IOWA STATE UNIVERSITY
OF SCIENCE AND TECHNOLOGY

Data-driven Outage Management and Restoration

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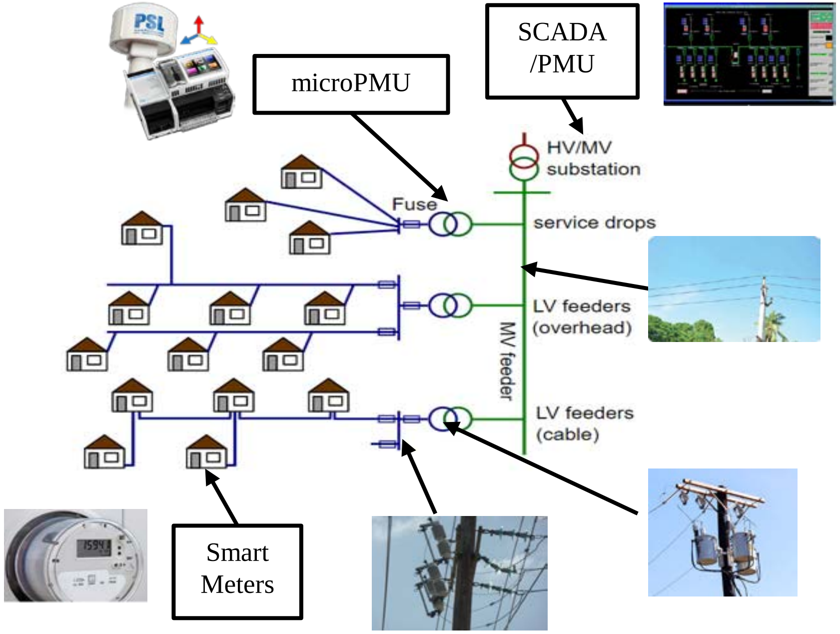
Presentation Overview

- Introduction to Smart Meter Data
- Outage Detection in Partially Observable Systems
  - Existing Work and Challenges
  - Outage Detection Zone Definition and Selection
  - GAN-based Outage Detection
- Conclusion and Future Work

Data in Power Distribution Grids



A Power distribution grid

- **Where does the data come from?**
  - SCADA (supervisory control and data acquisition); Smart Meters; Protection Devices; microPMUs (phasor measurement units)
  - Measures voltage/current/frequency at different resolutions
- **What are smart meters?**
  - Stay in your homes
  - Measure energy and voltage
  - 15/30/60-minute resolution

Exemplary Real Data from Utilities

Account		time	kWH or V	time	kWH or V	time
100000001	KWH	201704010100	0.392	201704010200	0.257	201704010300
100000001	VOLTS	201704010100	239	201704010200	239	201704010300
100000002	KWH	201704010100	0.245	201704010200	0.204	201704010300
100000002	VOLTS	201704010100	241	201704010200	240	201704010300
100000003	KWH	201704010100	1.479	201704010200	0.417	201704010300
100000003	VOLTS	201704010100	240	201704010200	239	201704010300
100000004	KWH	201704010100	1.009	201704010200	0.555	201704010300
100000004	VOLTS	201704010100	241	201704010200	237	201704010300
100000005	KWH	201704010100	0.798	201704010200	0.809	201704010300
100000005	VOLTS	201704010100	239	201704010200	238	201704010300
100000006	KWH	201704010100	0.109	201704010200	0.188	201704010300
100000006	VOLTS	201704010100	241	201704010200	240	201704010300
100000007	KWH	201704010100	1.199	201704010200	1.512	201704010300
100000007	VOLTS	201704010100	241	201704010200	240	201704010300
100000008	KWH	201704010100	0.422	201704010200	0.419	201704010300
100000008	VOLTS	201704010100	239	201704010200	239	201704010300
100000009	KWH	201704010100	2.288	201704010200	2.278	201704010300
100000009	VOLTS	201704010100	243	201704010200	242	201704010300
100000010	KWH	201704010100	0.223	201704010200	0.257	201704010300
100000010	VOLTS	201704010100	242	201704010200	241	201704010300

