

# PMU Data Analytics for Power Distribution

First Session

Hamed Mohsenian-Rad, University of California, Riverside  
**Nonintrusive Load Modeling Using Micro-PMUs**

Asja Derviskadic, Swiss Federal Institute of Tech of Lausanne  
**Synchronized Sensing for Wide-Area Situational Awareness of Power Distribution Networks**

Second Session

Wei Zhou, Huazhong University of Science and Technology  
**DPMU for Harmonic State Estimation**

Moosa Moghimi Haji, University of Alberta  
**Estimating Distribution System Parameters using DPMU and Smart Meter Data**

# Nonintrusive Load Modeling Using Micro-PMUs

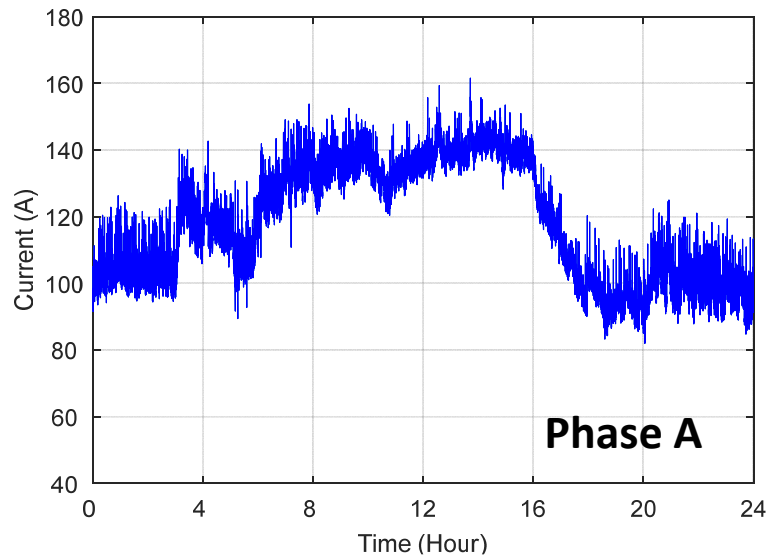
Smart Grid Comm 2019, Beijing, China

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. Shamsavari, M. Farajollahi, E. Stewart, E. Cortez,  
A. von-Meier, L. Alvarez, C. Roberts, F. Megala, Z. Taylor

# Background: Events in Micro-PMU Data Streams



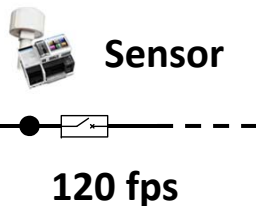
## Event Signature

- Current ( $I$ )
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- Active Power ( $P$ )
- Reactive Power ( $Q$ )

12 kV

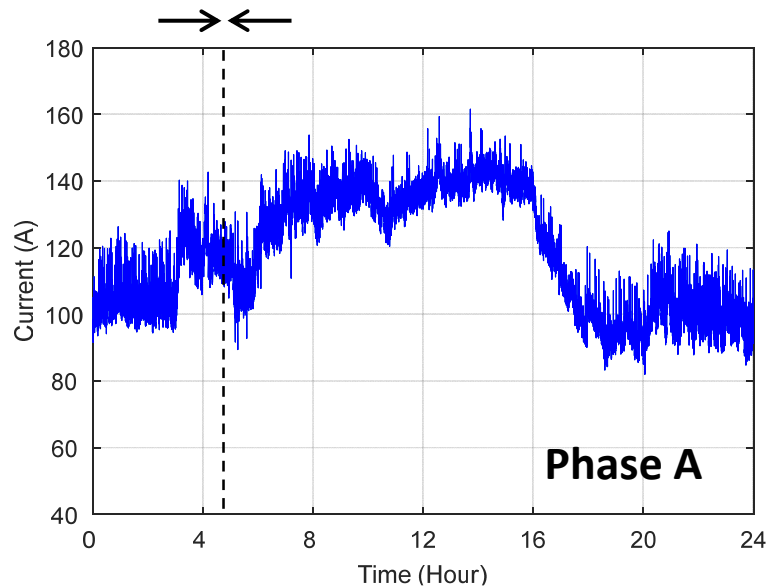


Micro-PMU  
(Riverside, CA)



