

Situational Awareness Using Distribution Synchrophasors: Application to Asset Monitoring

Talk at WCGEC ESTAP, 4/11/2019

Hamed Mohsenian-Rad

Associate Professor, Electrical Engineering, University of California, Riverside
Associate Director, Winston Chung Global Energy Center
Director, UC-National Lab Center for Power Distribution Cyber Security

Acknowledgements: A. Shahsavari, M. Farajollahi, E. Stewart, E. Cortez,
A. Von-Meier, L. Alvarez, C. Roberts, F. Megala, Z. Taylor

Situational Awareness Using Distribution Synchrophasors: Application to **Asset** Monitoring

 Distributed Energy Storage

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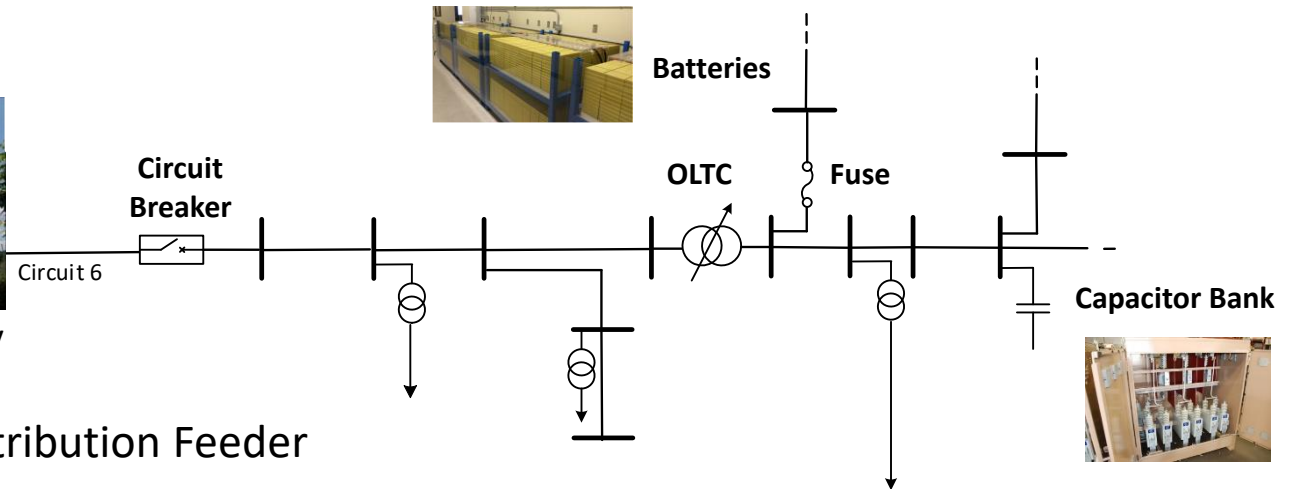
Acknowledgements: A. Shahsavari, M. Farajollahi, E. Stewart, E. Cortez,
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Distributed Energy Storage Resources



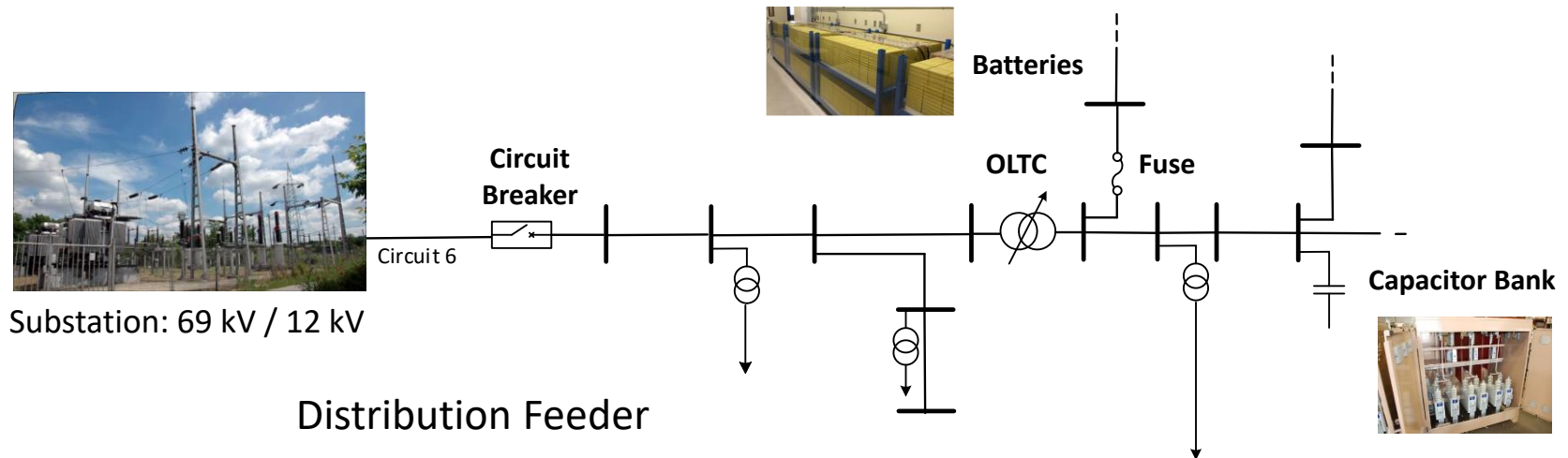
Substation: 69 kV / 12 kV

Distribution Feeder



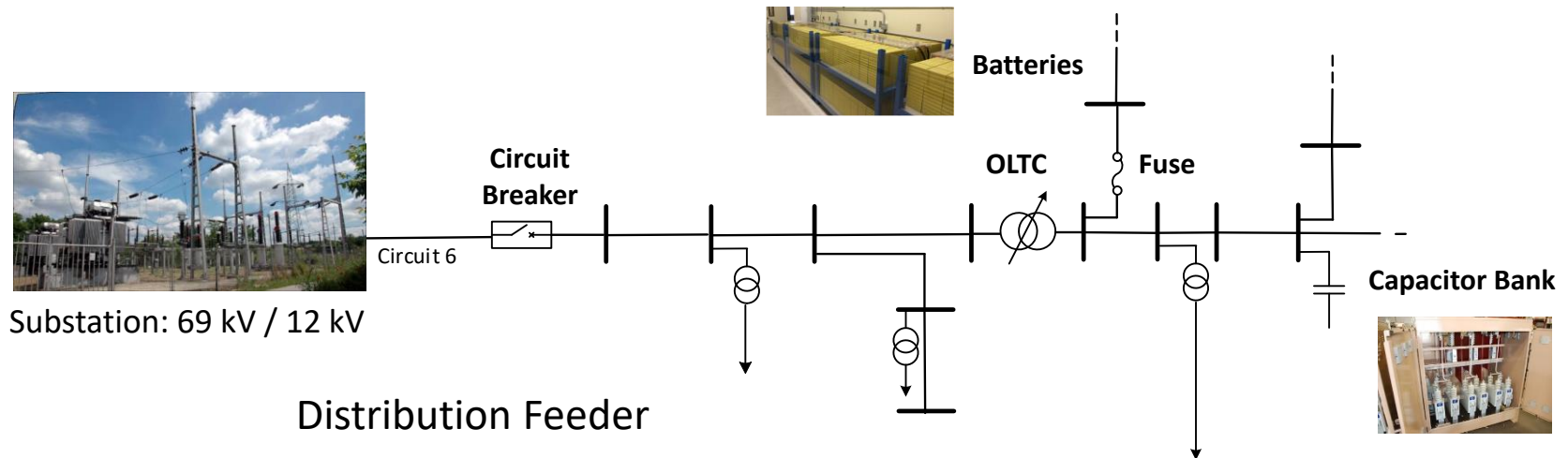
Distributed Energy Storage Resources

- They are often not monitored directly.



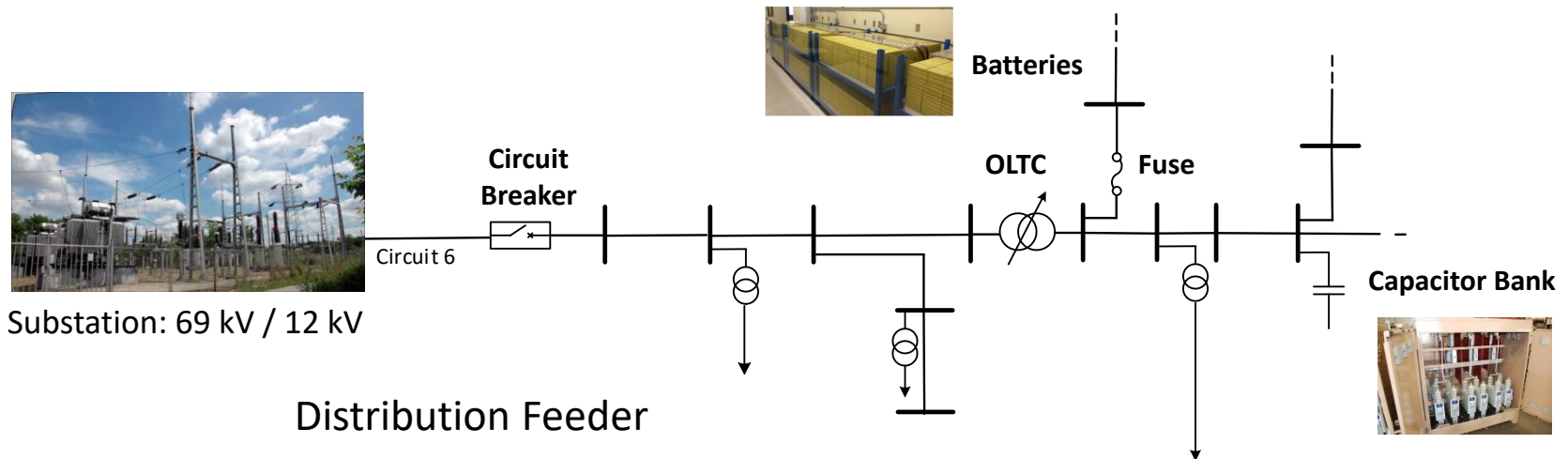
Distributed Energy Storage Resources

- They are often not monitored directly.
- They are potential targets for cyber attacks → physical botnet



Distributed Energy Storage Resources

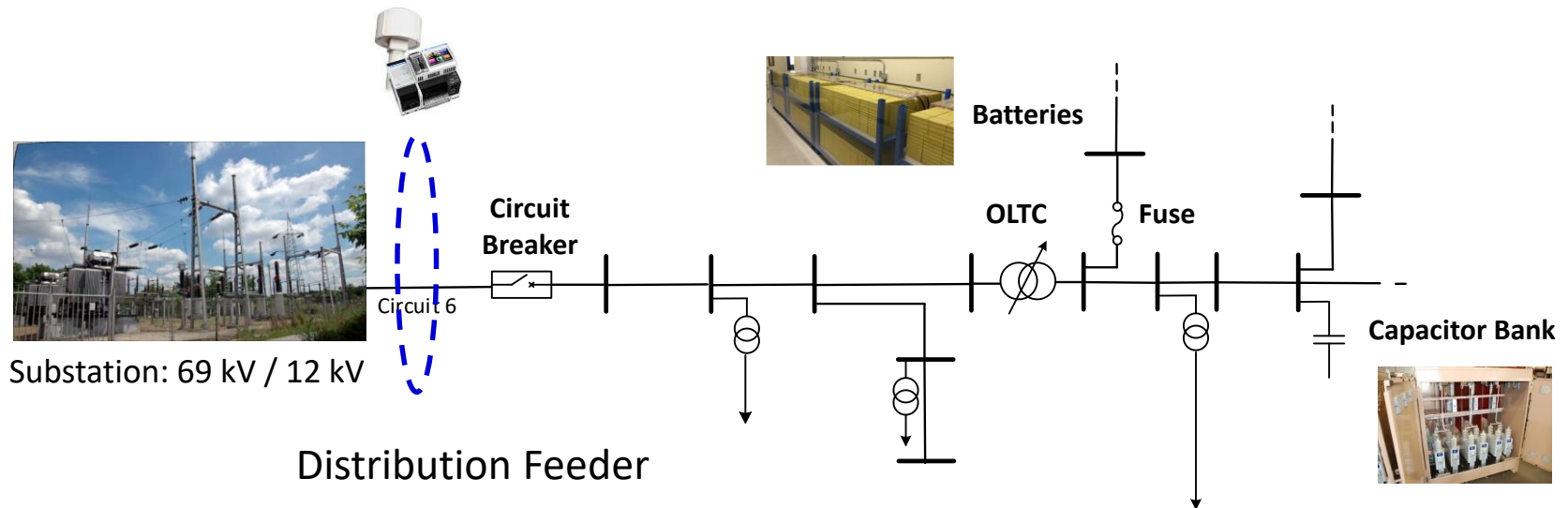
- They are often not monitored directly.
- They are potential targets for cyber attacks → physical botnet
- We want to monitor their **Health** and **Security**?
→ Remotely!



Distributed Energy Storage Resources

- They are often not monitored directly.
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- We want to monitor their **Health** and **Security**?
 → **Remotely!**

Micro-PMUs (GPS-equipped Phasor Sensors)

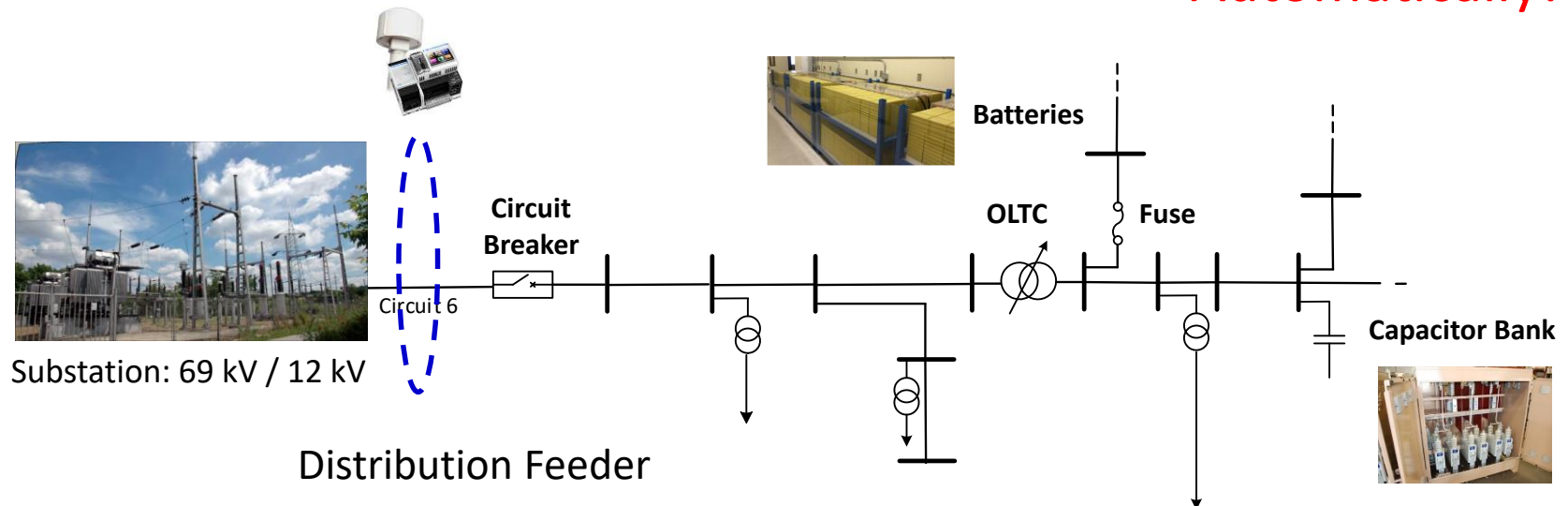


Distributed Energy Storage Resources

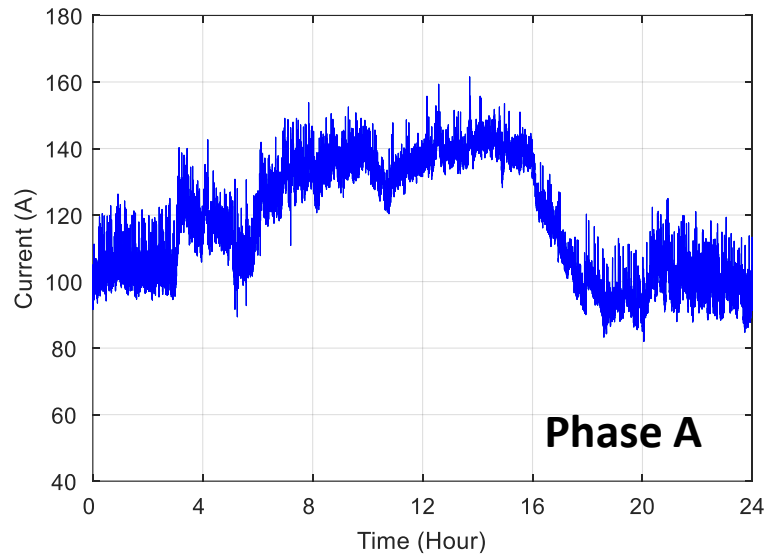
- They are often not monitored directly.
- They are potential targets for cyber attacks → physical botnet
- We want to monitor their **Health** and **Security**?

