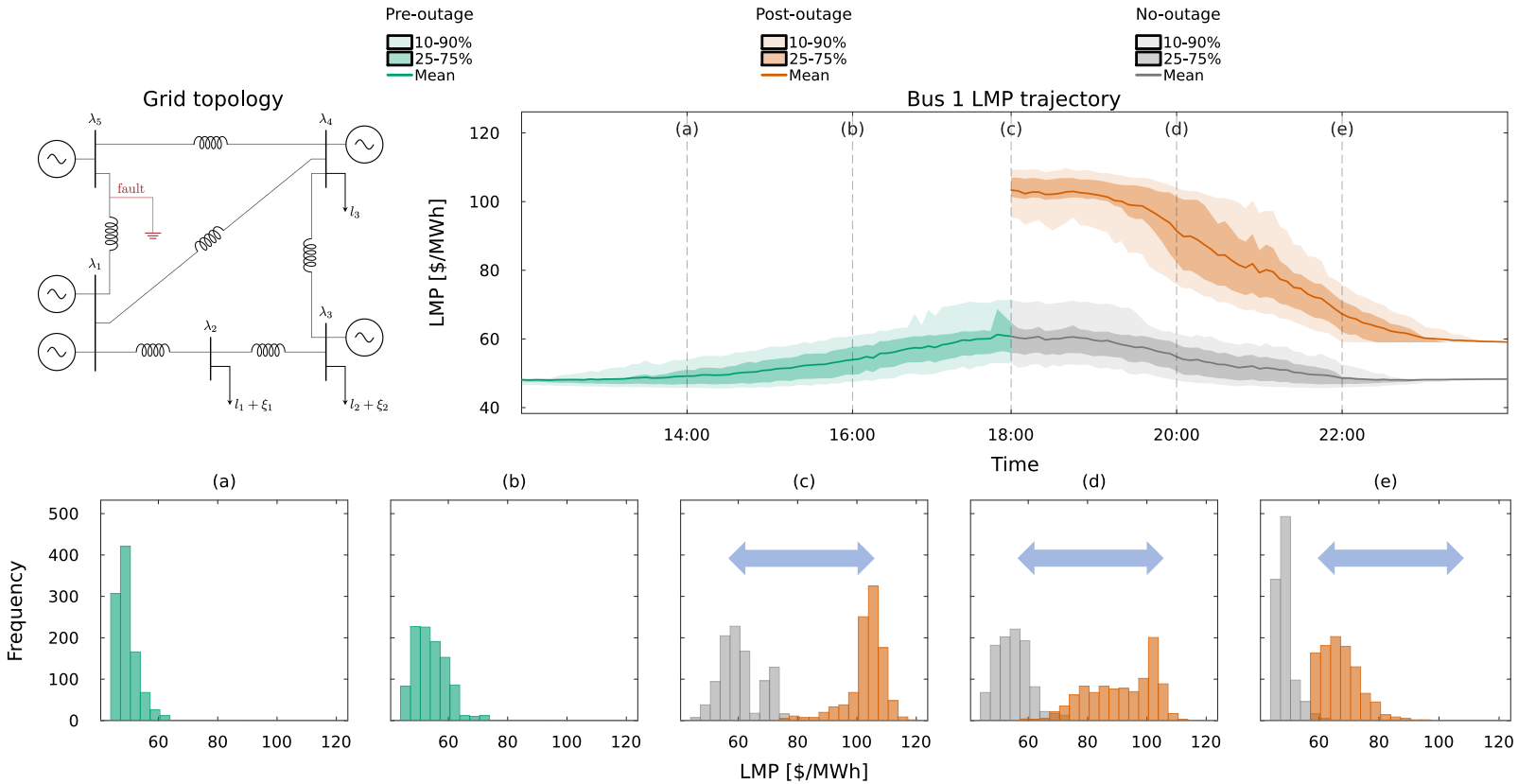


Figure: Topology-induced distributional shift in Bus 1 LMP under a line outage.