120 Million Data Points Per Day

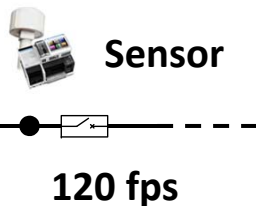
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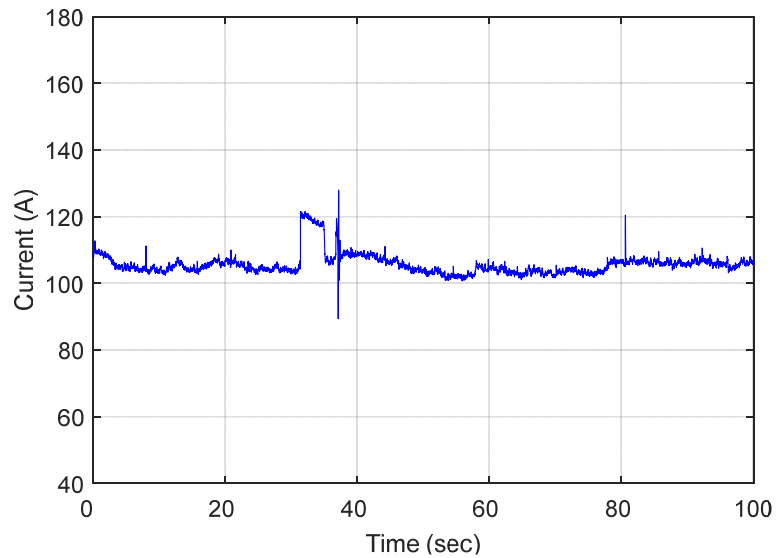


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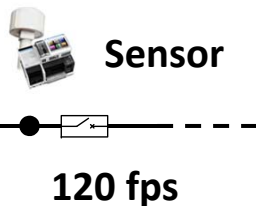
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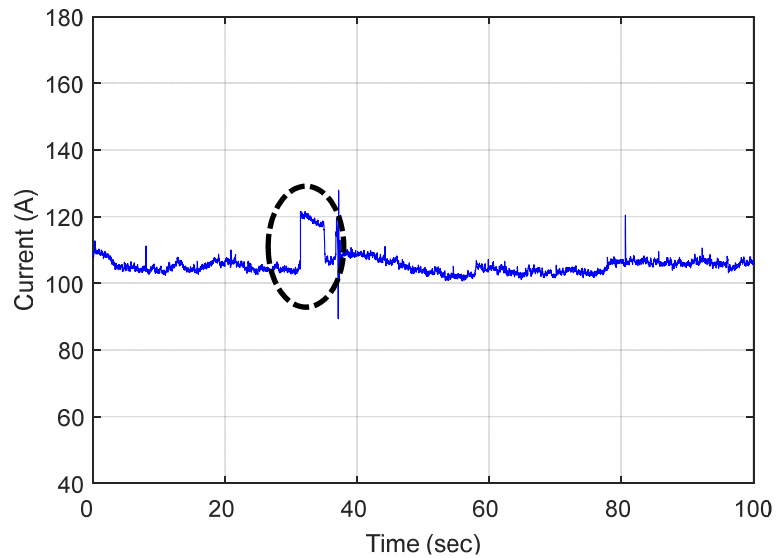