**Remotely &
Automatically!**

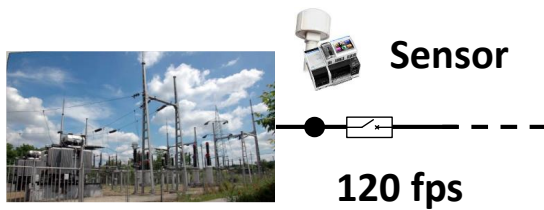
Micro-PMUs (GPS-equipped Phasor Sensors)



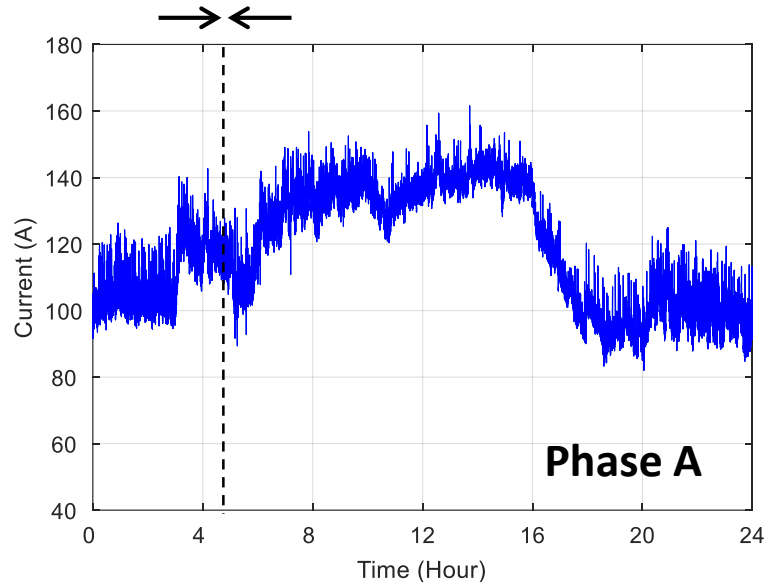
Event-Driven Study



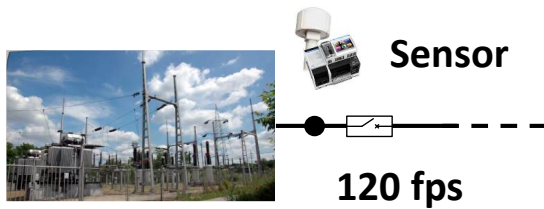
10,368,000 measurement points



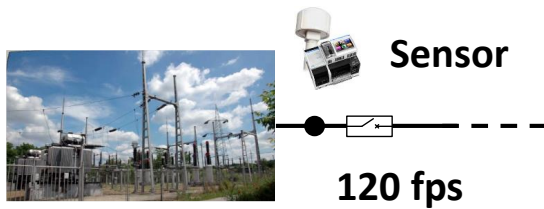
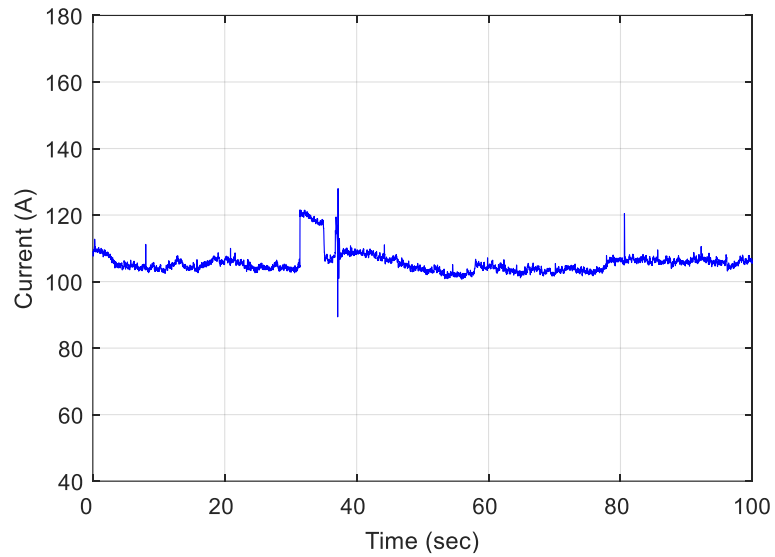
Event-Driven Study



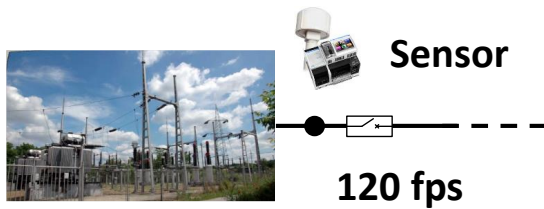
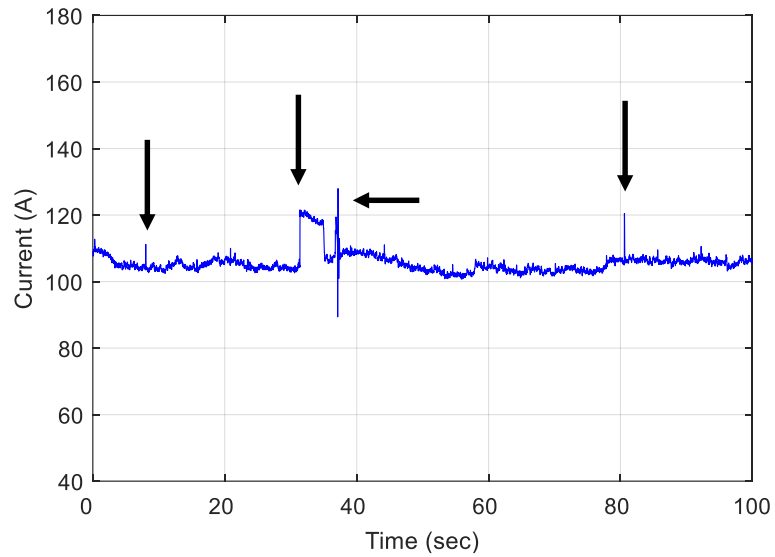
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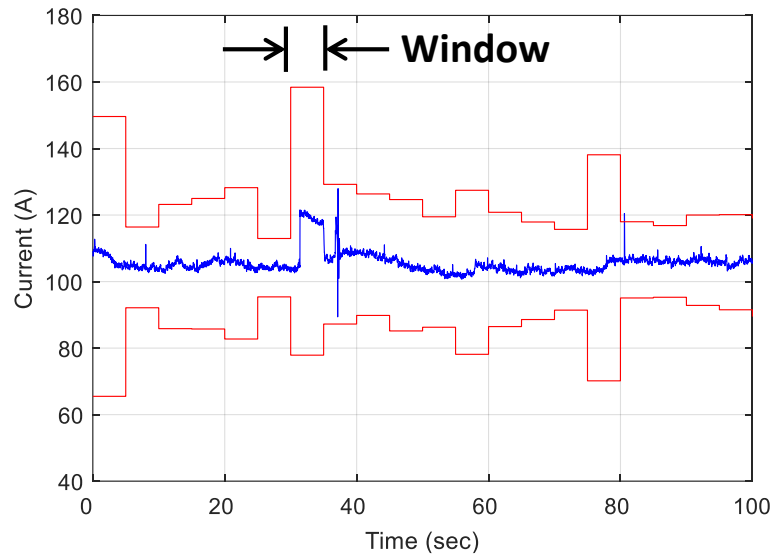
Event-Driven Study



Event-Driven Study

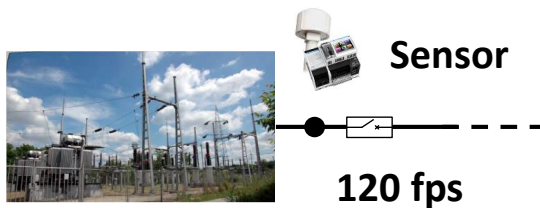


Phase 1: Event Detection

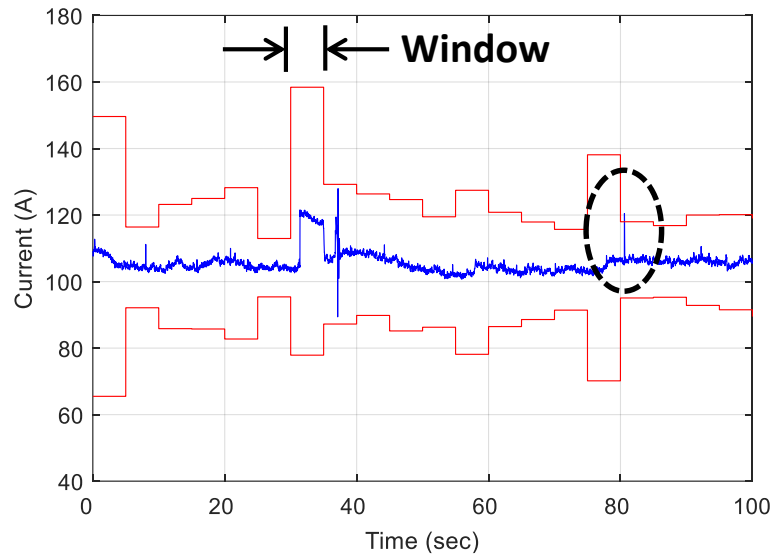


Anomaly Detection

Absolute Deviation Around the Median

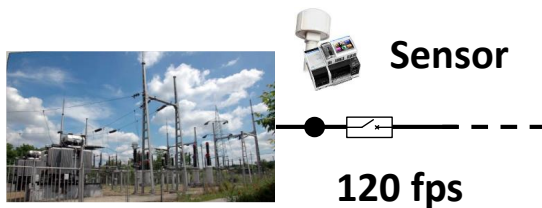


Phase 1: Event Detection

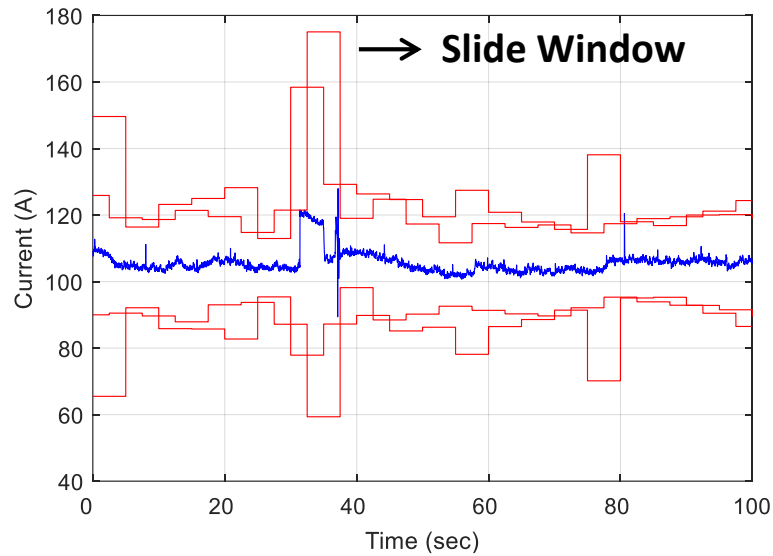


Anomaly Detection

Absolute Deviation Around the Median

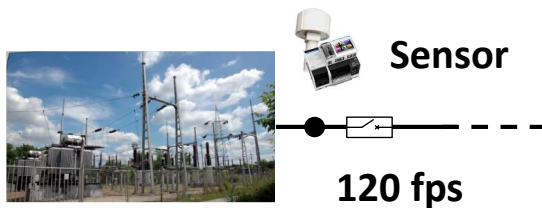


Phase 1: Event Detection

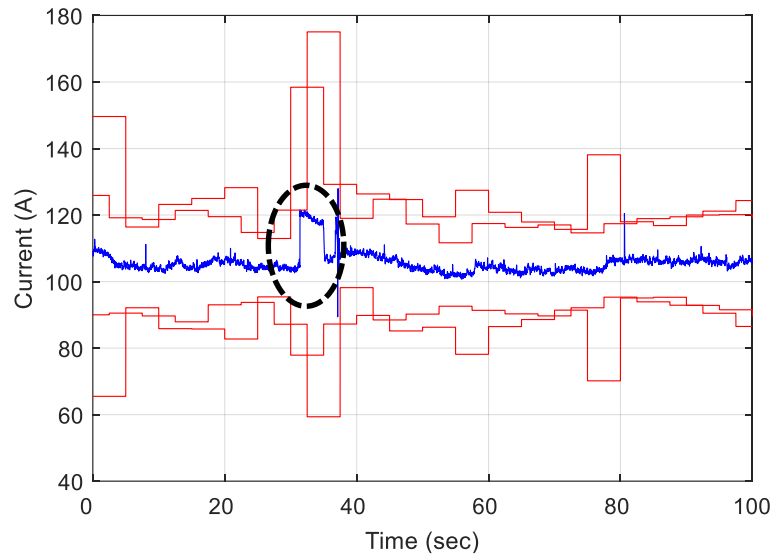


Anomaly Detection

Absolute Deviation Around the Median

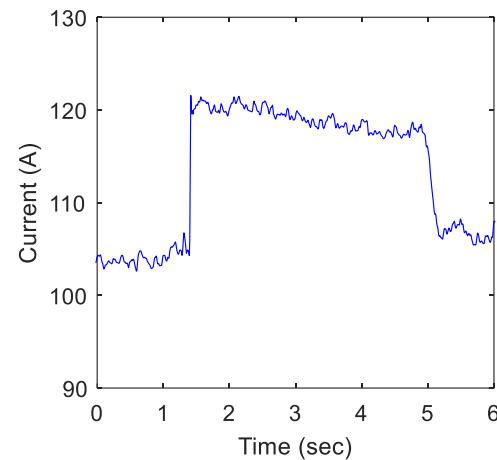
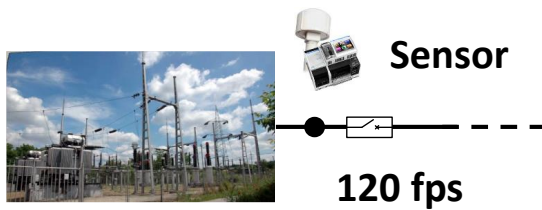


Phase 1: Event Detection



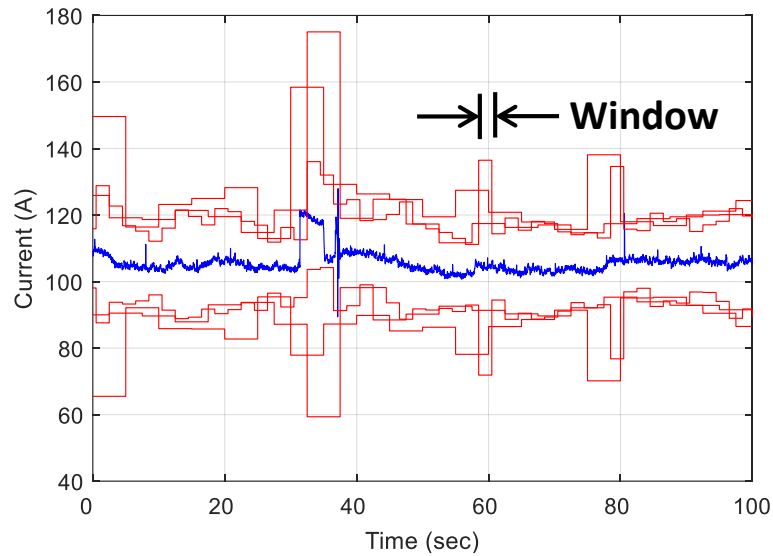
Anomaly Detection

Absolute Deviation Around the Median



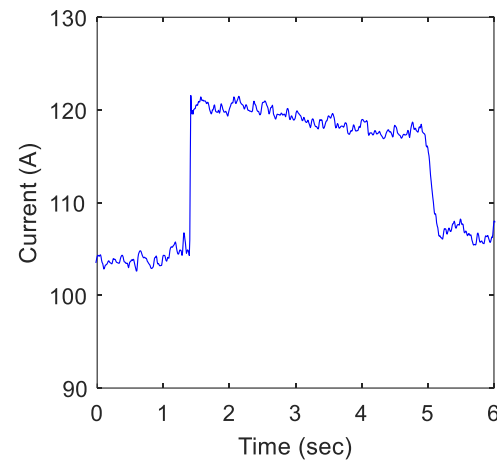
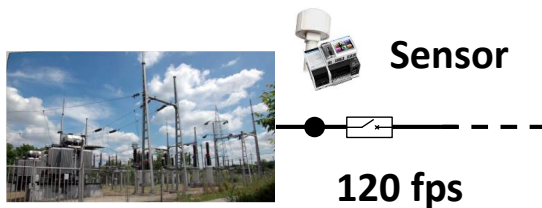
Event 1