Smart Meter Data-driven Outage Detection

- On August 10, a weather complex known as a "derecho" sent intense winds and thunderstorms over a 700-mile stretch in Midwest. Between August 10 and 13, total outaged customers were 1.9 million in Iowa.
- The delay and inaccuracy of outage detection can cause waste of up to 80% of the invaluable restoration time.
- Conventional expert-experience-based methods that use customer calls are laborious, costly, and time-consuming.

Ames, Iowa, 8/10/2020

Outage Detection in Partially Observable Systems

- **Problem Statement**: Developing a data-driven method for outage detection using smart meter data in partially observable distribution systems.

Reference	Data Source	Solution	Shortcoming
[1]	Smart meter-based	Multi-label support vector machine	System is fully observable.
[2]		Fuzzy Petri nets-based approach	
[3]		Probabilistic model-based method	
[4]	Non-smart meter-based (i.e., real-time power flow measurement, weather, social network data)	Hypothesis testing-based framework	Limiting data availability
[5]		Social network-based method	
[6]		Boosting algorithm	

[1] Z. S. Hosseini, M. Mahoor, and A. Khodaei, "AMI-enabled distribution network line outage identification via multi-label SVM," IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 5470–5472, Sep. 2018.
[2] S. J. Chen, T. S. Zhan, C. H. Huang, J. L. Chen, and C. H. Lin, "Nontechnical loss and outage detection using fractional-order self synchronization error-based fuzzy petri nets in micro-distribution systems," IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 411–420, Jan. 2015.
[3] K. Sridharan and N. N. Schulz, "Outage management through AMR systems using an intelligent data filter," IEEE Trans. Power Deli., vol. 16, no. 4, pp. 669–675, Oct. 2001.
[4] R. A. Sevlian, Y. Zhao, R. Rajagopal, A. Goldsmith, and H. V. Poor, "Outage detection using load and line flow measurements in power distribution systems," IEEE Trans. Power Syst., vol. 33, no. 2, pp. 2053– 2069, Mar. 2018.
[5] H. Sun, Z. Wang, J. Wang, Z. Huang, N. Carrington, and J. Liao, "Data driven power outage detection by social sensors," IEEE Trans. Smart Grid, vol. 7, no. 5, pp. 2516–2524, Sep. 2016.
[6] P. Kankanala, S. Das, and A. Pahwa, "Adaboost+: An ensemble learning approach for estimating weather-related outages in distribution systems," IEEE Trans. Power Syst., vol. 29, no. 1, pp. 359–367, Jan. 2014.

Outage Detection in Partially Observable Systems

Challenges:

- Smart meters can send last-gasp signals. However, most distribution systems are only **partially observable** (i.e., not every customer has smart meter).
- Most of the previous works handle the partially observable problem by involving extra data sources, such as real-time power-flow measurements and social network data.
- Outage detection can be considered as a **classification** problem (separating the data samples of normal and outage). However, the size of the outage data is far smaller compared to the data in normal conditions, which leads to a **data imbalanced problem**.

Outage Detection in Partially Observable Systems

Our Solution:

- ✓ Decomposing large-scale distribution networks into a set of intersecting **outage detection zones** and performing zone-based outage detection rather than branch-based outage detection.
- ✓ Optimizing the zone decomposition by exploiting the tree-like structure of distribution networks and the system observability (i.e., when system is fully observable, our method provides branch-based results).
- ✓ Developing an **unsupervised-based** model for outage detection (only utilize the data in normal conditions for model training).
- ✓ Providing an anomaly score coordination process to accelerate outage location in large-scale networks.