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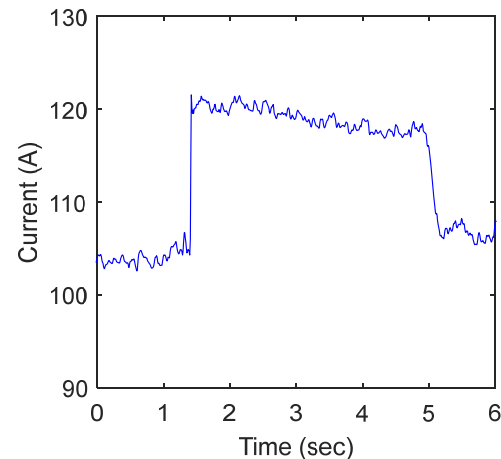
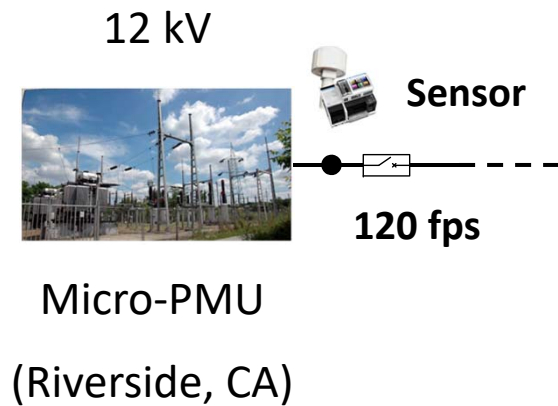
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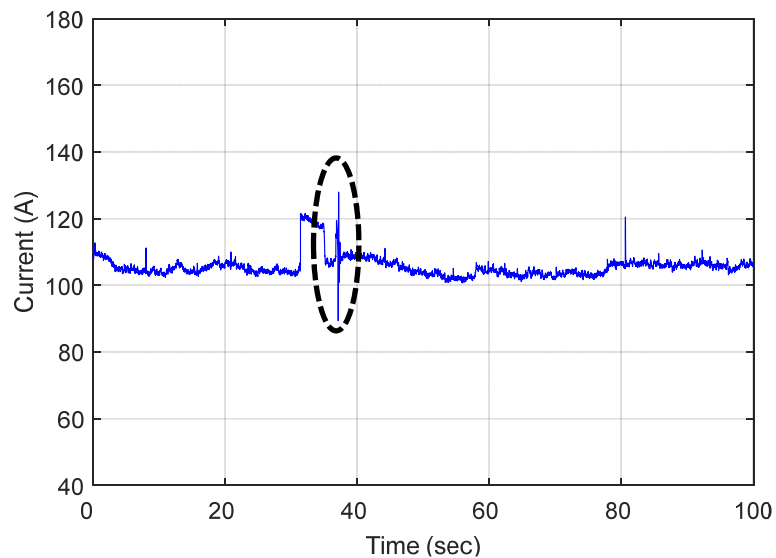


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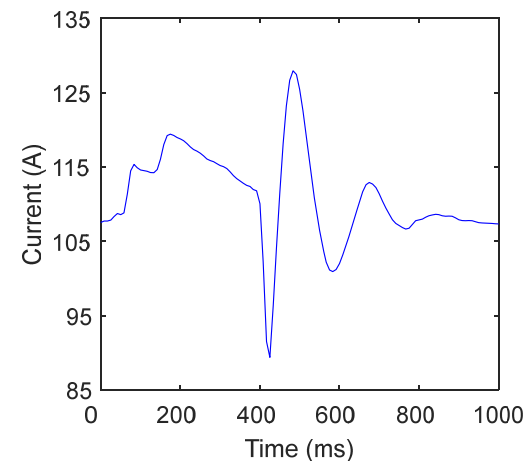
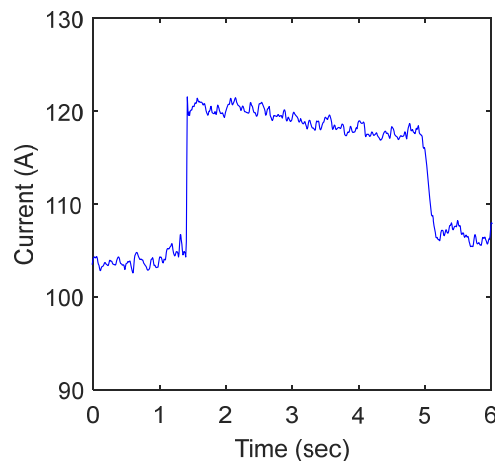
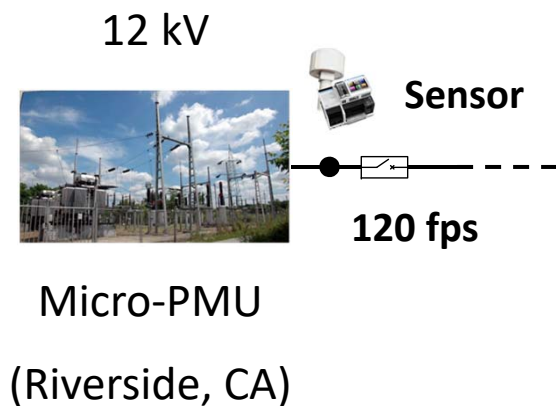