Phase 1: Event Detection



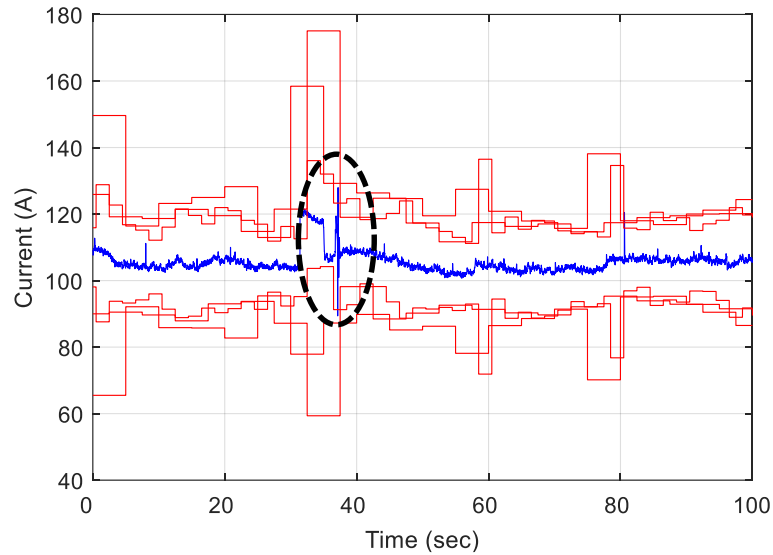
Anomaly Detection

Absolute Deviation Around the Median



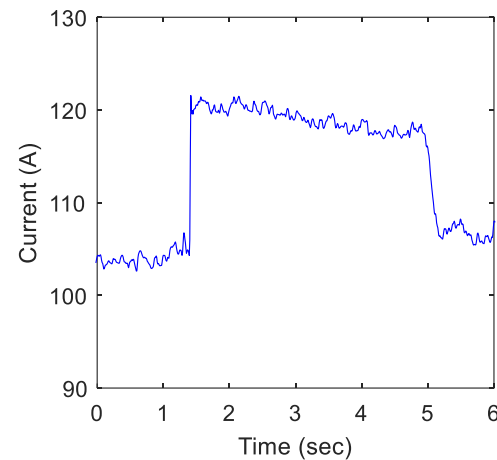
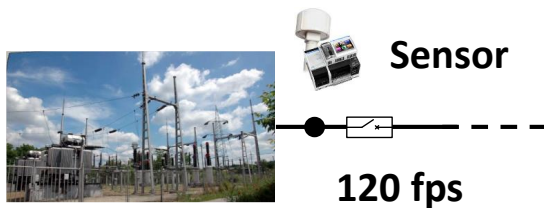
Event 1

Phase 1: Event Detection

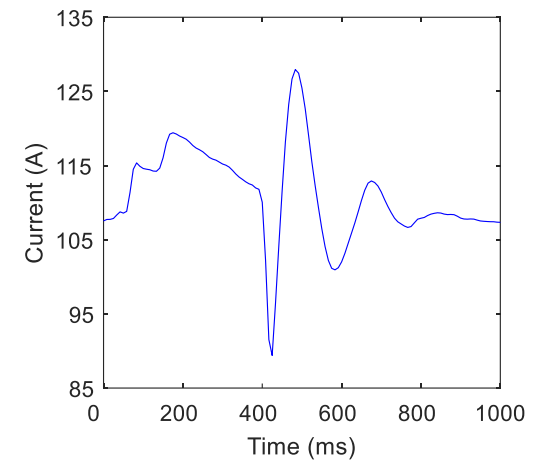


Anomaly Detection

Absolute Deviation Around the Median

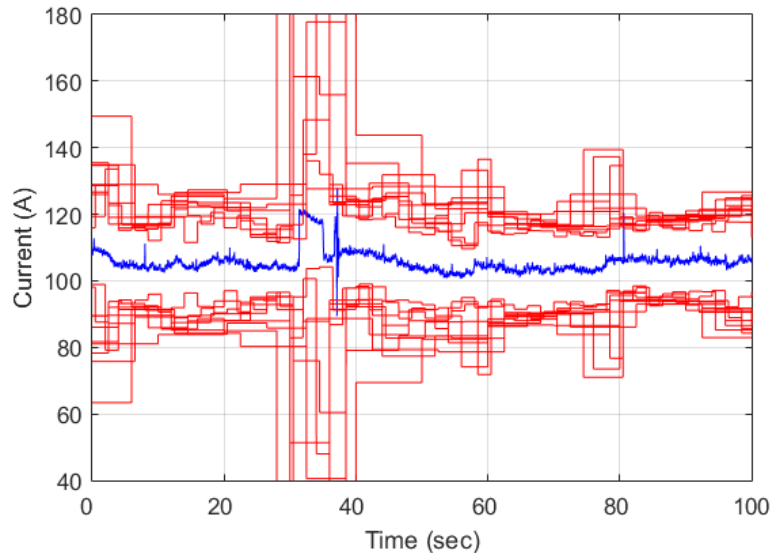


Event 1



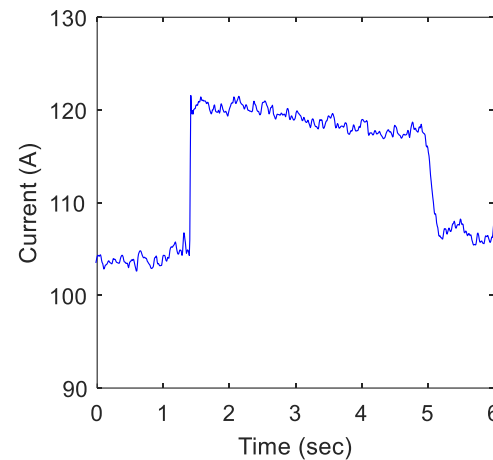
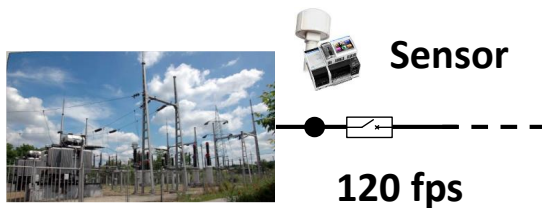
Event 2

Phase 1: Event Detection

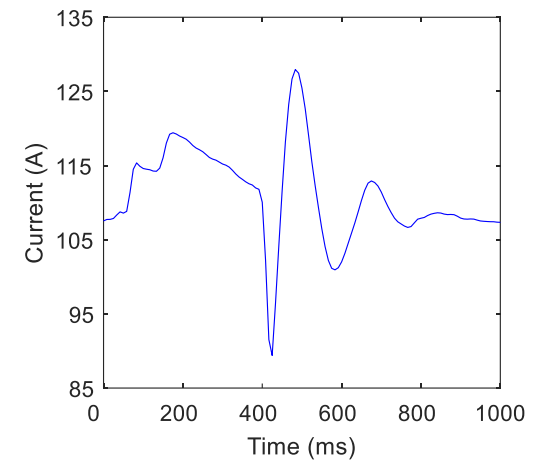


Anomaly Detection

Absolute Deviation Around the Median

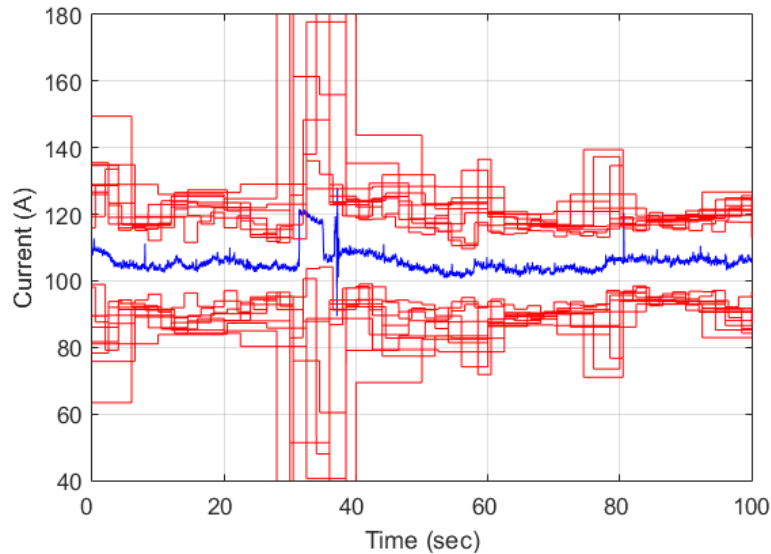


Event 1



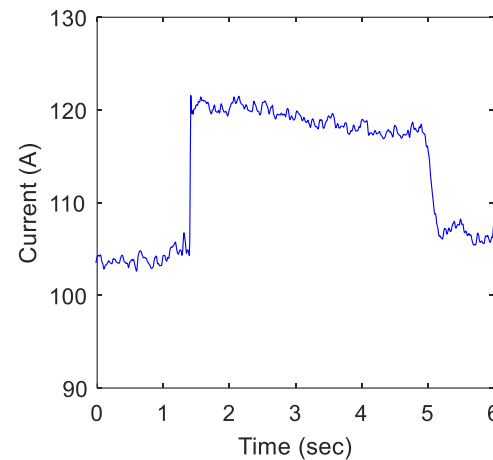
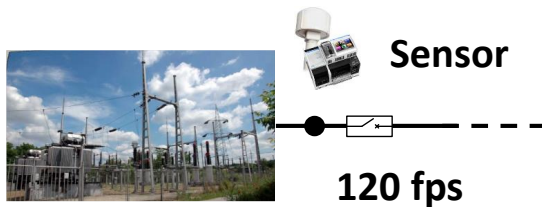
Event 2

Phase 1: Event Detection

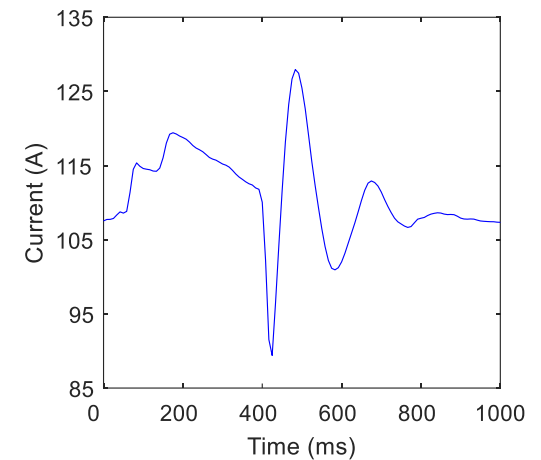


Anomaly Detection

- Current (I)
- Voltage (V)
- Active Power (P)
- Reactive Power (Q)

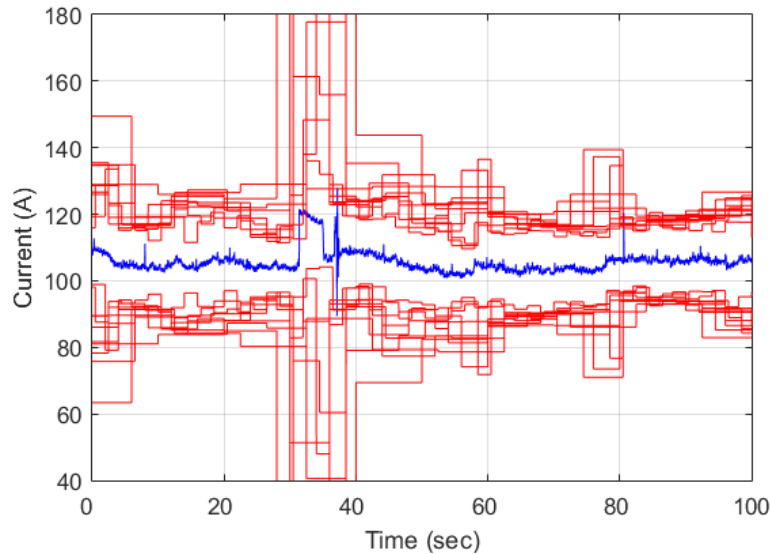


Event 1

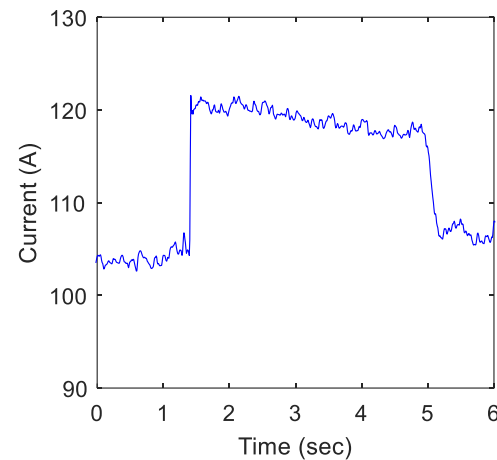
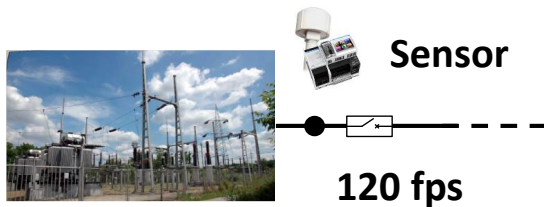