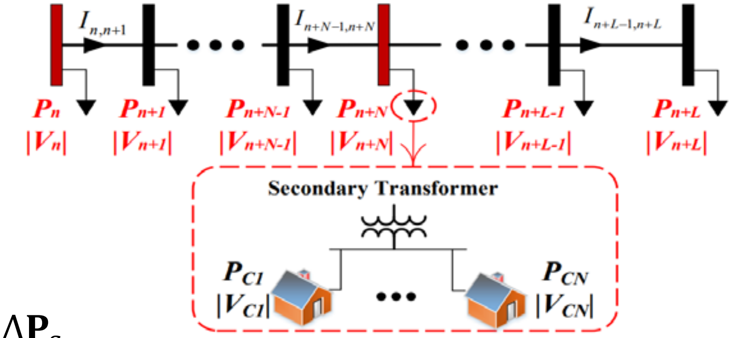
Y. Yuan, K. Dehghanpour, F. Bu, and Z. Wang, "Outage Detection in Partially Observable Distribution Systems using Smart Meters and Generative Adversarial Networks, " IEEE Trans. Smart Grid, vol. 11, no. 6, pp. 5418-5430, November 2020.

Outage Detection Zone Definition

Definition: In a radial network, an outage detection zone, Ψ_i, is defined as $\Psi_i = \{S_{o1}, S_{o2}, Z_{\Psi_i}\}$, where S_{o1} and S_{o2} are two observable nodes, with S_{o1} being upstream of S_{o2}, and Z_{Ψ_i} is the set of all the branches downstream of S_{o1}.

- ✓ Give that an outage event anywhere in the zone will lead to deviations from the (voltage-power) data distribution obtained from two observable nodes under normal operations.

$$\Delta \mathbf{V}_o = |\mathbf{V}_n| - |\mathbf{V}_{n+N}| \approx \Delta \mathbf{V} + \sum_{i=n+1}^{\min(s,n+N)} \mathbf{K}_{i-1,i} \otimes \mathbf{I}_{i-1,i} \otimes \frac{\Delta \mathbf{P}_s}{cos\phi_s}$$



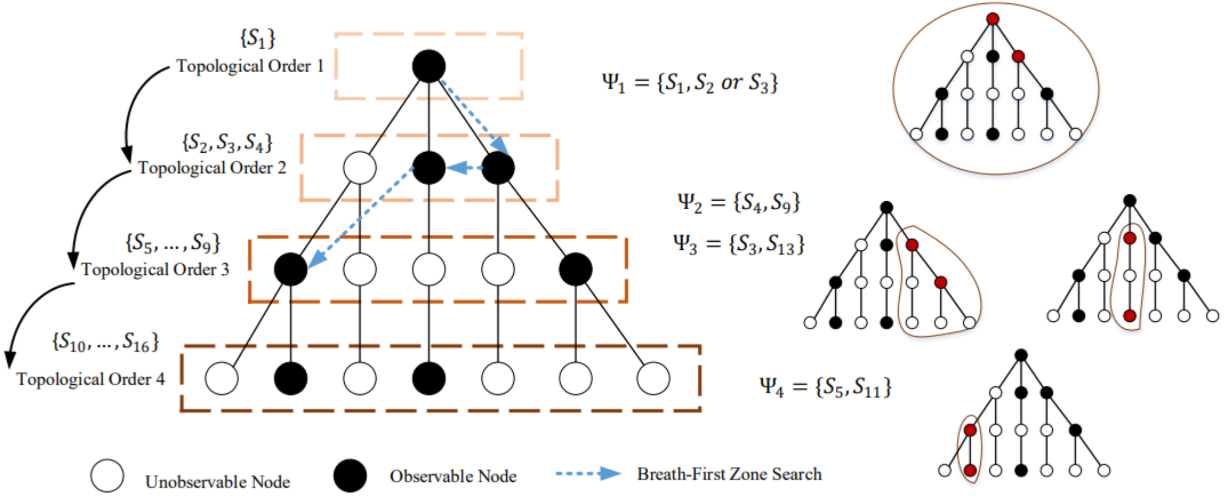
$|\boldsymbol{V}_{n+N}| \approx \boldsymbol{E}\{|\boldsymbol{V}_{C_i}|\}$ $\quad$ $\boldsymbol{P}_{n+N} \approx \sum \boldsymbol{P}_{C_i}$