Problem Setup

- Market participants observe a **sequence** of LMP increments $\{\Delta\boldsymbol{\lambda}_t\}$:

$$\Delta\boldsymbol{\lambda}_t = \boldsymbol{\lambda}_t - \boldsymbol{\lambda}_{t-1}, \qquad t = 1, 2, \ldots$$

- We sequentially test the nominal topology against possible outages:

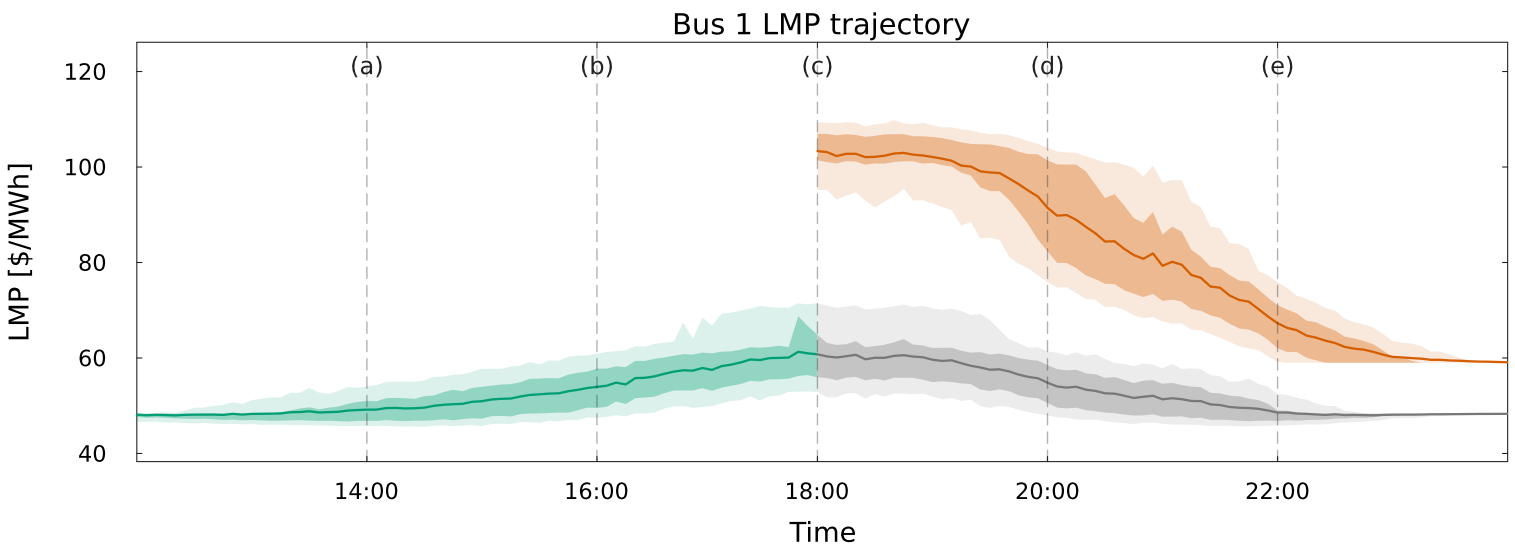
H_0: Nominal operation

$$\Delta\boldsymbol{\lambda}_t \sim f_t^0, \qquad \forall t \geq 1$$

$H_{1,a}$: Outage "a"

$$\Delta\boldsymbol{\lambda}_t \sim \begin{cases} f_t^0, & t < T, \\ f_t^a, & t \geq T, \end{cases} \qquad a \in \mathcal{A}$$

- T is the unknown change point, and $a \in \mathcal{A}$ identifies the outage.



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Outputs

(1) Detect the change as quickly as possible,

(2) Identify which outage $a \in \mathcal{A}$ occurred.