Event 2

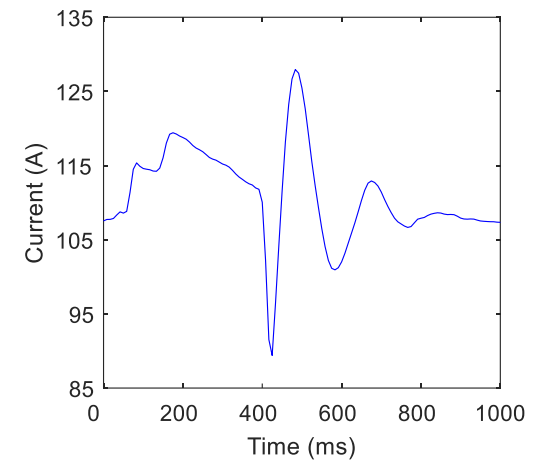
Phase 1: Event Detection



On Average: 500 Events Per Day Per Feeder



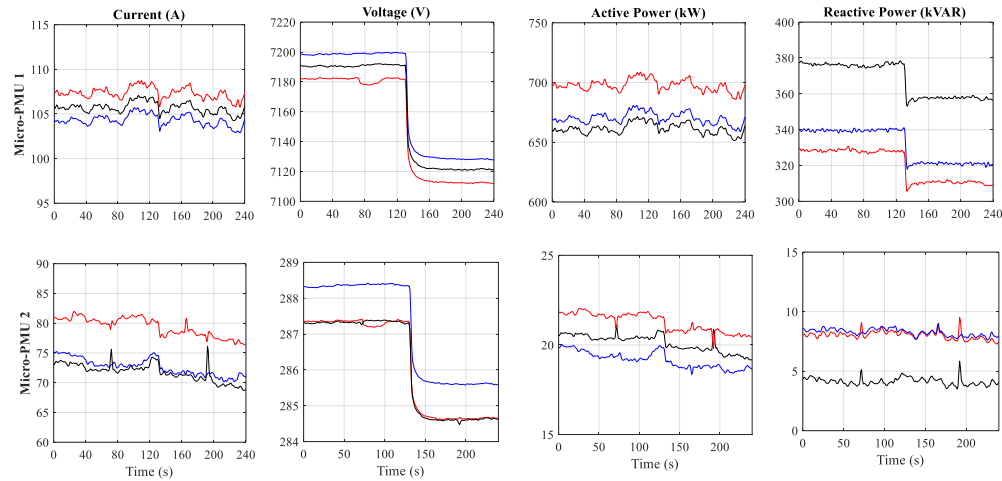
Event 1



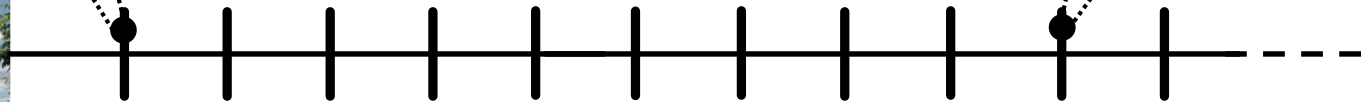
Event 2

Phase 2: Event Classification

Class 1



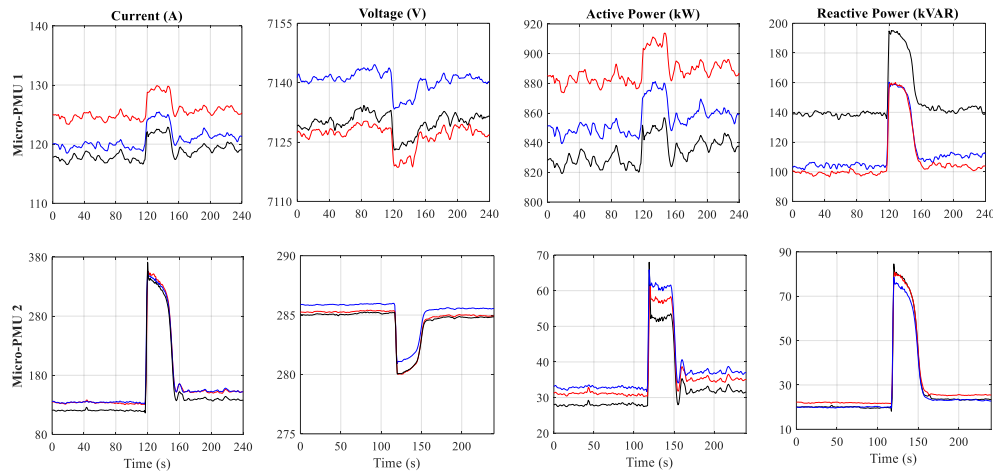
Micro-PMU 1



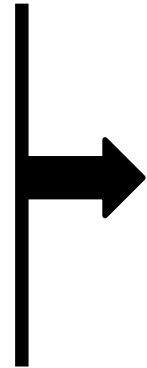
Micro-PMU 2



Phase 2: Event Classification



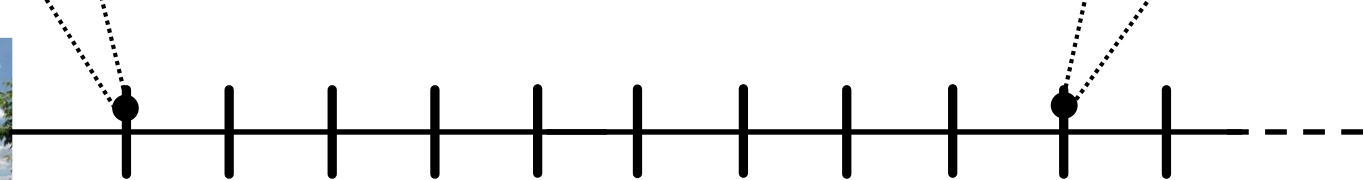
Class 2



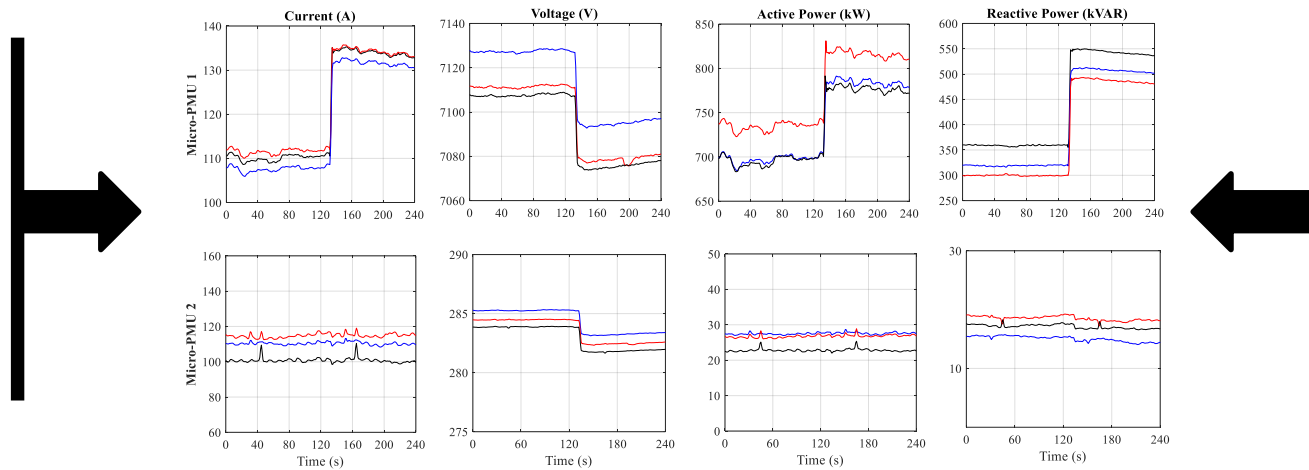
Micro-PMU 1



Micro-PMU 2

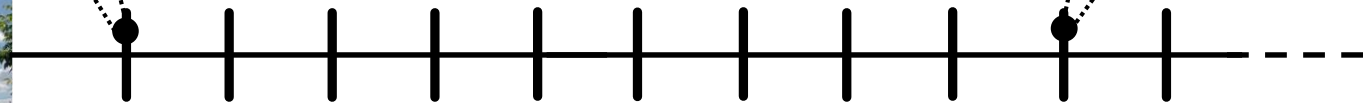


Phase 2: Event Classification



Class 3

Micro-PMU 1

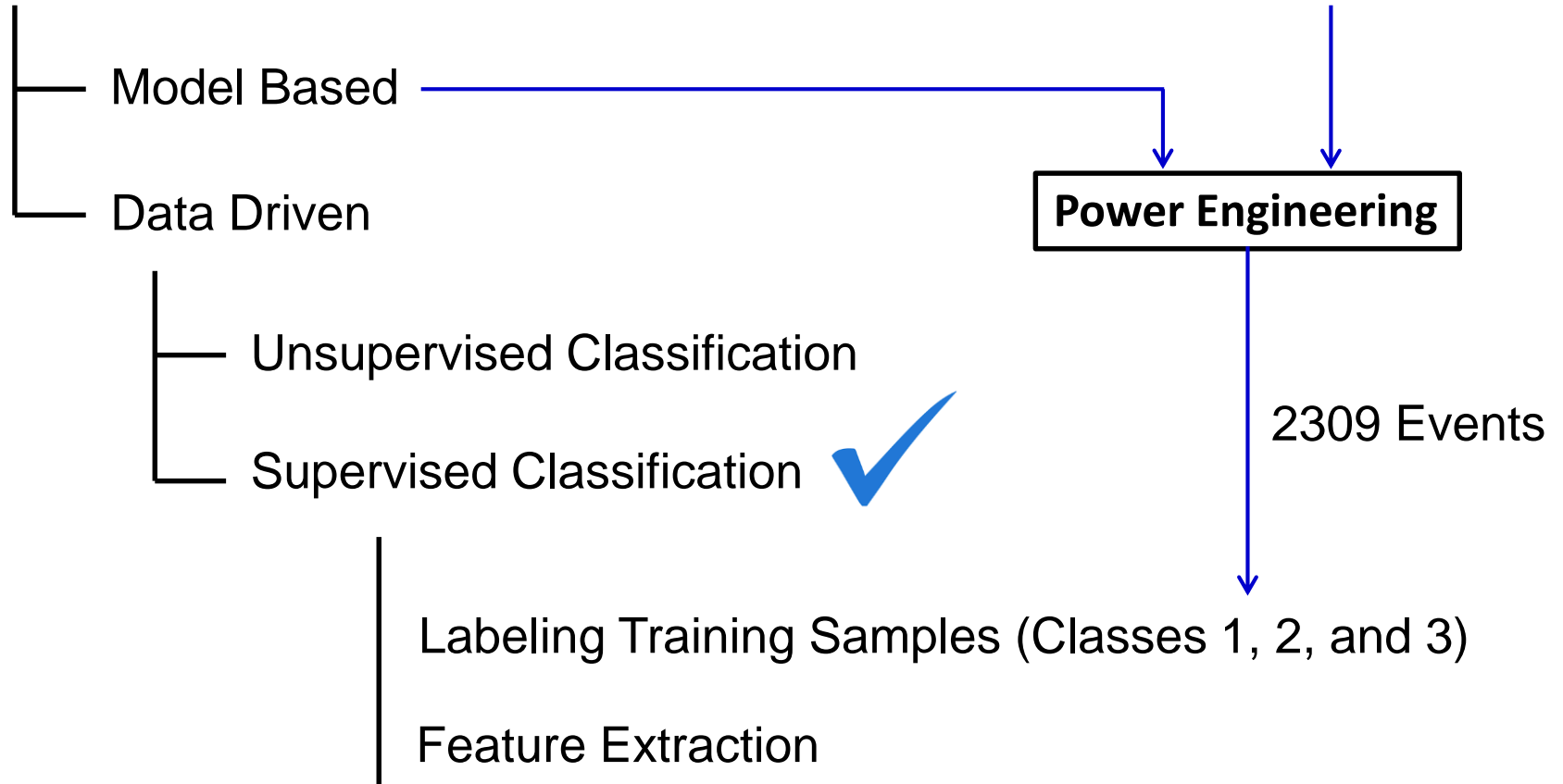


Micro-PMU 2



Phase 2: Event Classification

- **Methodology:**



Phase 2: Event Classification

- **Classification Results:**


—	Class 1:	368	1434
—	Class 2:	296	1896
	Class 3:	1645	5018

Features	
Detection Window	$\min\{W\}$
Detection Signal	$X_i \in \{I, V, P, Q\}$
Statistics	$\sigma(X_i)$
Difference	$ X_i^u - X_i^d $
Correlation	$\rho(X_i, Y_i)$

Phase 2: Event Classification

- **Classification Results:**

— Class 1:	368	1434
— Class 2:	296	1898
— Class 3:	1645	5018



Features	
Detection Window	$\min\{W\}$
Detection Signal	$X_i \in \{I, V, P, Q\}$
Statistics	$\sigma(X_i)$
Difference	$ X_i^u - X_i^d $
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Phase 2: Event Classification

- **Classification Results:**

— Class 1:	368	1434	→ Test Data
— Class 2:	296	1896	
Class 3:	1645	5018	

Features	
Detection Window	$\min\{W\}$
Detection Signal	$X_i \in \{I, V, P, Q\}$
Statistics	$\sigma(X_i)$
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Phase 2: Event Classification

- Classification Results:

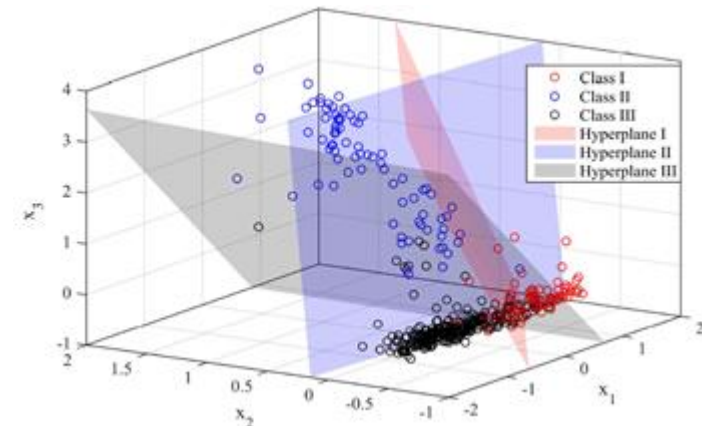
Class 1: 368 1434

Class 2: 296 1896

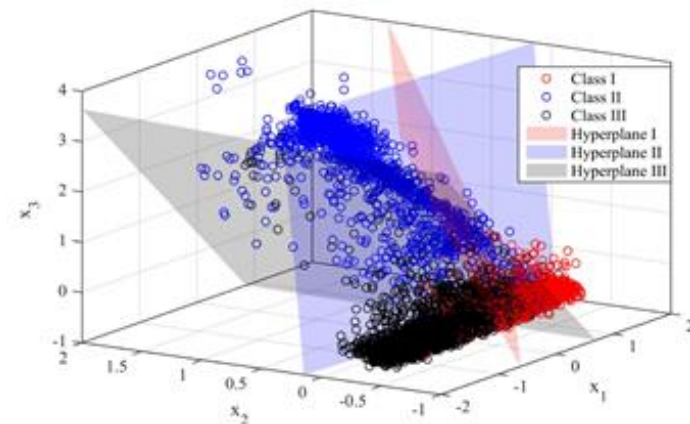
Class 3: 1645 5018

Features

Detection Window	$\min\{W\}$
Detection Signal	$X_i \in \{I, V, P, Q\}$
Statistics	$\sigma(X_i)$
Difference	$ X_i^u - X_i^d $
Correlation	$\rho(X_i, Y_i)$



Training Data

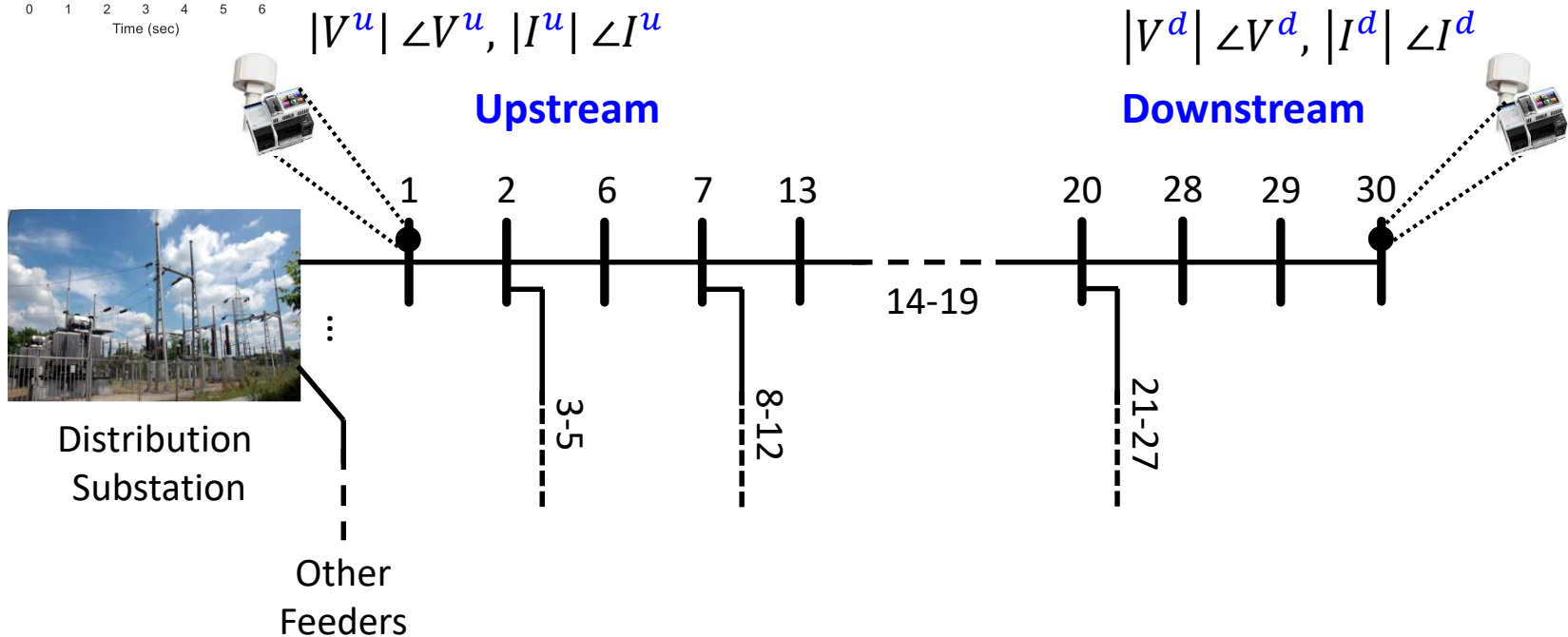
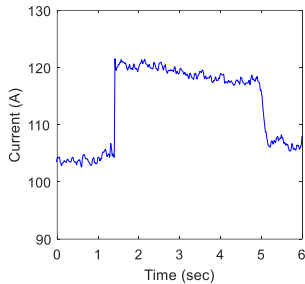


Test Data

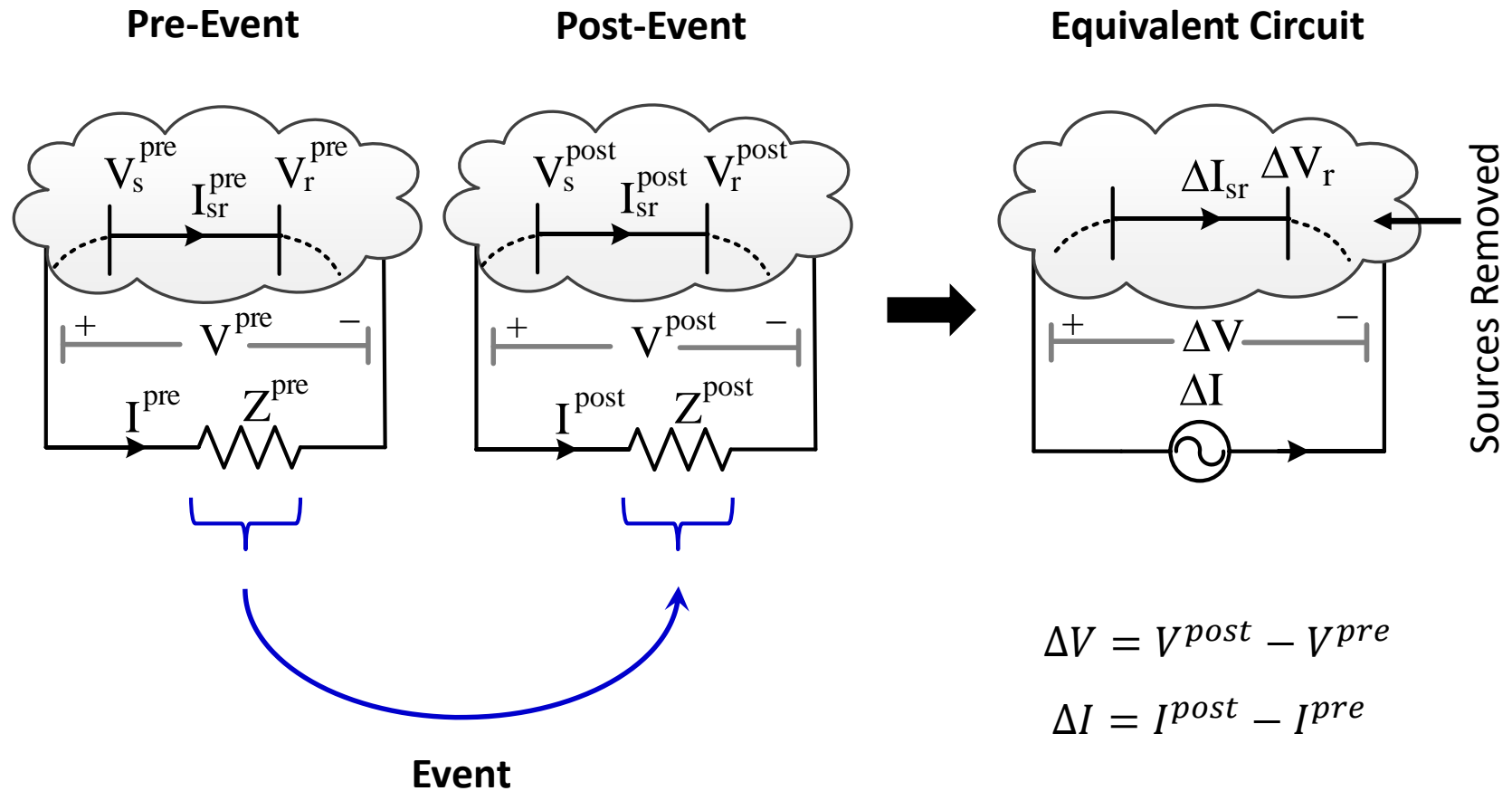
Phase 3: Event Source Identification

Class 3

Questions: What is the source location of this event?