Observable Node   Unobservable Node

Step I: Breath-First Search-Based Zone Selection

- **Problem**: How to optimally sectionalize networks into multiple zones based on the limited observability to maximize outage detectability?
- **Our Solution**: Proposing a breadth-first search-based mechanism to use **all observable node pairs** to build the zones.
  - Each branch in the system belongs to at least one zone.
  - Introducing a topological ordering, which simplifies outage location identification process.

Step I: Breath-First Search-Based Zone Selection



- Each zone is determined by two neighboring observable nodes and contains all branches downstream of these two nodes.
- Selecting the zones using observable nodes at the present layer before moving on the observable nodes at the next topological layer.

Step II: Zone-Based Data Distribution Learning

Challenge: Learning the distribution of measured variables $X = \{\Delta V^t, P_n^t, P_{n+N}^t\}_{t=1}^{T}$ within a time-window with length T (i.e., T = 3) for each zone (high-dimensional distribution).

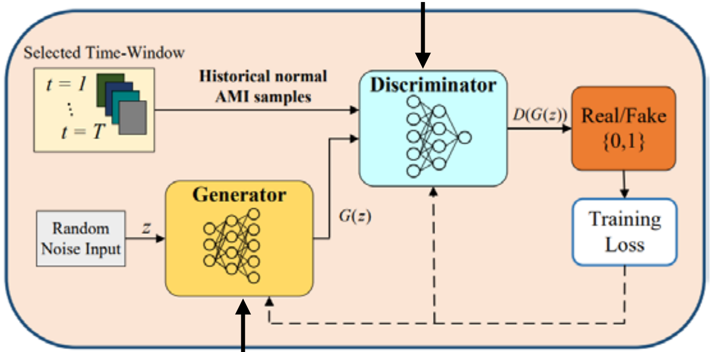
Existing methods:

- Parametric-based methods require distributional assumptions.
- Traditional nonparametric-based methods (e.g., KDE) lack of scalability for large dataset.

Our Solution: Using Generative Adversarial Network (GAN) to implicitly and efficiently represent complex distributions without any distributional assumptions.

- To address data imbalanced problem, we only use the data in normal conditions.

D: Distinguishing the generated data from real data



G: Generating data using random noise

Objective Function:

$$V(D,G) = \min_{\theta_G} \max_{\theta_D} \mathbb{E}_{x_{\Psi_i} \sim p_{x_{\Psi_i}}(x_{\Psi_i})}\left[\log\left(D(x_{\Psi_i})\right)\right] + \mathbb{E}_{z \sim p_z(z)}\left[\log\left(1 - D(G(z))\right)\right]$$

Probability of D assigning the correct label to real samples.
Probability of D assigning the incorrect label to artificial samples from G.

Step III: Zone-Based Outage Detection

- Zone-based outage detection is achieved by defining a **GAN-based anomaly score** that **quantifies deviations** between the learned normal data distribution and real-time measurements.

- The deviation is defined as follows:

$$\zeta_{\Psi_i}(x^t_{new}) = (1-\lambda)\cdot\delta_R(x^t_{new}) + \lambda\cdot\delta_D(x^t_{new})$$