Sequential Detection via Cumulative Sum (CuSum)

- **Instantaneous evidence (log-likelihood ratio):**

$$\ell_t = \log \frac{f_t^a(\Delta\lambda_t)}{f_t^0(\Delta\lambda_t)} \longrightarrow \begin{cases} \mathbb{E}_a[\ell_t] = D_{\mathrm{KL}}(f_t^a \| f_t^0) > 0 & \text{post-outage} \\ \mathbb{E}_0[\ell_t] = -D_{\mathrm{KL}}(f^0 \| f^a) < 0 & \text{nominal} \end{cases}$$

- **Accumulate evidence over time:**

$$W_t = \max(0,\ W_{t-1} + \ell_t), \quad W_0 = 0$$

- **Detection rule:**

$$\tau = \inf\{t \geq 1 : W_t \geq \eta\}$$

Key challenge: How can we construct the distributions f_t^0 and f_t^a?

Page, Ewan S. "Continuous inspection schemes." Biometrika, 1954.

Probabilistic Model of Market-Clearing Problem

Perturbed Market-Clearing Problem

Introduce demand uncertainty as a perturbation:

$$\boldsymbol{l} \;\to\; \boldsymbol{l} + \boldsymbol{\xi}, \quad \boldsymbol{\xi} \sim \mathcal{N}(0, \Sigma)$$

$$\min_{\mathbf{p},\,\boldsymbol{\ell}} \quad \underbrace{\tfrac{1}{2}\mathbf{p}^\top \mathbf{C}\mathbf{p} + \mathbf{c}^\top \mathbf{p}}_{\text{generation cost}} + \underbrace{\tfrac{1}{2}\boldsymbol{\ell}^\top \mathbf{S}\boldsymbol{\ell} + \mathbf{s}^\top \boldsymbol{\ell}}_{\text{load-shedding cost}}$$

$$\text{s.t.} \quad \mathbf{1}^\top(\mathbf{M}_\mathrm{p}\mathbf{p} - \mathbf{M}_\mathrm{l}(\mathbf{l} + \boldsymbol{\xi} - \boldsymbol{\ell})) = 0 \qquad \text{power balance}$$

$$|\mathbf{F}(\mathbf{M}_\mathrm{p}\mathbf{p} - \mathbf{M}_\mathrm{l}(\mathbf{l} + \boldsymbol{\xi} - \boldsymbol{\ell}))| \leqslant \bar{\mathbf{f}} \qquad \text{transmission limits}$$

$$\underline{\mathbf{p}} \leqslant \mathbf{p} \leqslant \bar{\mathbf{p}} \qquad \text{generation limits}$$

$$\mathbf{0} \leqslant \boldsymbol{\ell} \leqslant \mathbf{l} + \boldsymbol{\xi} \qquad \text{load shedding}$$

Variables

$\mathbf{p}(\boldsymbol{\xi})$	generation
$\boldsymbol{\ell}(\boldsymbol{\xi})$	load shedding
$\boldsymbol{\mu}(\boldsymbol{\xi})$	dual variable
$\boldsymbol{\lambda}(\boldsymbol{\xi}) = \boldsymbol{\Lambda}\boldsymbol{\mu}(\boldsymbol{\xi})$	LMPs

Network model

$\mathbf{F}$	PTDF matrix
$\bar{\mathbf{f}}$	line limits
$\mathbf{M}_\mathrm{p}$	generator mapping
$\mathbf{M}_\mathrm{l}$	load mapping

The auxiliary matrix to compute LMPs from the dual variables: $\boldsymbol{\Lambda} = \begin{bmatrix} \mathbf{1} & -\mathbf{F}^\top & \mathbf{F}^\top & \mathbf{0} \end{bmatrix}$

Mapping from Demand Uncertainty to Market Outcomes



For each $\boldsymbol{\xi}$, the market-clearing problem induces the **optimization mapping**

$$\boldsymbol{\xi} \longmapsto \boldsymbol{\lambda}^\star = \mathcal{M}(\boldsymbol{\xi}).$$

Goal: Given $f_{\boldsymbol{\xi}}$, construct the induced density $f_{\boldsymbol{\lambda}}$.