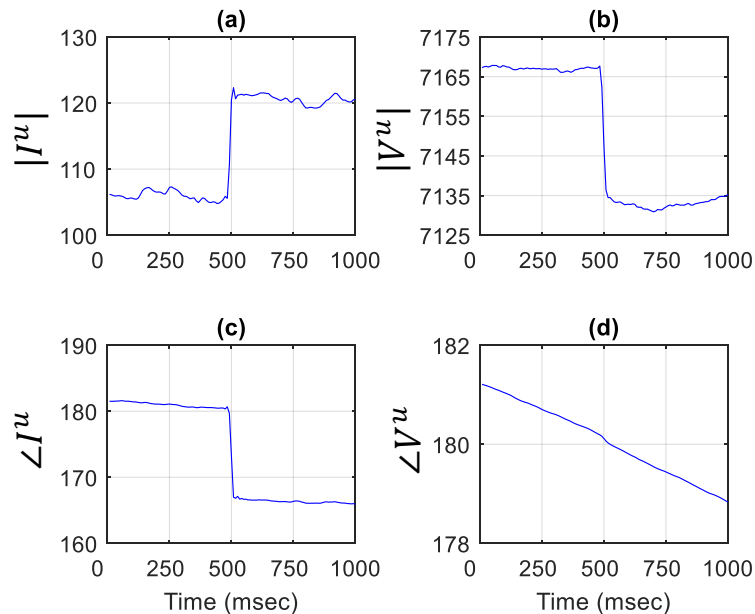
Phase 3: Event Source Identification



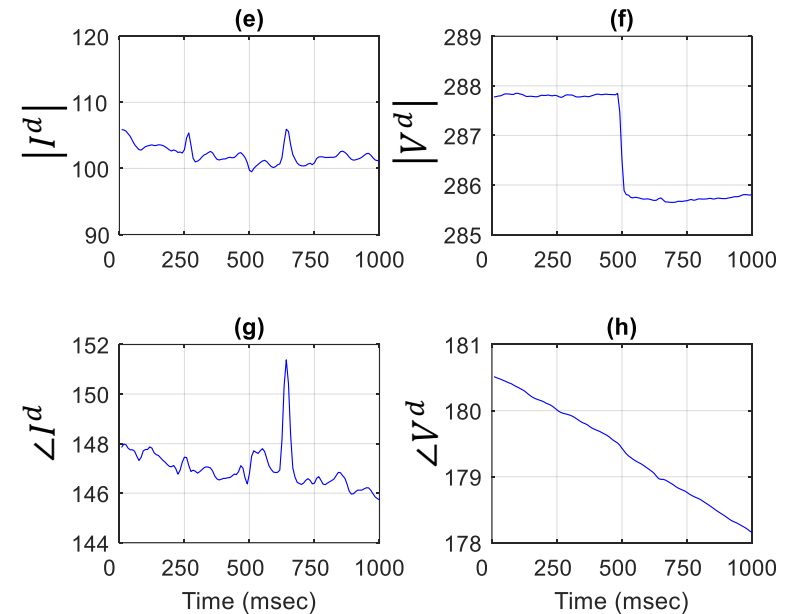
Theoretical Foundation: Compensation Theorem

Step 3-1: Extract Differential Synchrophasors

Upstream Sensor

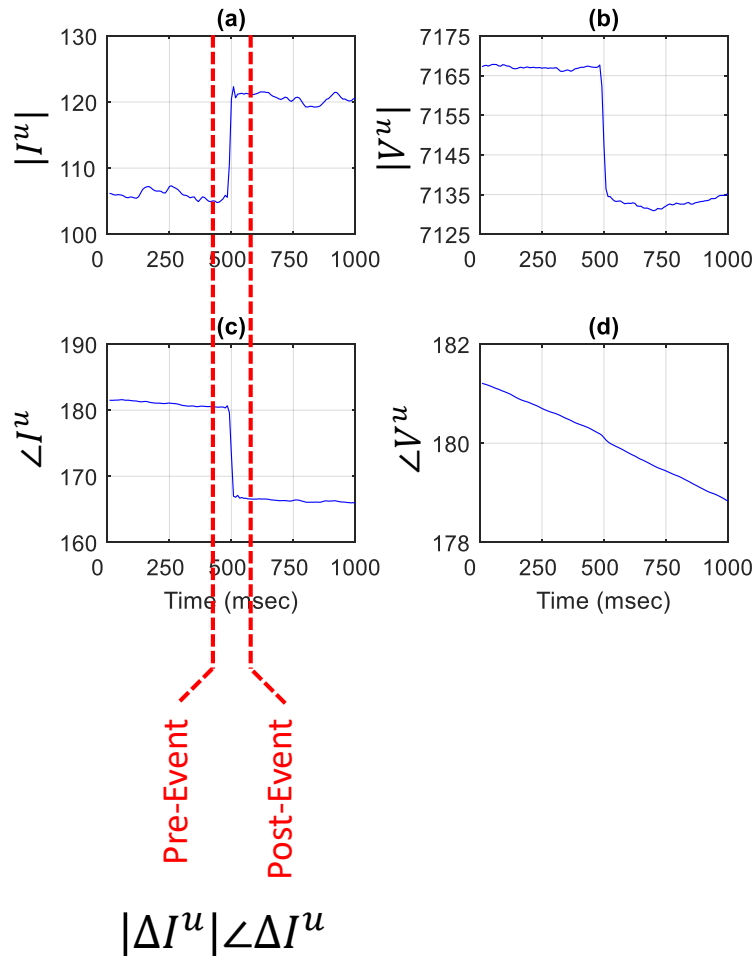


Downstream Sensor

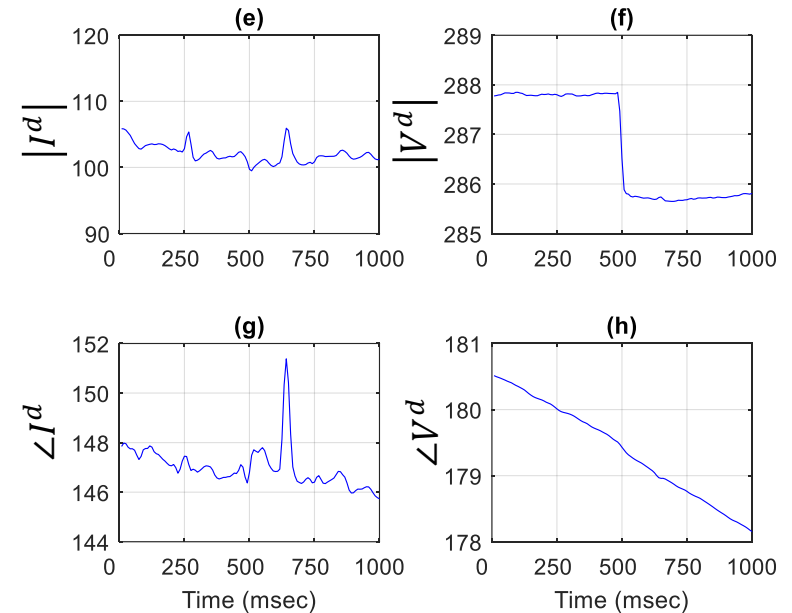


Step 3-1: Extract Differential Synchrophasors

Upstream Sensor

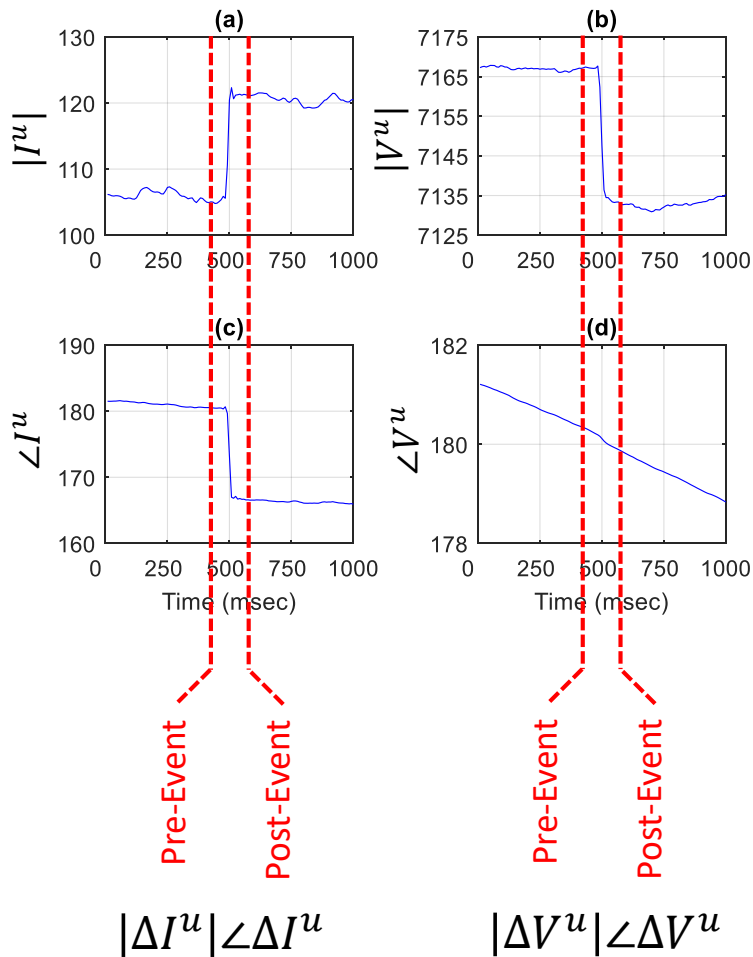


Downstream Sensor

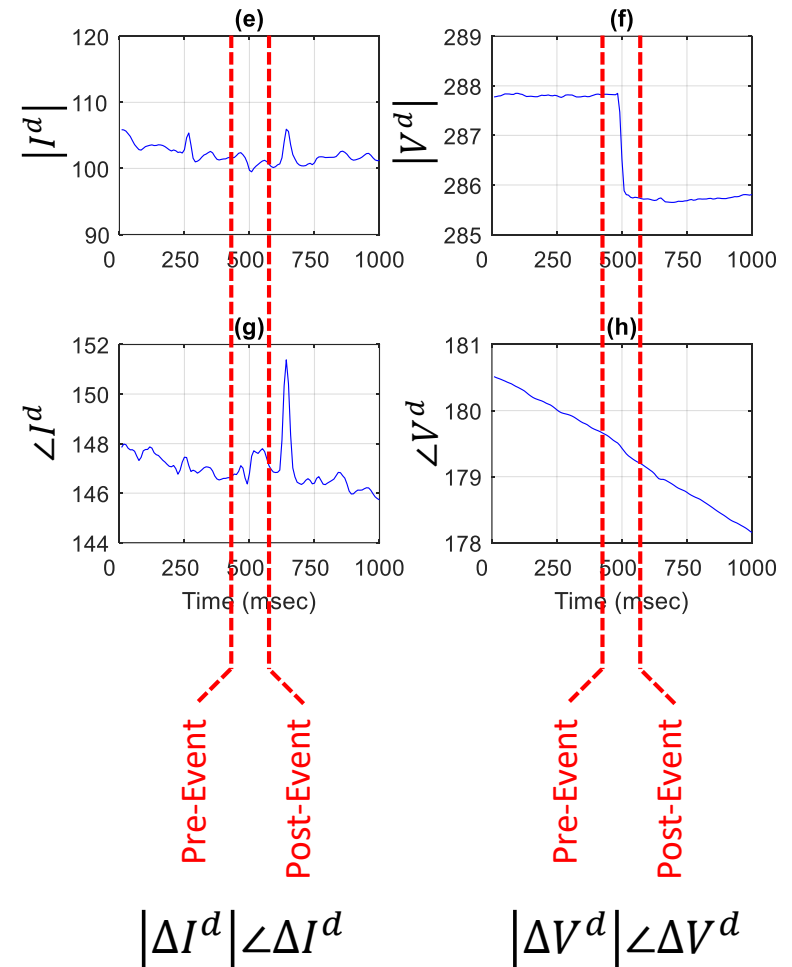


Step 3-1: Extract Differential Synchrophasors

Upstream Sensor



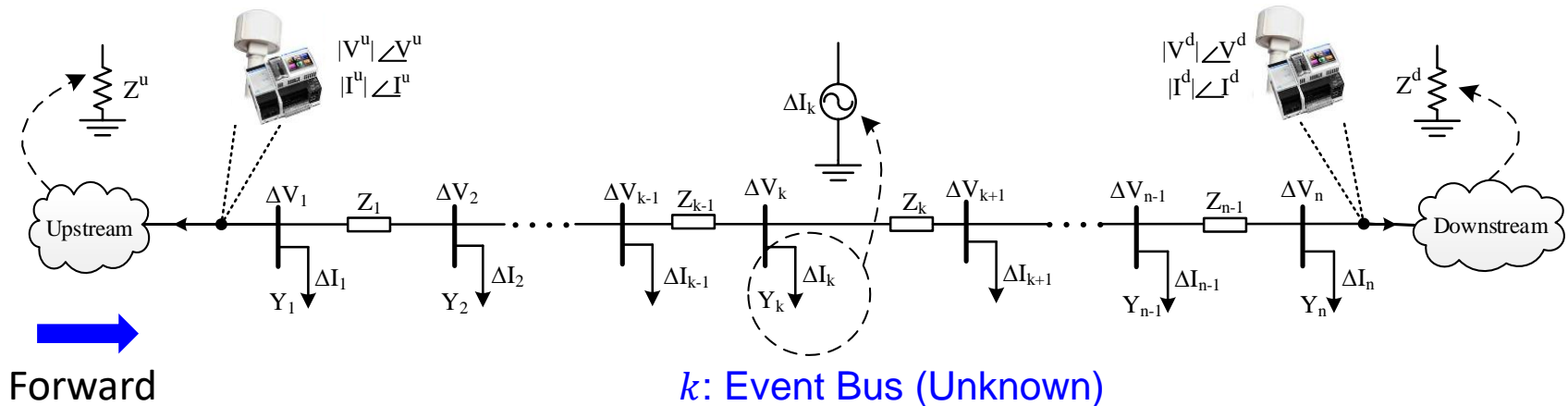
Downstream Sensor



Step 3-2: Forward Nodal Voltage Calculation

$$\begin{aligned}
 \Delta V_1^f &= \Delta V^u \\
 \Delta V_2^f &= \Delta V_1^f + (\Delta I^u + Y_1 \Delta V_1^f) Z_1 \\
 &\vdots \\
 \Delta V_k^f &= \Delta V_{k-1}^f + (\Delta I^u + Y_1 \Delta V_1^f + \dots + Y_{k-1} \Delta V_{k-1}^f) Z_{k-1} \\
 \Delta V_{k+1}^f &\neq \Delta V_k^f + (\Delta I^u + Y_1 \Delta V_1^f + \dots + Y_{k-1} \Delta V_{k-1}^f + Y_k \Delta V_k^f) Z_k \\
 &\vdots \\
 \Delta V_n^f &\neq \Delta V_{n-1}^f + (\Delta I^u + Y_1 \Delta V_1^f + \dots + Y_{n-1} \Delta V_{n-1}^f) Z_{n-1}
 \end{aligned}$$