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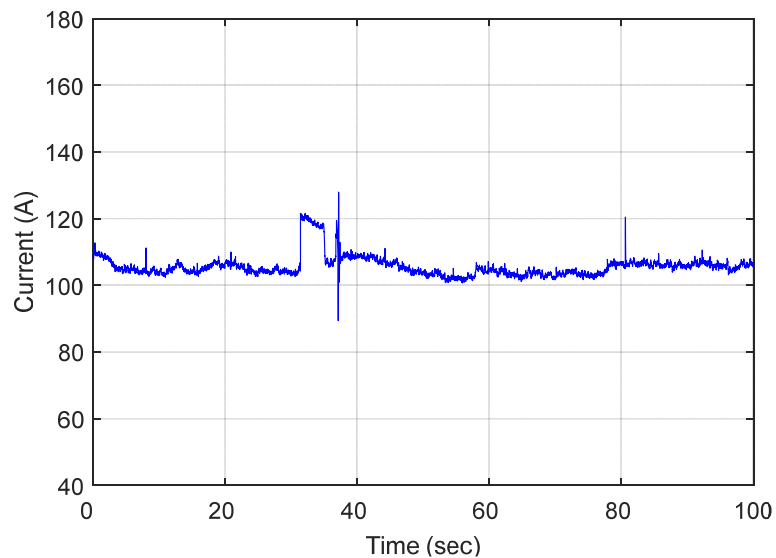


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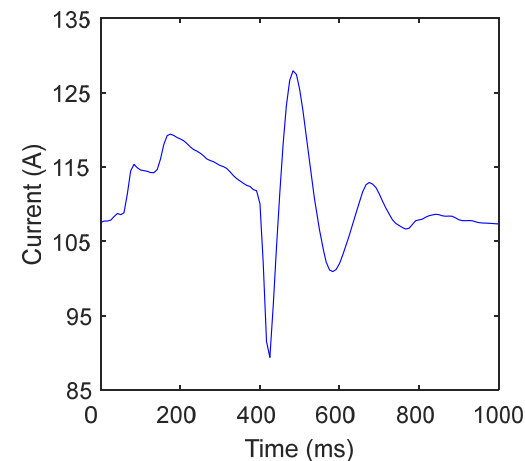
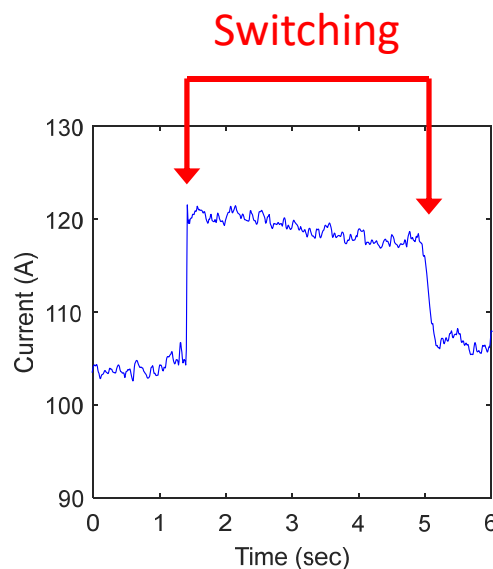
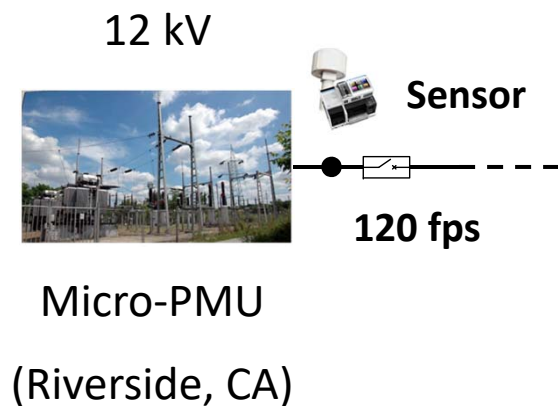