- $\mathcal{M}(\cdot)$ is defined **implicitly** through an optimization problem.
- Generic density transformation may require **inverse** and the **Jacobian** of $\mathcal{M}$.

Challenge: How can we make this optimization-induced mapping explicit and tractable?

Multi-Parametric Programming: Making the Mapping Explicit

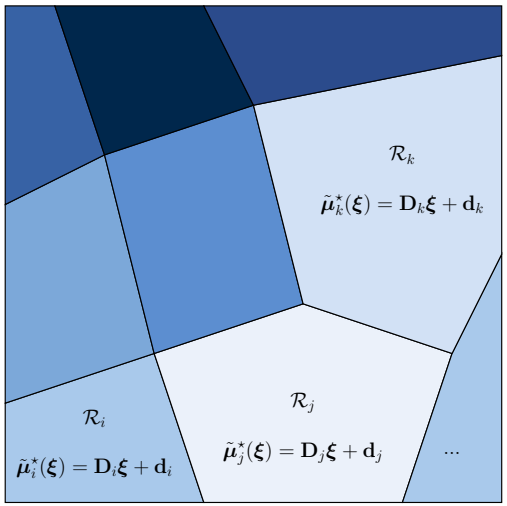
Idea: Globally implicit optimization mapping becomes piecewise affine and explicit.

Parametric QP Form

$$\min_{\mathbf{x}} \quad \tfrac{1}{2}\mathbf{x}^\top \mathbf{Q}\mathbf{x} + \mathbf{q}^\top \mathbf{x}$$
$$\text{s.t.} \quad \mathbf{A}\mathbf{x} \leqslant \mathbf{B}\boldsymbol{\xi} + \mathbf{b} \quad : \boldsymbol{\mu}.$$

$\mathbf{x} = [\mathbf{p}^\top, \boldsymbol{\ell}^\top]^\top$

MPP



Each region $\mathcal{R}_r$ corresponds to a **fixed active set**.

For a fixed set of **active constraints**, the KKT conditions are **linear** in $\hat{\boldsymbol{\xi}}$:

$$\tilde{\boldsymbol{\mu}}^\star(\hat{\boldsymbol{\xi}}) = \mathbf{D}\hat{\boldsymbol{\xi}} + \mathbf{d}.$$

$$\mathbf{D} = -\left(\tilde{\mathbf{A}}\mathbf{Q}^{-1}\tilde{\mathbf{A}}^\top\right)^{-1}\tilde{\mathbf{B}}, \qquad \mathbf{d} = -\left(\tilde{\mathbf{A}}\mathbf{Q}^{-1}\tilde{\mathbf{A}}^\top\right)^{-1}\left(\tilde{\mathbf{b}} + \tilde{\mathbf{A}}\mathbf{Q}^{-1}\mathbf{q}\right).$$

– Ji, Yuting and Thomas, Robert J. and Tong, Lang, "Probabilistic Forecasting of Real-Time LMP and Network Congestion," IEEE Trans. Power Systems, 2017.

– $\tilde{\mathbf{A}}$, $\tilde{\mathbf{B}}$, $\tilde{\mathbf{b}}$ contain those entries of $\mathbf{A}$, $\mathbf{B}$, $\mathbf{b}$ that correspond to the active constraints.