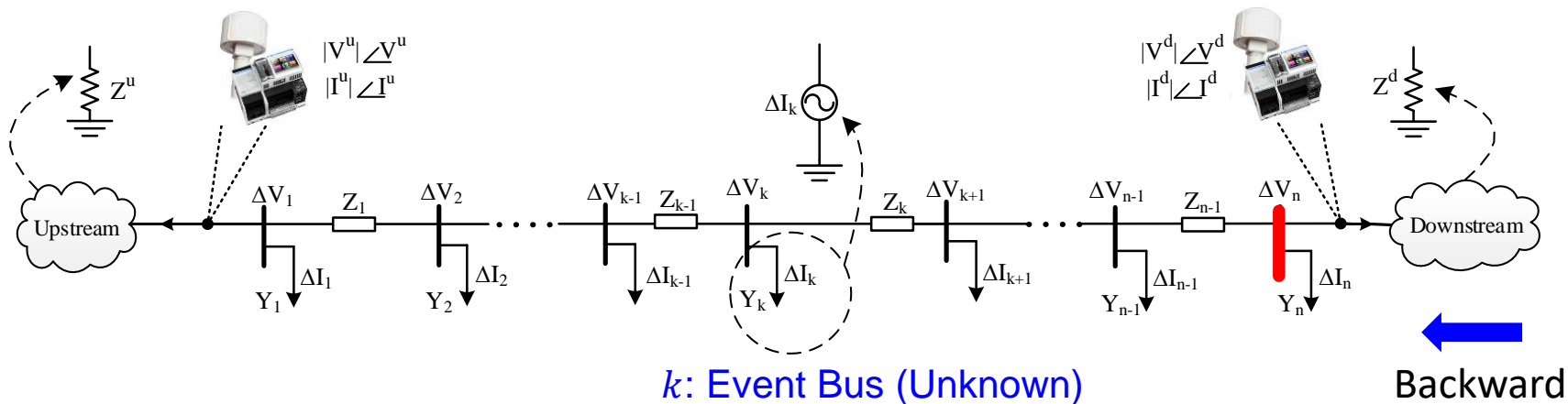
(I)



Step 3-3: Backward Nodal Voltage Calculation

$$\begin{aligned}
 \Delta V_n^b &= \Delta V^d \\
 \Delta V_{n-1}^b &= \Delta V_n^b + (\Delta I^d + Y_n \Delta V_n^b) Z_{n-1} \\
 &\vdots \\
 \Delta V_k^b &= \Delta V_{k+1}^b + (\Delta I^u + Y_n \Delta V_n^b + \dots + Y_{k+1} \Delta V_{k+1}^b) Z_k \\
 \Delta V_{k-1}^b &\neq \Delta V_k^b + (\Delta I^u + Y_n \Delta V_n^b + \dots + Y_{k+1} \Delta V_{k+1}^b + Y_k \Delta V_k^b) Z_{k-1} \\
 &\vdots \\
 \Delta V_1^b &\neq \Delta V_2^b + (\Delta I^u + Y_n \Delta V_n^b + \dots + Y_2 \Delta V_2^b) Z_1
 \end{aligned}$$

II



Step 3-4: Analysis of Discrepancy Index

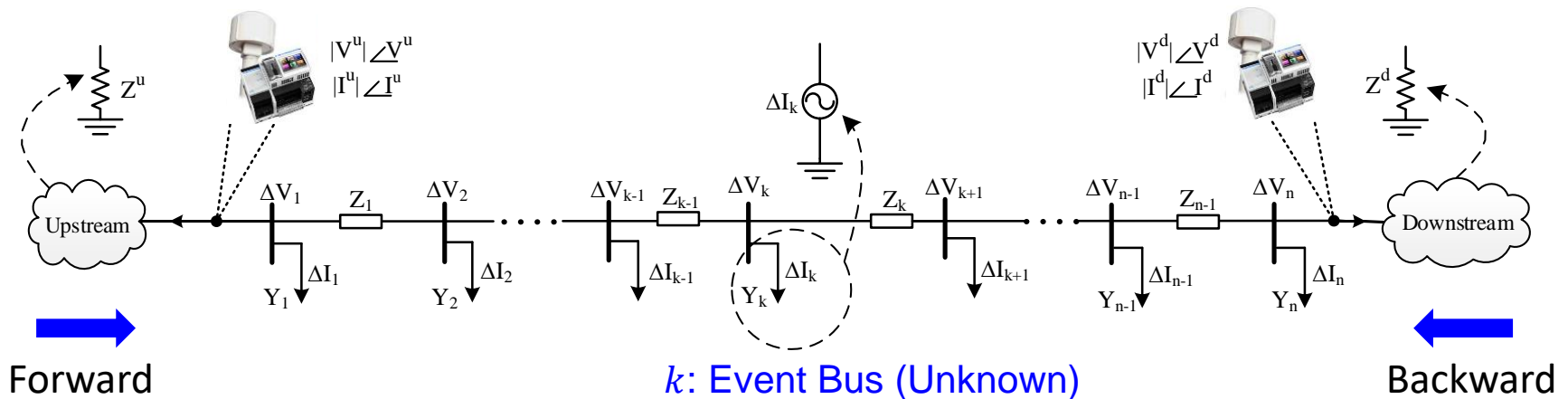
Forward: $\{\Delta V_1^f, \dots, \Delta V_{k-1}^f, \Delta V_k^f, \Delta V_{k+1}^f, \dots, \Delta V_n^f\}$

Correct
Incorrect

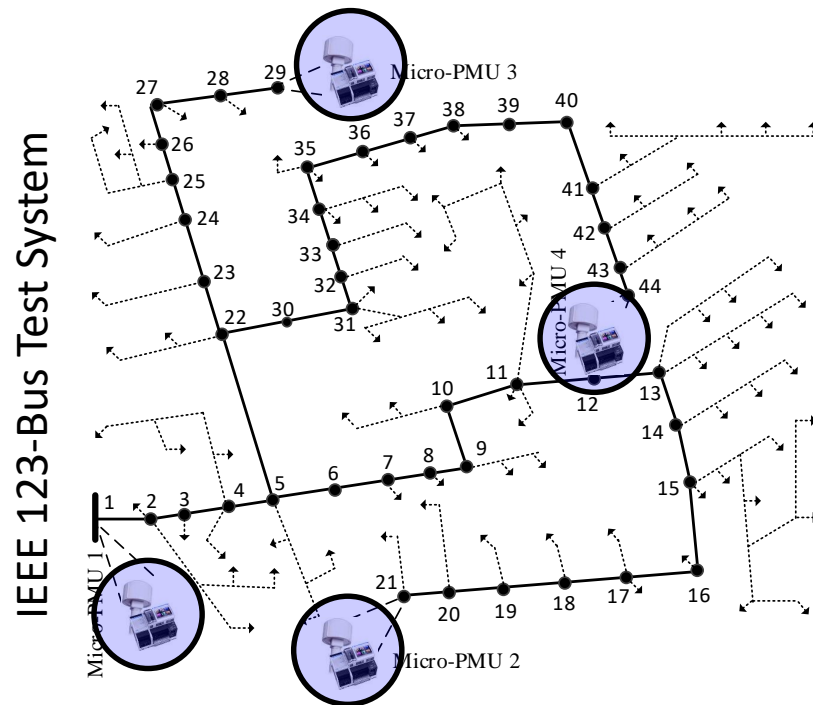
Backward: $\{\Delta V_1^b, \dots, \Delta V_{k-1}^b, \Delta V_k^b, \Delta V_{k+1}^b, \dots, \Delta V_n^b\}$

Incorrect
Correct

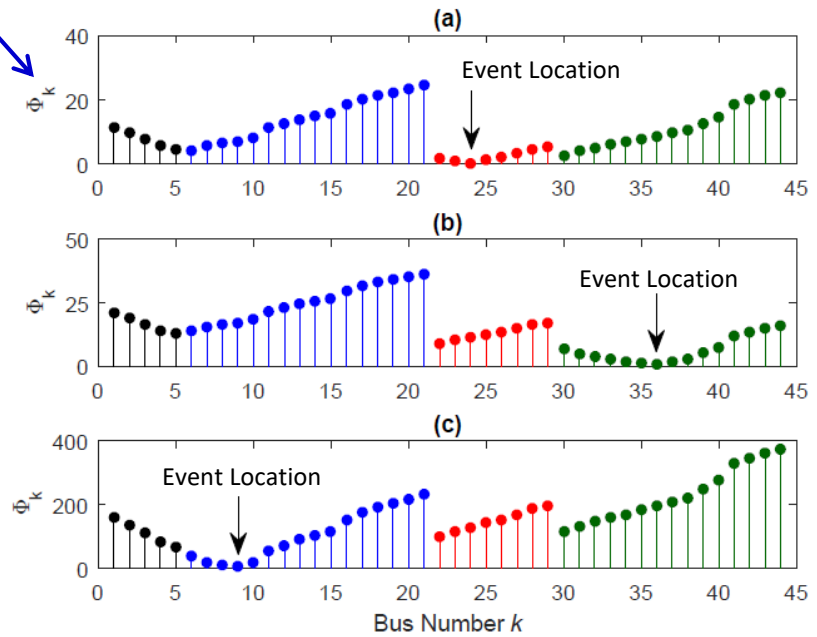
Discrepancy Index Φ_i
 $k = \underset{i}{\operatorname{argmin}} |\Delta V_i^f - \Delta V_i^b|$



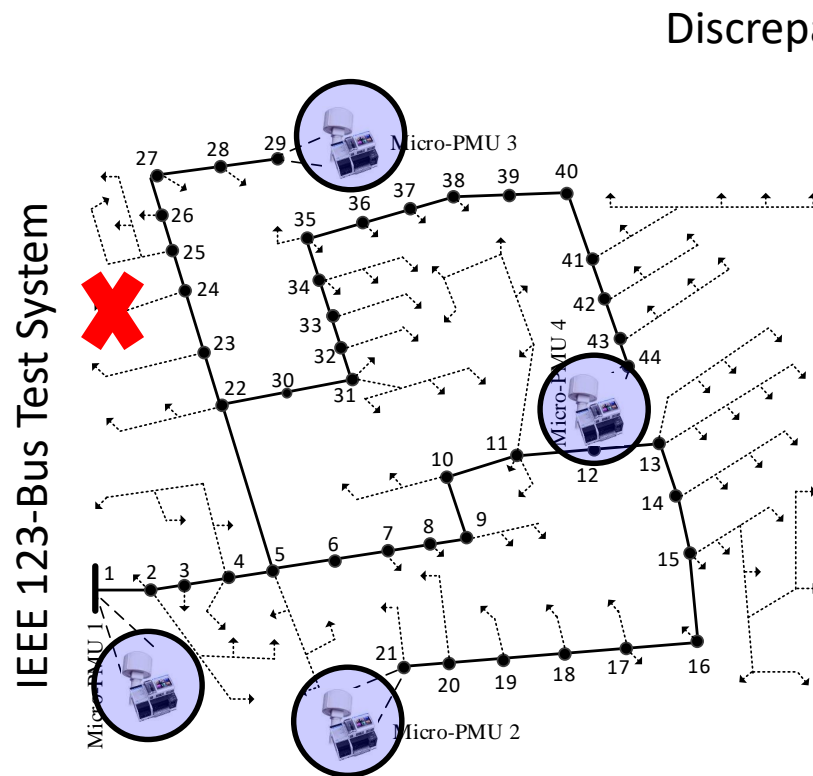
Phase 3: Event Source Identification



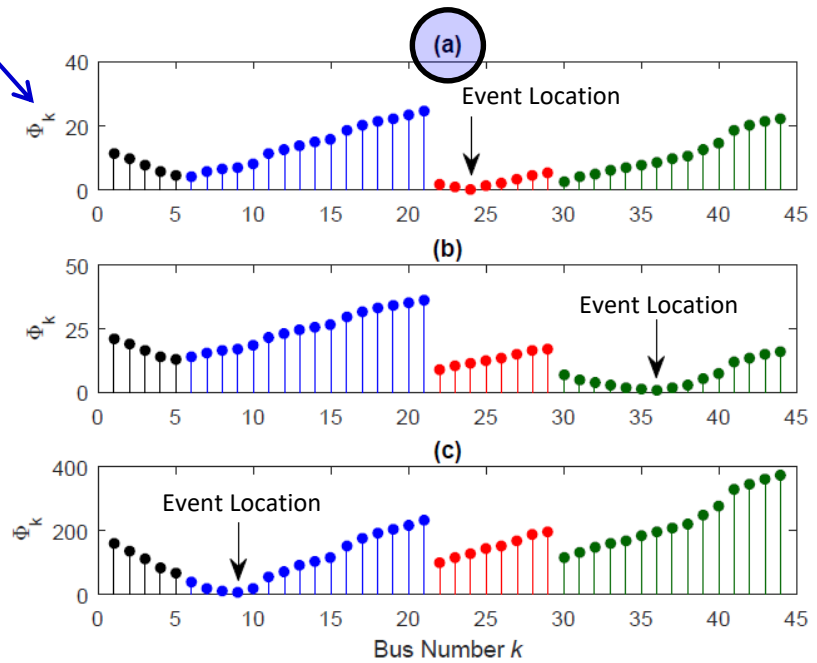
Discrepancy Index



Phase 3: Event Source Identification

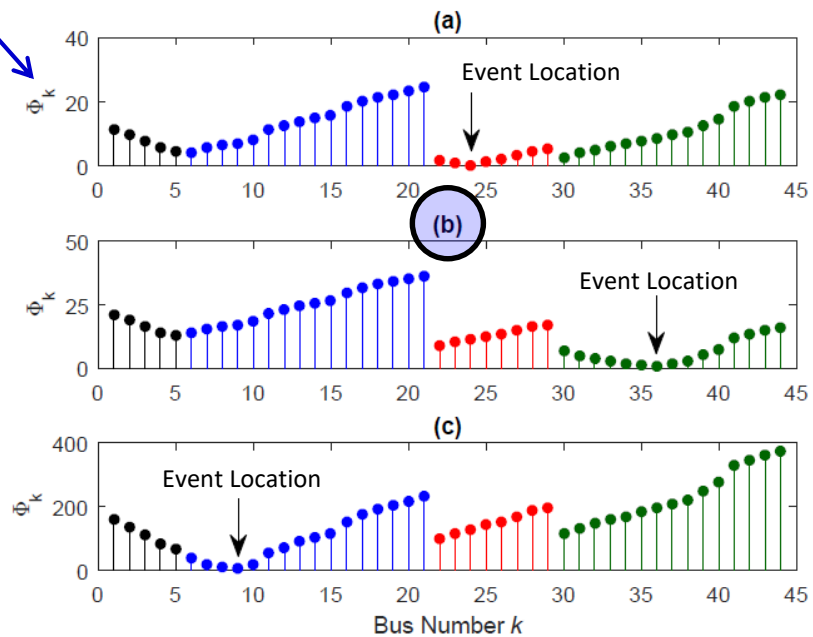
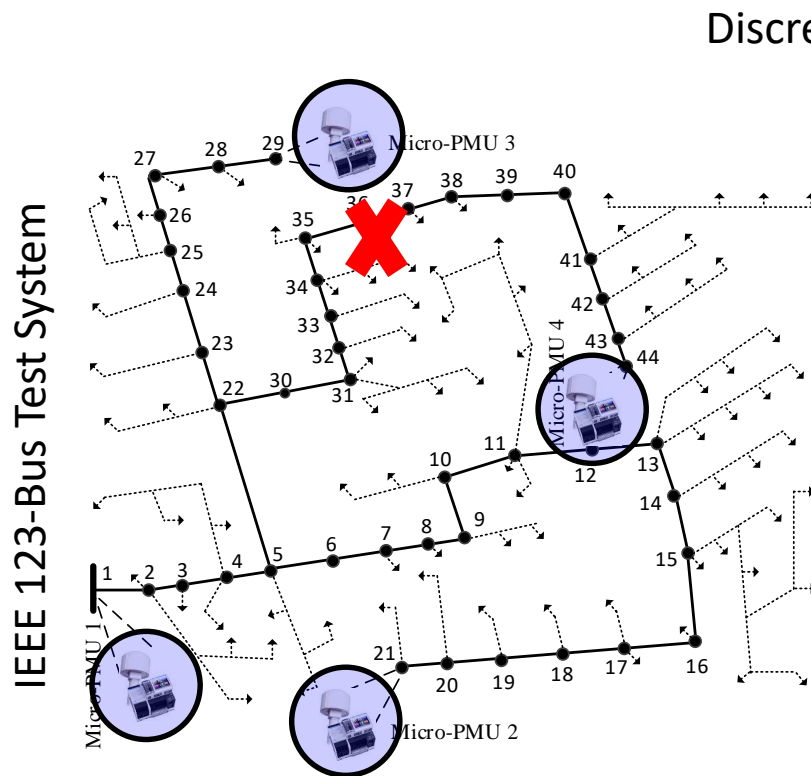