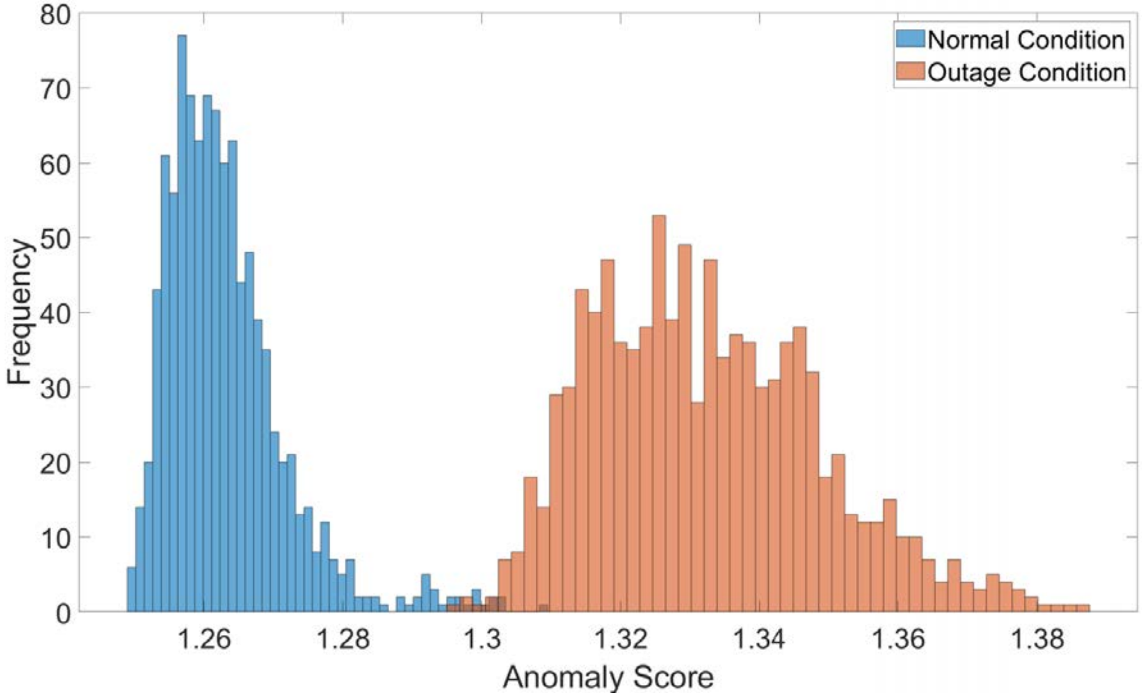
δ_R is the **residual error** that describes the extent to which new measurement follows the learned distribution of the GAN:

$$\delta_R(x^t_{new}) = \min_z |x^t_{new} - G(z)|$$

δ_D is the **discriminator error** that measures how well the optimal solution of the above optimization (z^*) follows the learned data distribution of the GAN.