Construction of Critical Regions

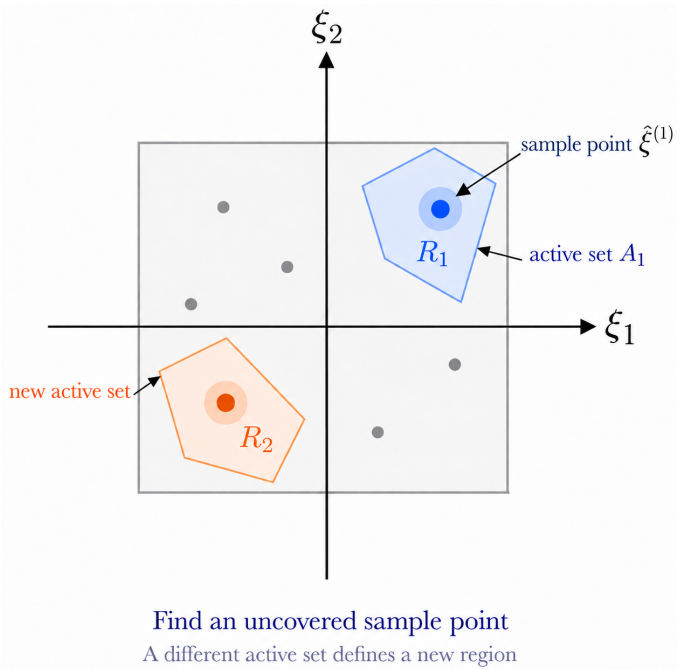
- This solution is valid only when the same constraints remain **active**.
- This defines a **critical region** $\mathcal{R}_i$:
  - inactive constraints remain **strictly feasible**
  - active constraints retain **nonnegative dual variables**

$$\mathcal{R}_i = \left\{ \boldsymbol{\xi} \;\middle|\; (\overline{\mathbf{A}}\mathbf{P}_i - \overline{\mathbf{B}})\boldsymbol{\xi} < \overline{\mathbf{b}} - \overline{\mathbf{A}}\mathbf{p}_i,\ \mathbf{D}_i\boldsymbol{\xi} + \mathbf{d}_i \geqslant \mathbf{0} \right\}$$

Algorithm: Constructing the Critical Regions

Input: Parametric QP and uncertainty set Ξ
Output: Critical regions $\mathcal{CR}$

1: Initialize $\mathcal{CR} \leftarrow \emptyset$
2: **while** there are uncovered points in Ξ **do**
3: Select an uncovered point $\hat{\boldsymbol{\xi}} \in \Xi$
4: Solve the QP at $\boldsymbol{\xi} = \hat{\boldsymbol{\xi}}$
5: Identify the **active constraints**
6: Derive the corresponding critical region $\mathcal{R}_i$
7: Add $\mathcal{R}_i$ to $\mathcal{CR}$
8: **return** $\mathcal{CR}$



From Critical Regions to Probability Distributions

- LMPs follow as an affine mapping:

$$\boldsymbol{\lambda}_i(\boldsymbol{\xi}) = \tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i \boldsymbol{\xi} + \tilde{\boldsymbol{\Lambda}}_i \mathbf{d}_i$$

- Consider LMP increments:

$$\Delta\boldsymbol{\lambda}_t = \boldsymbol{\lambda}_i(\boldsymbol{\xi}_t) - \boldsymbol{\lambda}_i(\boldsymbol{\xi}_{t-1}) = \tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i \ (\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t-1})$$

- Since $\boldsymbol{\xi}_t - \boldsymbol{\xi}_{t-1} \sim \mathcal{N}(0, \Sigma)$:

$$\mathbb{E}[\Delta\boldsymbol{\lambda}_t] = \mathbf{0}, \quad \mathrm{Cov}[\Delta\boldsymbol{\lambda}_t] = \tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i \Sigma (\tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i)^\top$$

- Within each region $\mathcal{R}_i$, the **likelihood** for $f_i(\Delta\boldsymbol{\lambda}_t)$ for **CuSum** detection is

$$\Delta\boldsymbol{\lambda}_t \sim \mathcal{N}(\mathbf{0},\ \Sigma_i)\,, \quad \Sigma_i = \tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i \Sigma (\tilde{\boldsymbol{\Lambda}}_i \mathbf{D}_i)^\top$$

$$f_i(\Delta\boldsymbol{\lambda}_t) = \frac{1}{(2\pi)^{n/2}} \frac{1}{|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2} \Delta\boldsymbol{\lambda}_t^\top \Sigma_i^{-1} \Delta\boldsymbol{\lambda}_t \right).$$