Discrepancy Index



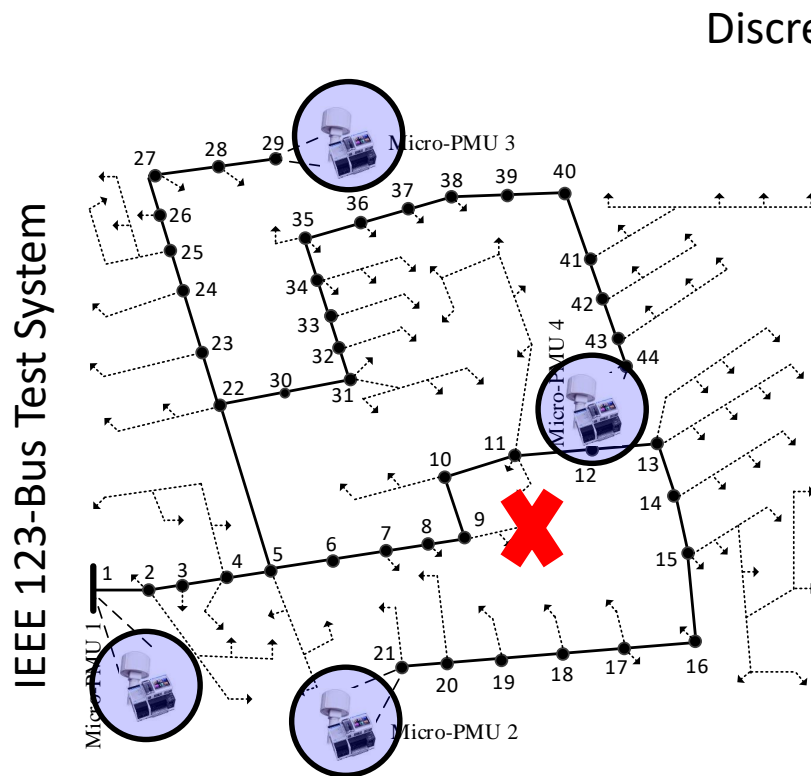
Event Source Location

Phase 3: Event Source Identification

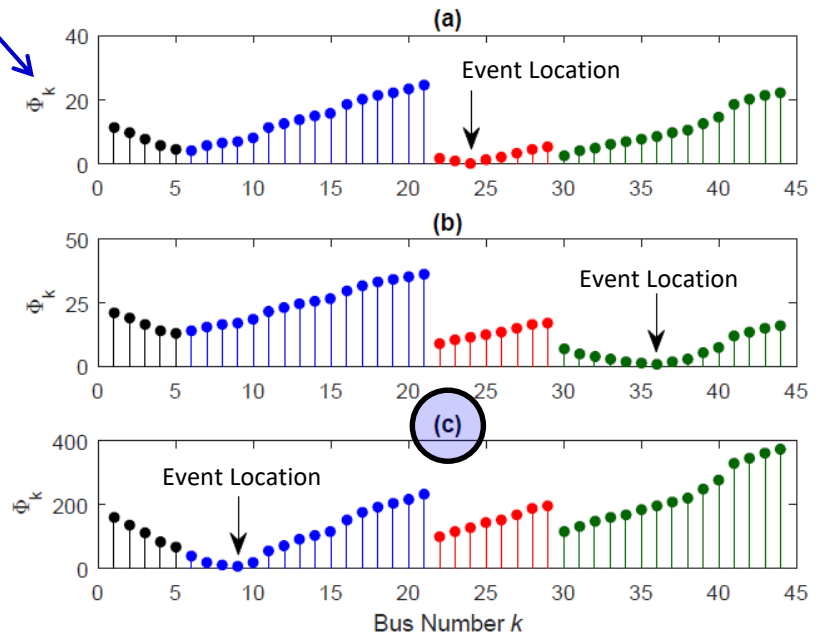


X Event Source Location

Phase 3: Event Source Identification



Discrepancy



Event Source Location

- **Data-Analytics Package for Distribution Synchrophasors**

- Event Detection
- Event Classification
- Event Source Identification

Billions of Data Points

Device-Specific Event Signatures

- **Case Study: Remote Asset Monitoring**

Recap: Big Data?

- **Data-Analytics Package for Distribution Synchrophasors**

- Event Detection
- Event Classification
- Event Source Identification

Billions of Data Points

Device-Specific Event Signatures

- **Case Study: Remote Asset Monitoring**

 Distributed Energy Storage

Case Study: Asset Monitoring

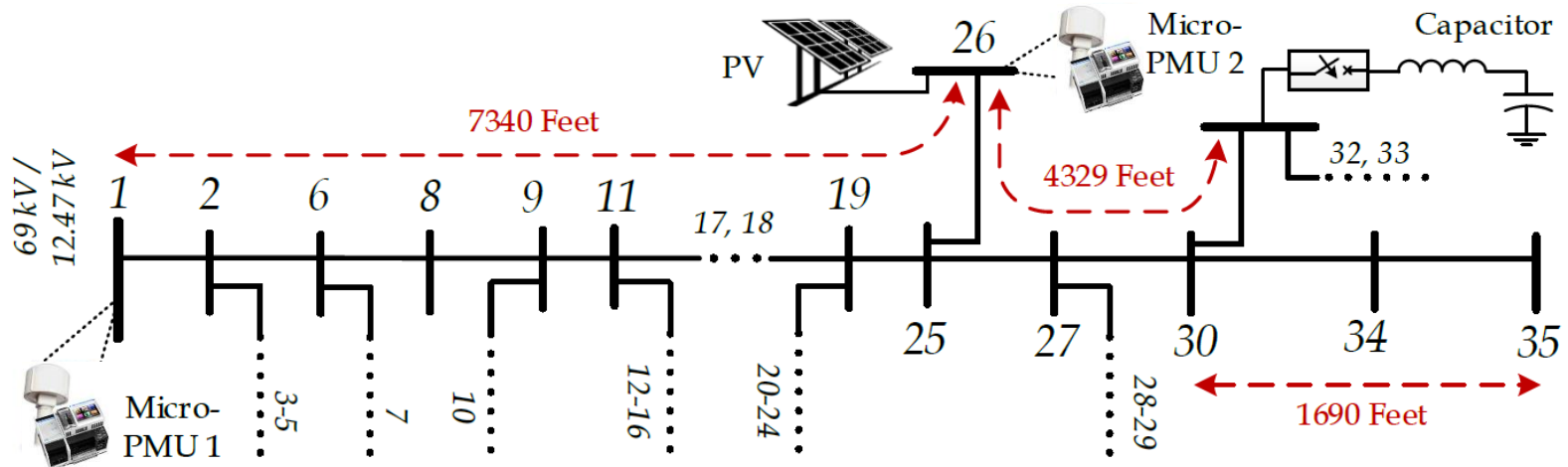
Three-Phase Switched Capacitor Bank

Rating: $3 \times 300 \text{ kVAR} = 900 \text{ kVAR}$

Volt/VAR Control

Onsite Switch On / Switch Off Controller

No Monitoring

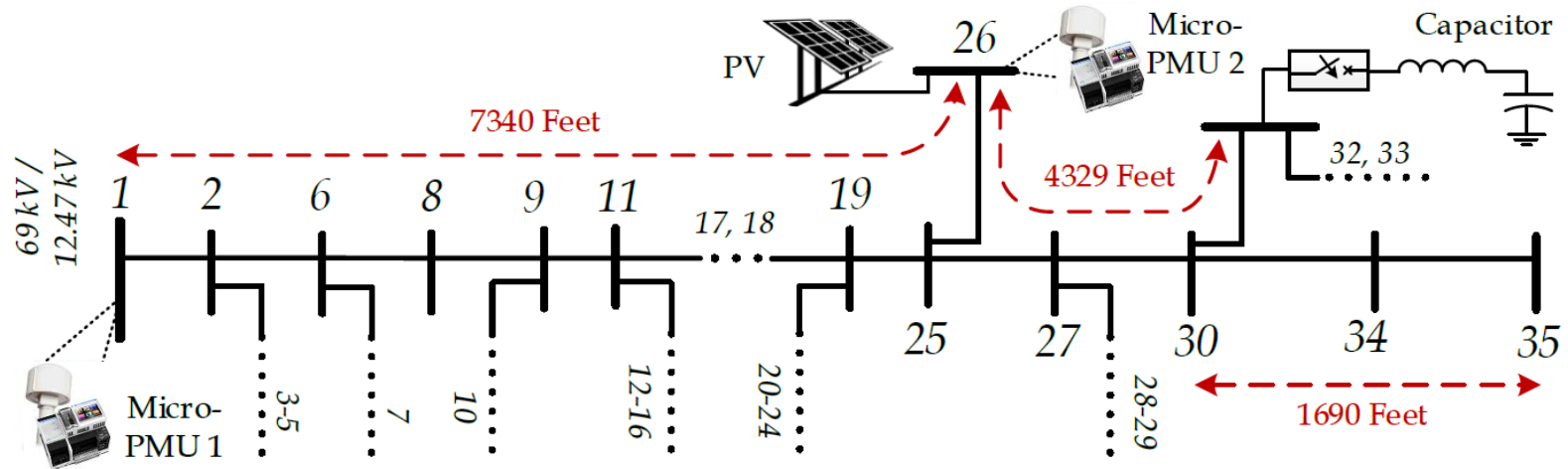


Case Study: Asset Monitoring

Typical Issues:

① Unbalanced Operation (Fuses)

② Switching Operation (Controllers)

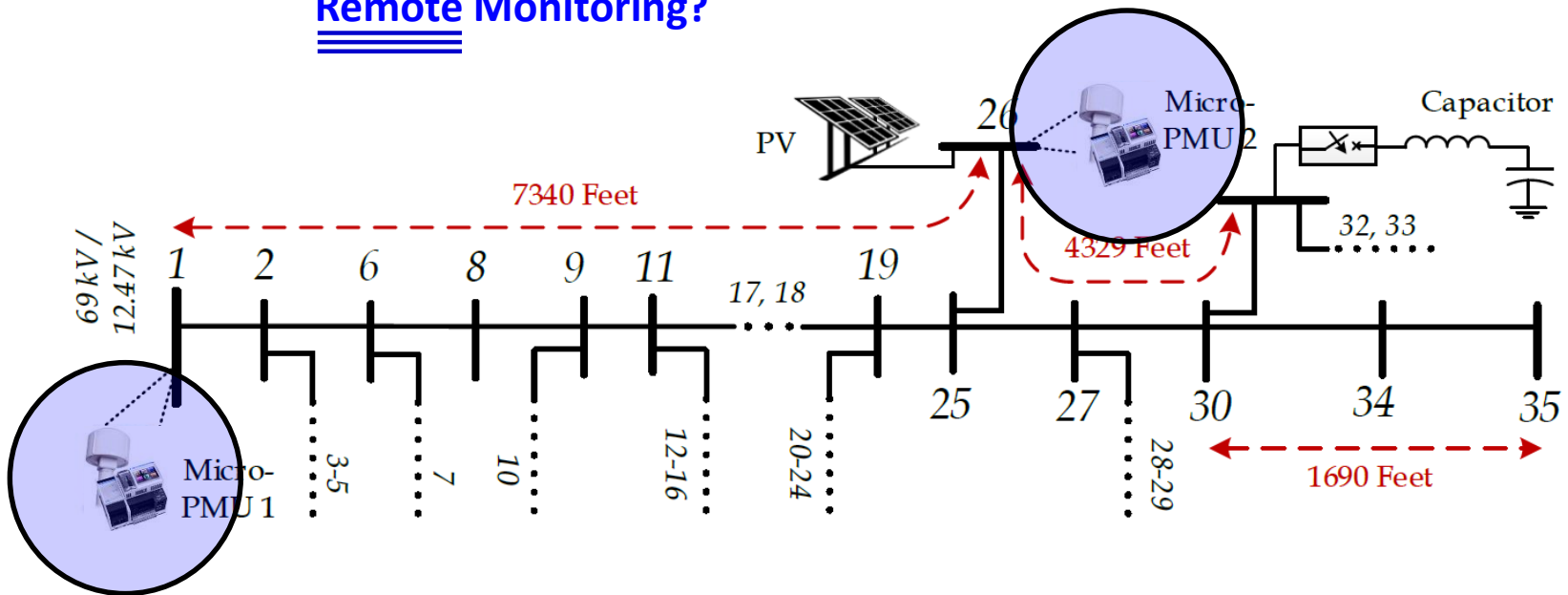


Case Study: (Remote) Asset Monitoring

Typical Issues:

- ① Unbalanced Operation (Fuses)
- ② Switching Operation (Controllers)

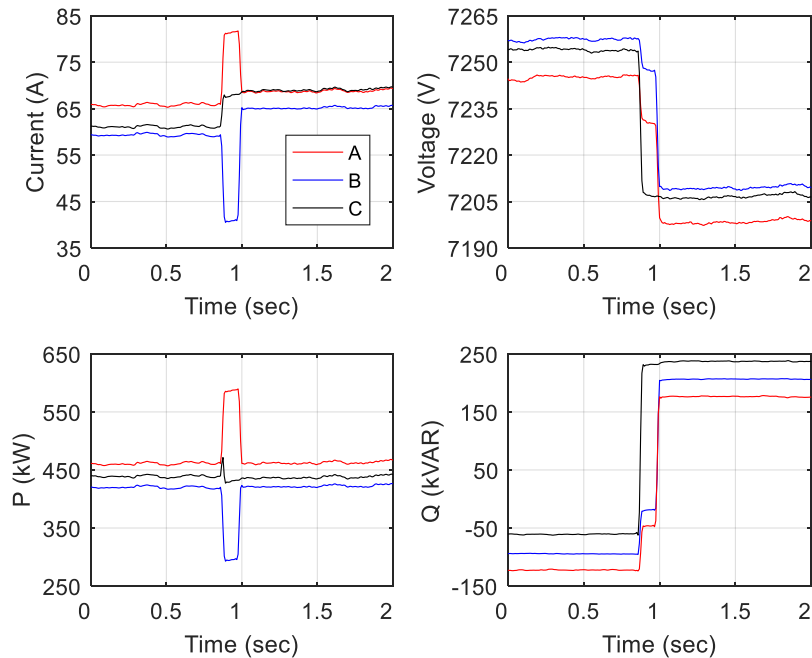
Remote Monitoring?