$$\delta_D(x^t_{new}) = -\log D(x^t_{new}) - \log(1 - D(G(z^*)))$$

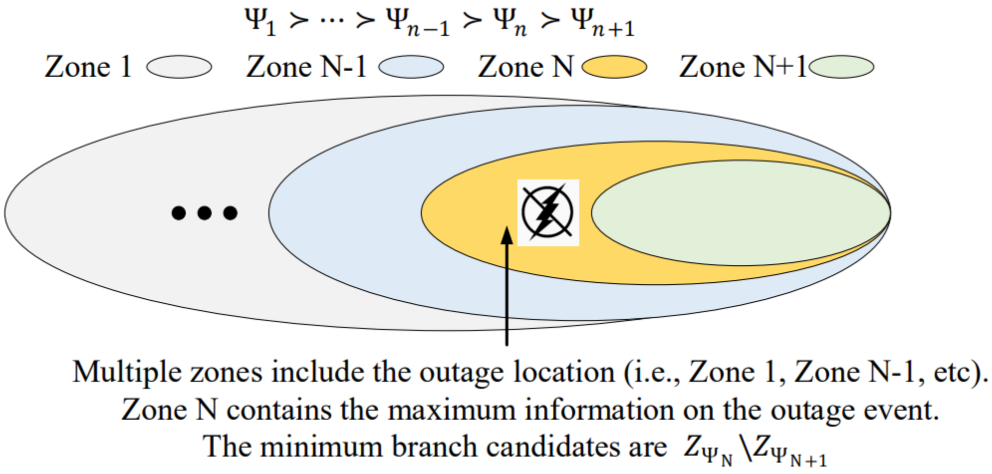
Step III: Zone-Based Outage Detection



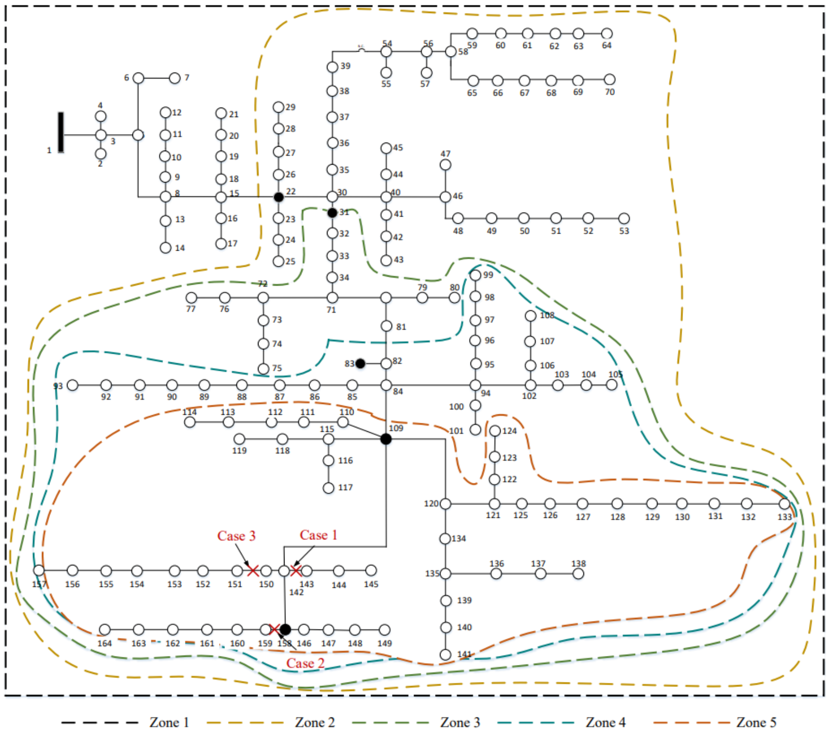
✓ **A high anomaly score implies outage somewhere in the zone.**

Step IV: GAN-Based Zone Coordination

- **Problem**: Multiple zones may contain the same outaged branch. How to down select the zone?
- **Solution**: Using the topological ordering and multiple anomaly scores.
- Zone coordination follows a bottom-up fashion until no outage-related zone exits.



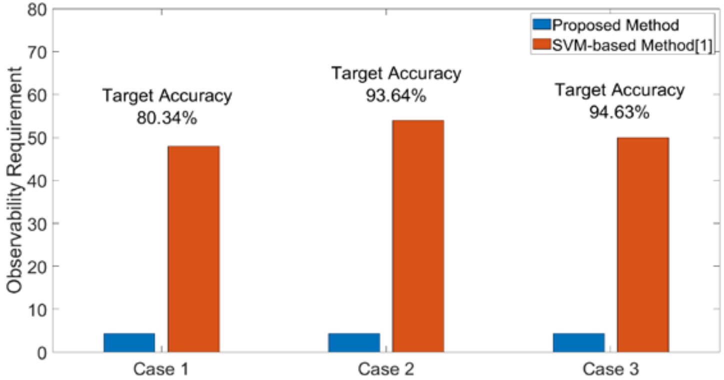
Numerical Results: 164-node Feeder Topology



- Six observable nodes are assumed in this feeder (Node 1, 22, 31, 83, 109, 158).
- Five zones are defined based on these nodes $\Psi_1 \succ \Psi_2 \succ \Psi_3 \succ \Psi_4 \succ \Psi_5$.
- Three outage events are simulated with different outage magnitudes (**Case 1**: 20 customers are disconnected; **Case 2**: 50 customers are disconnected; **Case 3**: 80 customers are disconnected.)