Constructing the CuSum Statistic

- Compare nominal operation vs outage scenario $a \in \mathcal{A}$:

$$f^0_{i(t)} : \mathcal{N}(\mathbf{0}, \Sigma^0_i), \qquad f^a_{j(t)} : \mathcal{N}(\mathbf{0}, \Sigma^a_j)$$

- Log-likelihood ratio (instantaneous evidence):

$$\ell_t^{(a)} = \log\left(\frac{f_j^a(\Delta\boldsymbol{\lambda}_t)}{f_i^0(\Delta\boldsymbol{\lambda}_t)}\right) = \frac{1}{2}\log\left(\frac{|\Sigma_i^0|}{|\Sigma_j^a|}\right) + \frac{1}{2}\Delta\boldsymbol{\lambda}_t^\top \left[(\Sigma_i^0)^{-1} - (\Sigma_j^a)^{-1}\right]\Delta\boldsymbol{\lambda}_t.$$

- Accumulate evidence via CuSum:

$$W_t^{(a)} = \max(0,\ W_{t-1}^{(a)} + \ell_t^{(a)}), \quad \forall a \in \mathcal{A}.$$

Threshold Selection

- Run CuSum statistics in **parallel** for all outage candidates $a \in \mathcal{A}$.
- Detection and identification rules:

$$\underbrace{\tau}_{\text{alarm time}} = \inf \left\{ t \geq 1 : \max_{a \in \mathcal{A}} \overbrace{W_t^{(a)}}^{\text{CuSum}} \geq \underbrace{\eta}_{\text{threshold}} \right\}$$

$$\hat{a} = \arg\max_{a \in \mathcal{A}} W_\tau^{(a)}$$

- Choose η such that **Average Run Length** (ARL) meets a desired target:

$$\text{ARL}_0 = \mathbb{E}_{\mathbb{H}_0}[\tau]$$

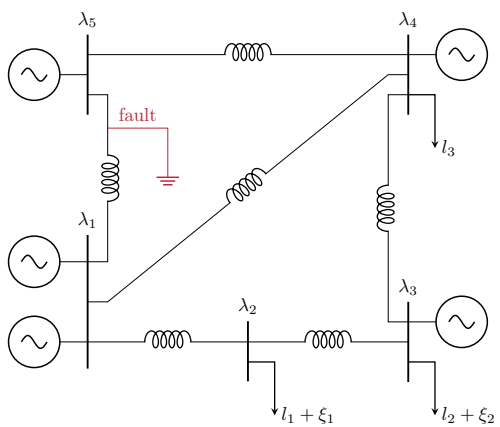
- Expected detection delay in post-outage operation (performance metric):

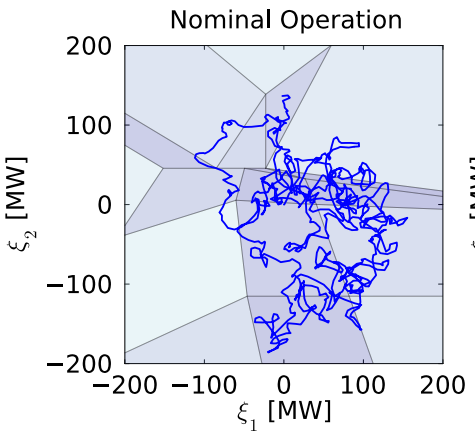
$$\mathbb{E}_{\mathbb{H}_1}[\tau - T \,|\, \tau \geq T]$$

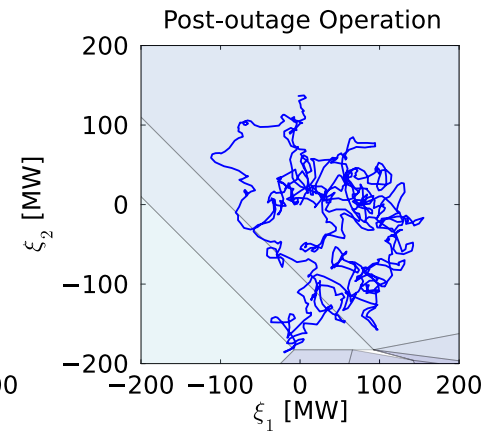
Results

Experiment Setup

- Fault on the line connecting buses 1 and 5 at $T = 500$.
- The outage alters the multi-parametric geometry of the market-clearing problem for the nominal and the post-outage market operation.
- PJM system and the corresponding critical regions:

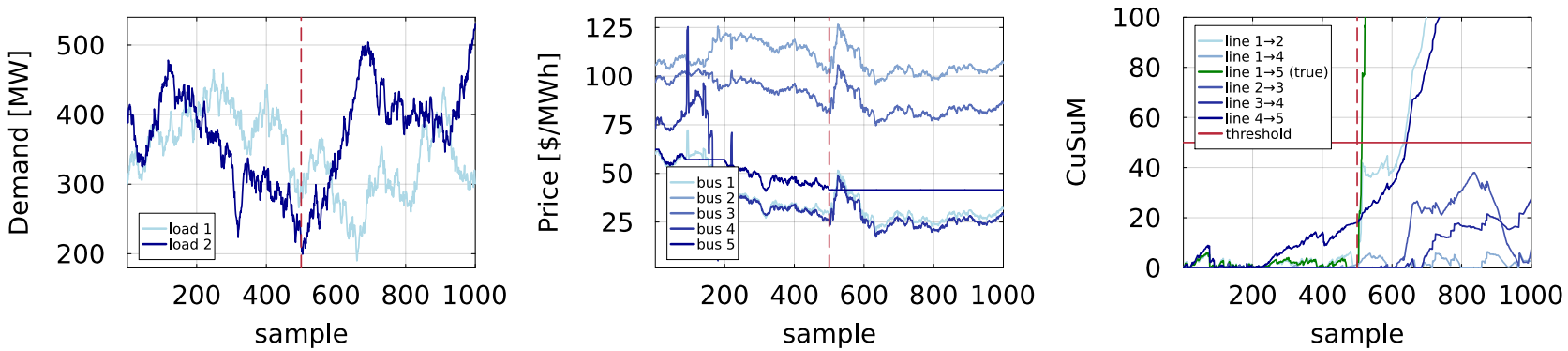






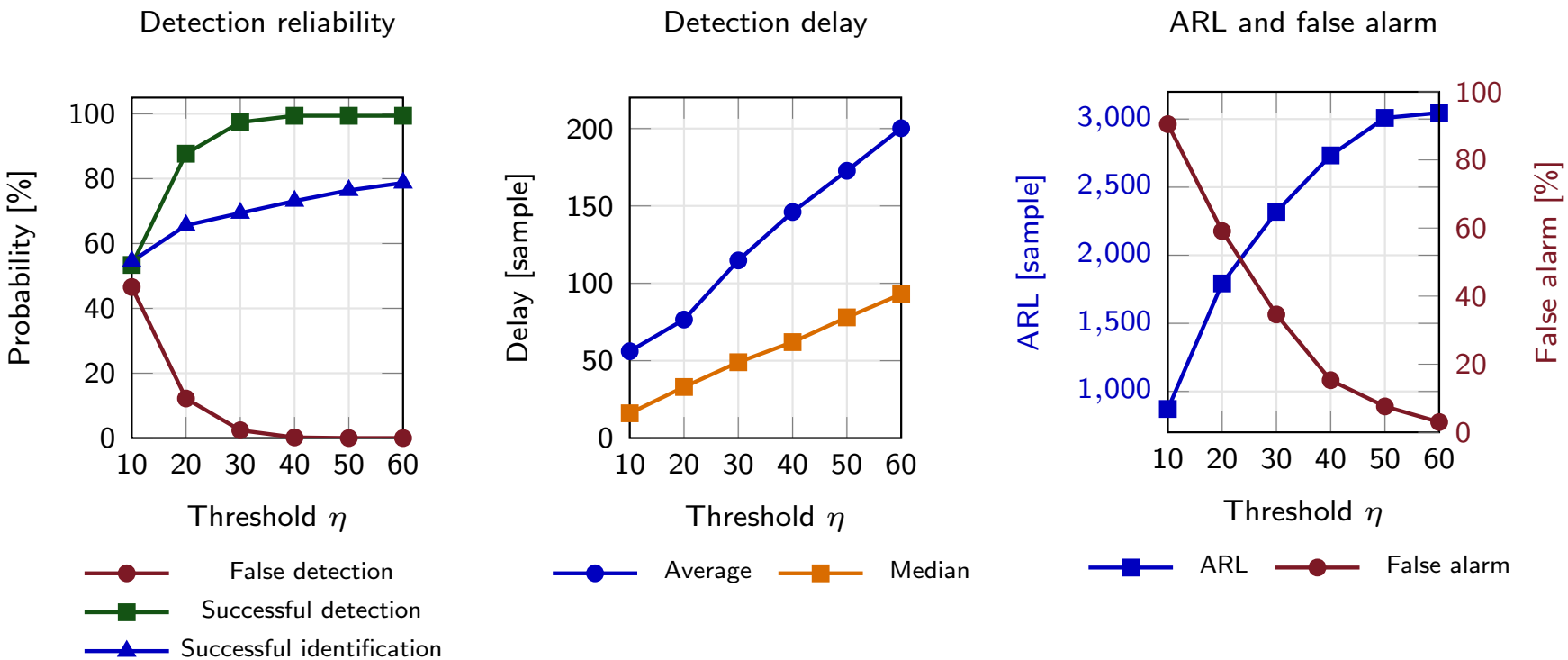
Distinguishing Line Outages from Demand Variation