Case Study: (Remote) Asset Monitoring

Detection & Classification

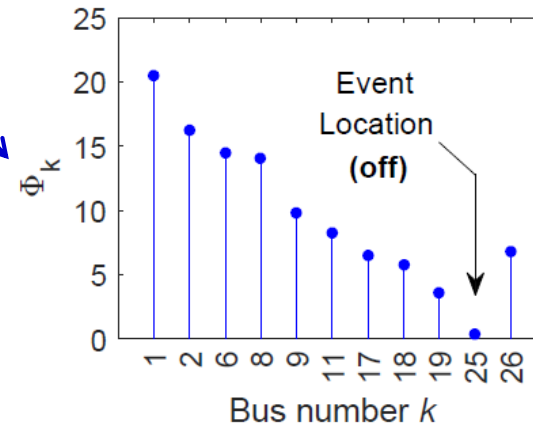
Switch Off Event



(Micro-PMU 1)

Discrepancy Index

Location Identification



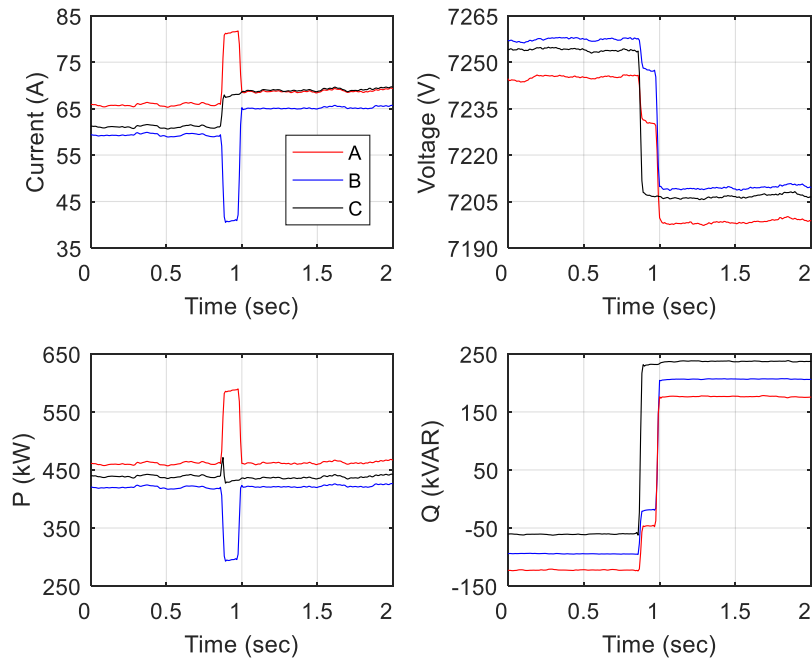
Event Bus: 25 (Correct)

(Micro-PMU 2)

Case Study: (Remote) Asset Monitoring

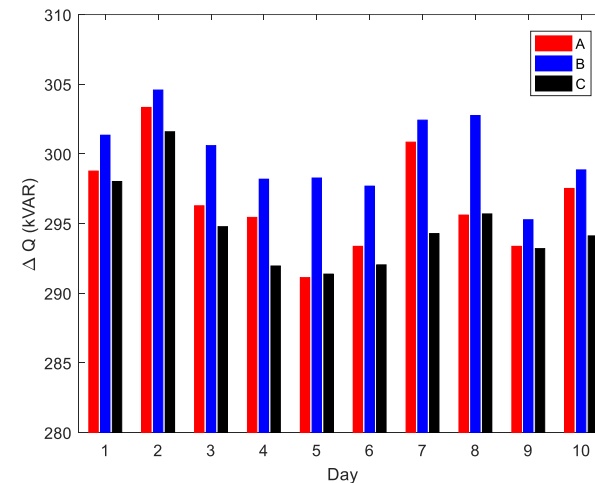
Detection & Classification

Switch Off Event



(Micro-PMU 1)

Reactive Power Support



Slightly Unbalanced Operation

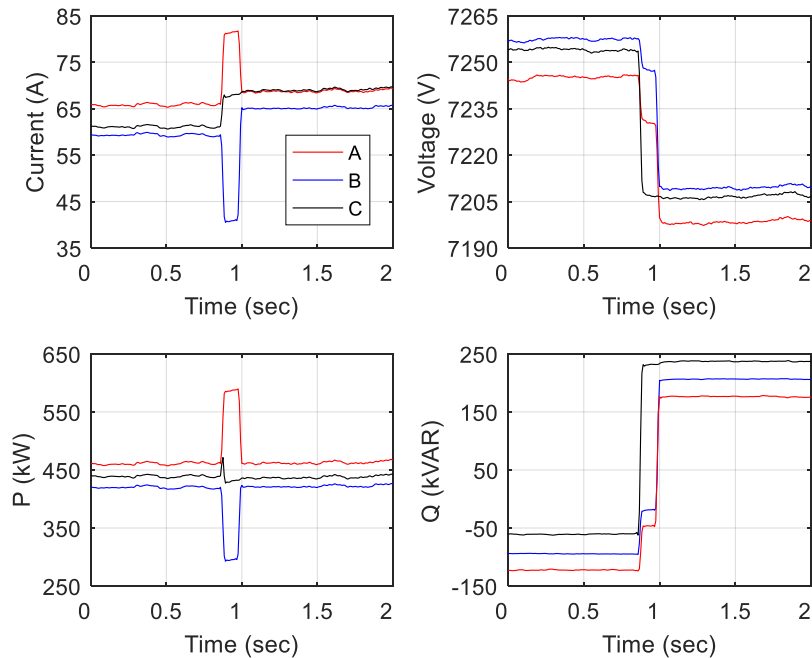
Phase B is always higher

Likely fuse blowing on C and A

Case Study: (Remote) Asset Monitoring

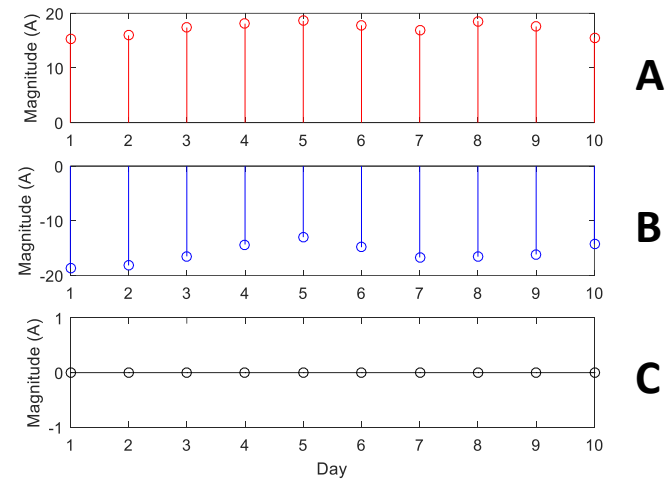
Detection & Classification

Switch Off Event



(Micro-PMU 1)

Switching Transient



Two-Step 3-Phase Switch

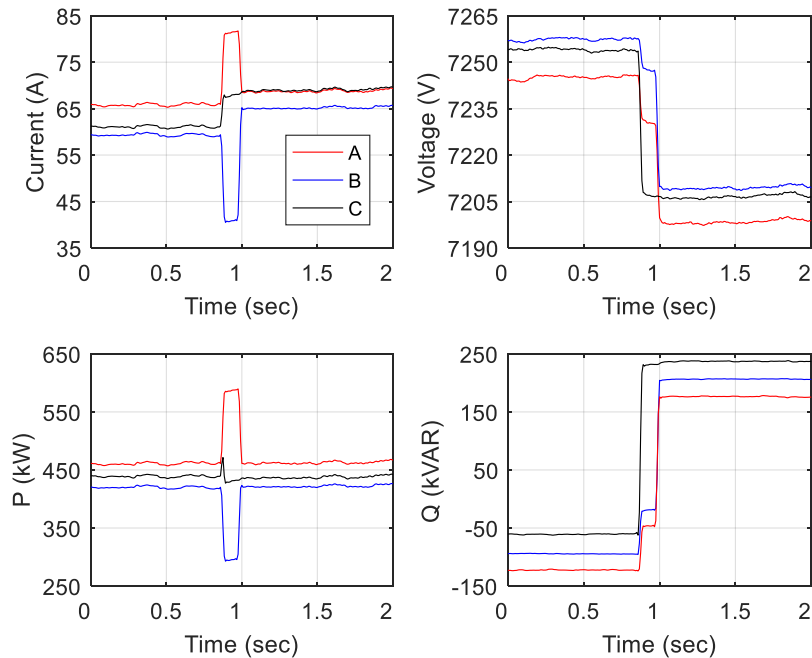
Step 1: Phase C (Zero Crossing)

Step 2: Phase A/B (Possible Malfunction)

Case Study: (Remote) Asset Monitoring

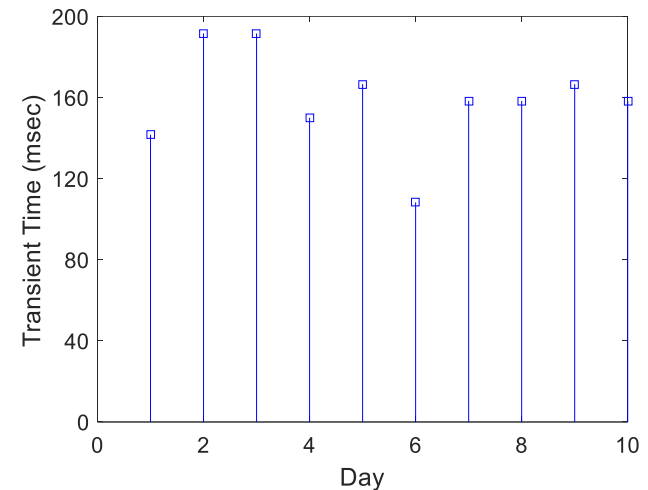
Detection & Classification

Switch Off Event



(Micro-PMU 1)

Switching Transient



$C \mapsto A/B$
Unbalanced System

Two-Step 3-Phase Switch

Step 1: Phase C (Zero Crossing)

Step 2: Phase A/B (Possible Malfunction)

Distribution Synchrophasors

By Hamed Mohsenian-Rad, Emma Stewart, and Ed Cortez

IN THE EVOLUTION OF ADVANCED SENSING TECHNOLOGIES, transmission systems have had distribution. The visibility and diagnostics of the transmission grid have been transformed over the past decade with the systematic deployment of phasor measurement units (PMUs). Similar and even more advanced new information sources are now becoming available at the distribution grid, using distribution-level PMUs, also called micro-PMUs (μPMUs). μPMUs provide voltage and current measurements at higher resolution and precision to facilitate a level of visibility into the distribution grid that is currently not achievable. However, mere data availability in itself will not lead to enhanced situational awareness and operational intelligence. Data must be paired with useful analysis to translate these data to actionable information. In this article, we explore some of the opportunities to leverage μPMU data, combined with data-driven analysis, to help electrical distribution system planners and operators to get out from problems as they evolve.

The data generated by μPMUs are a position example of big data in power systems. Each μPMU generates 124,416,600 readings per day. Therefore, μPMUs installed on a handful of utility distribution bases can generate terabytes of data on daily basis. Because μPMUs

stream their measurements continuously, the data must be collected, cleaned, and processed, all in real time. The collected μPMU data must then be dissected into descriptive, predictive, and prescriptive analytics. While descriptive analytics focuses on what happened in the past, predictive analytics aims at what may happen in the future. Both are stepping stones toward prescriptive analytics—optimizing the future with informed decisions. Here, we consider case studies in both descriptive and predictive analytics and provide a sampling of the benefits derived from μPMU data.



Locating the Source of Events in Power Distribution Systems Using Micro-PMU Data

Mohammad Farajollahi, Student Member, IEEE, Alireza Shahsavari, Student Member, IEEE, Emma M. Stewart, Senior Member, IEEE, and Hamed Mohsenian-Rad, Senior Member, IEEE

Abstract—A novel method is proposed to locate the source of events in power distribution systems by using distribution-level phasor measurement units, a.k.a., micro-PMUs. An event in this paper is defined rather broadly to include any major change in any component across the distribution feeder. The goal is to enhance situational awareness in distribution grid by keeping track of the operation (or misoperation) of various grid equipment, assets, distribution energy resources, loads, etc. The proposed method is built upon the compensation theorem in circuit theory to generate an equivalent circuit to represent the event by using voltage and current synchrophasors that are captured by micro-PMUs. Importantly, this method makes critical use of not only magnitude but also synchrophasor phase angle measurements, thus, it justifies the need to use micro-PMUs, as opposed to ordinary RMS-based voltage and current sensors. The proposed method can work with data from as few as only two micro-PMUs. The effectiveness of the developed method is demonstrated through computer simulations on the IEEE 123-bus test system, and also on micro-PMU measurements from a real-life 12.47 kV test feeder in Riverside, CA. The results verify that the proposed method is accurate and robust in locating the source of different types of events on power distribution systems.

Index Terms—Distribution synchrophasors, micro-PMUs, event source location, power quality and reliability events, data-driven method, compensation theorem, measurement differences.

I. INTRODUCTION

DISTRIBUTION-LEVEL phasor measurement units (μPMUs), a.k.a., micro-PMUs (μPMUs), have recently been introduced as new sensor technologies to enhance real-time monitoring in power distribution systems. Micro-PMUs provide GPS-synchronized measurements of three-phase voltage and current phasors at a high resolution, 120 readings per second [1]. Several emerging applications of micro-PMUs, including model validation, distribution system state estimation, topology detection, phase identification, distributed generation,

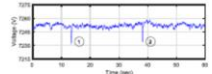


Fig. 1. Voltage phase magnitude that is measured in a distribution substation in Riverside, CA. Only one phase is shown here. From 1 to 14 ms there is no event in the transmission system. From 15 to 16 ms there is the distribution system, and transient analysis, as discussed in a recent survey in [2] and the references therein.

A. Motivation

Consider one minute of voltage phase measurements in Fig. 1 from a micro-PMU at a real-life 12.47 kV distribution substation in Riverside, CA. As expected, there are fluctuations in voltage magnitude, including two voltage sag events. Each event has a root cause at either transmission network or distribution network [3]. Common root causes of distribution level events include load switching, capacitor bank switching, connection or disconnection of distributed energy resources (DERs), inverter malfunction, a minor fault, etc. Accordingly, in this paper, we seek to answer the following question: *For these events with root causes in distribution network, what is the location of each root cause, i.e., at what exact distribution bus does the load switching, capacitor bank switching, DER connection/disconnection, or device malfunction occur?*

Answering the above question is the key to achieving situational awareness in power distribution systems, so as to keep track of how various grid equipment, assets, DERs, and loads operate or misoperate. The applications are diverse, ranging from identifying incipient failures [11, 14] or cyber attacks [5], to reducing demand side resources to compensate a self-organizing power distribution system [6]–[8]. Here, an event is defined rather broadly to include any major change in a component across the distribution feeder. This of course includes the two traditional classes of electric distribution system events, namely power-quality (PQ) events, such as drooping below or exceeding upper acceptable nodal voltage limits, as well as reliability events, such as interrupting service due to faults that cause fuse blowing or relay tripping [9]. However, since the goal in this paper is to enhance situational awareness in power distribution systems, we are interested also in PQ events that do not necessarily violate PQ requirements or undermine reliability, but they

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Situational Awareness in Distribution Grid Using Micro-PMU Data: A Machine Learning Approach

Alireza Shahsavari, Student Member, IEEE, Mohammad Farajollahi, Student Member, IEEE, Emma Stewart, Senior Member, IEEE, Ed Cortez, Hamed Mohsenian-Rad, Senior Member, IEEE

Abstract—The recent development of distribution-level phasor measurement units, a.k.a., micro-PMUs, has been an important step towards achieving situational awareness in power distribution networks. The challenge however is to transform the large amount of data that is generated by micro-PMUs to actionable information and then match the information to use cases with practical value to system operators. This open problem is addressed in this paper. First, we introduce a novel data-driven event detection technique to pick out valuable portion of data from extremely large raw micro-PMU data. Subsequently, a data-driven event classifier is developed to effectively classify power quality events. Importantly, we use field expert knowledge and utility records to conduct an extensive data-driven event labeling. Moreover, certain aspects from event detection methods are adopted as additional features to be fed into the classifier model. In this regard, a multi-class support vector machine (SVM) classifier is trained and tested over 15 days of real-world data from two micro-PMUs on a distribution feeder in Riverside, CA. In total, we analyze 12 billion measurement points, and 10,760 events. The effectiveness of the developed event classifier is compared with prevalent multi-class classification methods, including k-nearest neighbor method as well as decision-tree method. Importantly, two real-world use-cases are presented for the proposed data analytics tools, including remote asset monitoring and distribution-level outflow analysis.

Keywords—Machine learning, distribution synchrophasors, situational awareness, event detection, event classification, Big Data.

I. INTRODUCTION

The proliferation of distributed energy resources, electric vehicles, and controllable loads has introduced new and unpredictable sources of disturbance in distribution networks. This calls for developing new monitoring systems that can support achieving situational awareness at distribution level; thus, allowing the distribution system operator to make the best operational decisions in response to such disturbances. Traditionally, there have been three major challenges in achieving situational awareness in power distribution systems. First is the lack of high-resolution measurements. Metering in distribution systems is often limited to supervisory control and data acquisition (SCADA) at substations with minority reporting intervals. As for smart meters, their report measurements once every 15 minutes or hourly. Second is the lack of accurate and up-to-date models for most practical distribution circuits. Third, due to the lower voltage and the larger number and

variety of utility and customer equipment, distribution systems are subject to a huge number of events on a daily basis. The first challenge above has recently been resolved by the advent of micro-PMUs [1]. A typical micro-PMU is connected to single- or three-phase distribution circuits to measure GPS time-referenced magnitudes and phase angles of voltage and current phasors at 120 readings per second. Since 2013, several micro-PMUs have been installed at pilot test sites in the state of California, including some in the city of Riverside [2].

This paper makes use of real-world micro-PMU data from a feeder in Riverside, CA, see Fig. 1. It seeks to address the second and the third challenges listed above. Specifically, we propose a novel model-free situational awareness framework for power distribution systems to turn micro-PMU data in to actionable information for tangible use cases. This is done by introducing a novel data-driven event detection technique as well as a novel data-driven event classification technique. Event detection is applied to eight non-linearly dependent data streams for each micro-PMU, including voltage magnitude, current magnitude, active power, and reactive power. Event classification is done by extracting the inherent features of detected events, and by constructing an machine that can learn from and make predictions of various events. The main contribution in this paper can be summarized as follows:

- 1) A novel situational awareness framework is introduced for power distribution systems using micro-PMU data, that is model-free; it works by going through a sequence of event detection, event classification, and event normalization efforts to transform the large amount of measurement data from micro-PMUs to information that are useful for distribution system operators.
- 2) The approach in this paper makes use of field expert knowledge and utility records in order to conduct an extensive data-driven event labeling for micro-PMU data. The detected events are labeled according to event type and event type. As for the event detection phase prior to event labeling, our approach is comprehensive; it involves moving windows to help compensate the lack of information about the start time of each event. It also involves dynamic window sizes to help compensate the lack of information about the duration of each event.
- 3) Different feature selection approaches and different classification methods are examined and compared, including multi-SVM, k-nearest neighbor, and decision-tree, with considering certain aspects of events from micro-PMUs, e.g., stream datasets and features of multi-stream signals. It is shown that a use of the proposed detection features, such as detection window and detection indicator, is critical, regardless of the method of classification.

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