Numerical Results: Accuracy Analysis

	Outage Detection Accuracy
Case 1	80.34%
Case 2	93.64%
Case 3	94.63%



- ✓ For three cases, we have tested if our method can detect outages in zone 5. The table shows the results for three cases.
- ✓ We have conducted numerical comparisons with a previous method.
- ✓ The previous method uses the last gasp signal from smart meters as the input of SVM to identify event location.
- ✓ The previous method requires a much higher level of observability (i.e., around 10 times) to achieve similar accuracy as our method.

Z. S. Hosseini, M. Mahoor, and A. Khodaei, “AMI-enabled distribution network line outage identification via multi-label SVM,” IEEE Trans. Smart Grid, vol. 9, no. 5, pp. 5470–5472, Sep. 2018.

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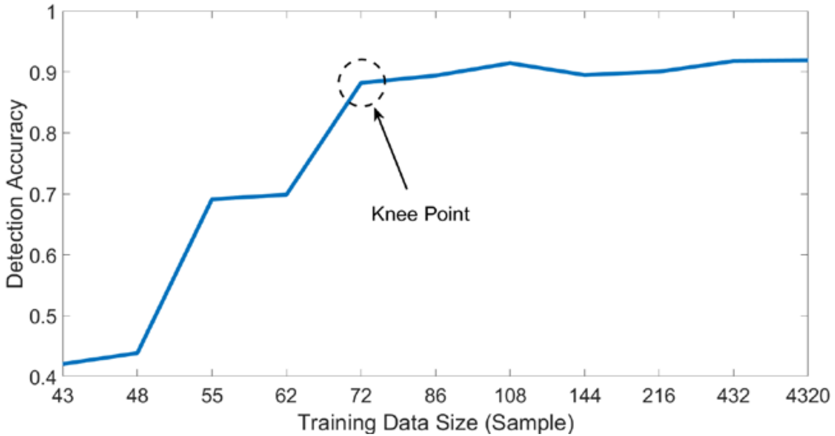
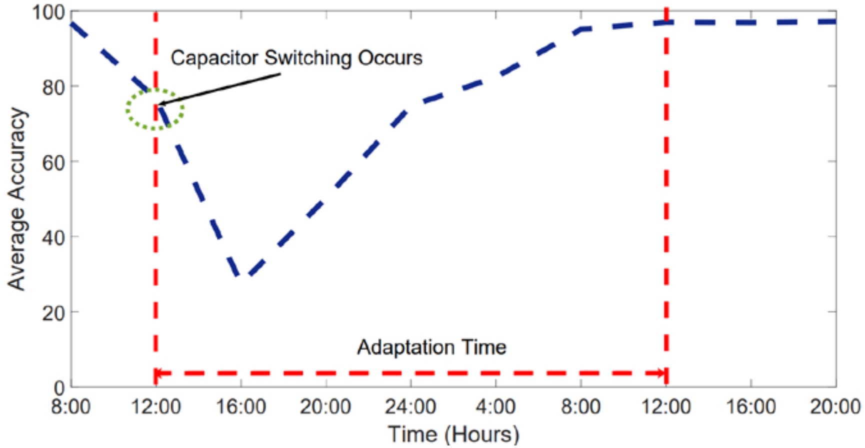
Sensitivity Analysis and Method Adaption





- ✓ The performance of our model can reach reasonable detection accuracy with a small training set (around 3 days of data, hourly smart meter data).
- ✓ Our method can adapt to changes in system conditions (i.e., capacitor switching) with a relatively short time (around 1 day).

Conclusion and Future Work

- Smart meter data, although may be of low resolution and limited measurement variables, can be used to significantly enhance distribution system outage management.

- Many utilities do not have full smart meter coverage. We demonstrated how to use available smart meter data together with machine learning to detect outages in partially observable systems.

- In the future, we will focus on using smart meter data with other available data sources to perform branch-level outage detection and location.

Thank you!

Q&A