- The outage at $T = 500$ coincides with a sudden demand growth.
- Demand and price trajectories might mistakenly attribute the price spike to demand growth rather than the outage.
- Demand (left) and LMP (middle) data streams and the dynamics of the six CuSum statistics (right). The outage occurs at $T = 500$ (red dashed line):



Performance Analysis of the CuSum Statistic

- Increasing the threshold η improves **detection reliability**, but at the cost of a longer **detection delay**.
- Higher thresholds increase **ARL** and reduce the **false-alarm probability**.

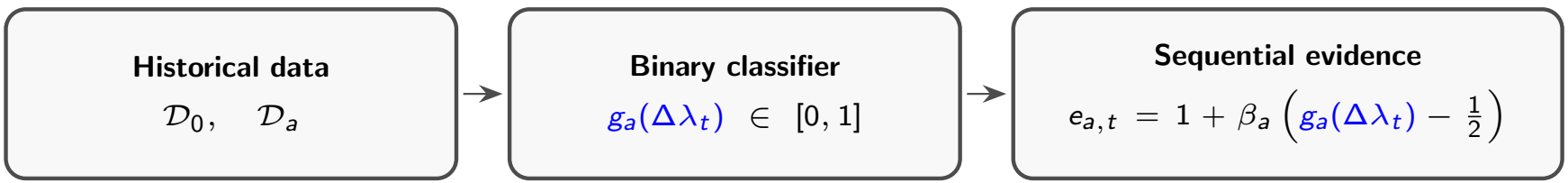


Summary

- Developed a **sequential detector** for power systems outages using **stream** of real-time LMP data
- Leveraged **multi-parametric programming** to obtain tractable **probabilistic models** of LMPs
- Controlled **false alarms** through ARL-based threshold calibration
- Future work: Develop classifier-based **non-parametric** detector under model **misspecification**.

Future work: Classifier-based non-parametric detection

- MPP-based CuSum enables detection when the **system parameters** and induced observation densities are accurately specified.
- We develop a **non-parametric** detector that learns outage-discriminating information directly from historical observations.



- Accumulate evidence through the **e-process**

$$W_{a,t} = \prod_{s=1}^{t} e_{a,s}.$$

- Given a threshold $\eta > 0$, stopping time is

$$\tau = \inf \left\{ t \geq 1 : \max_{a \in \mathcal{A}} W_{a,t} \geq \eta \right\}.$$

Thank You!



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