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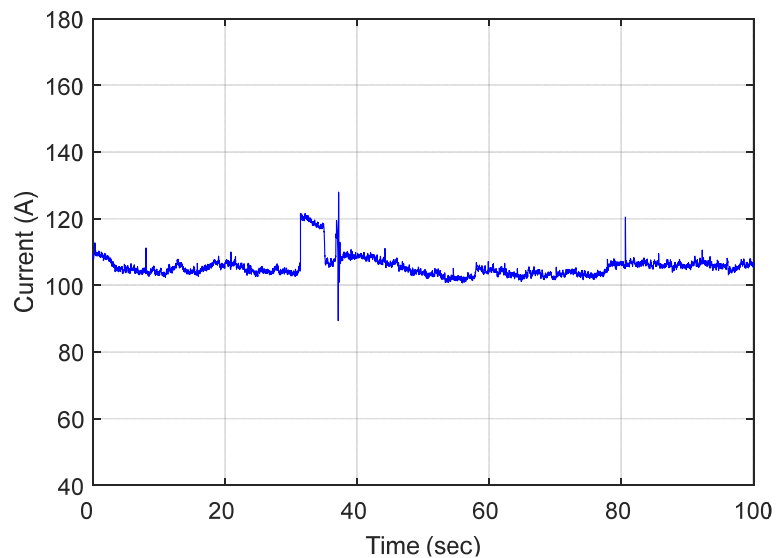
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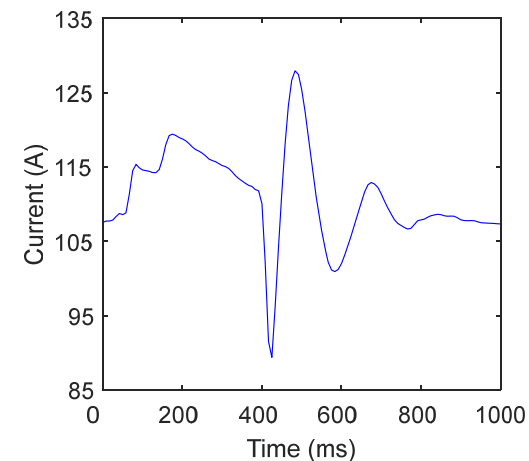
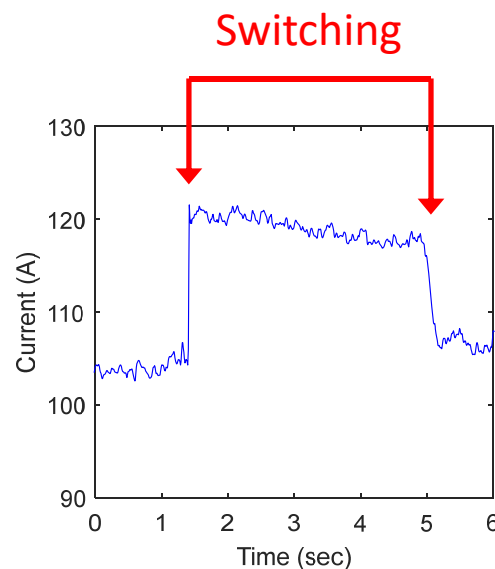
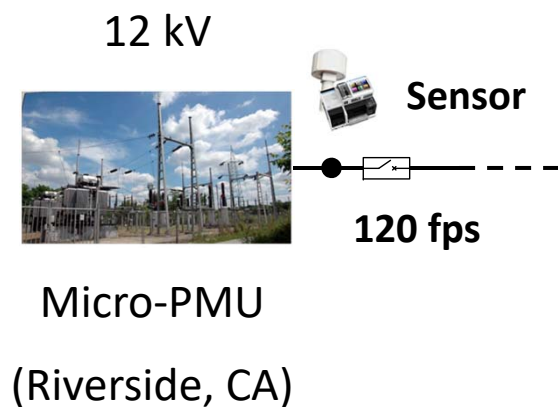




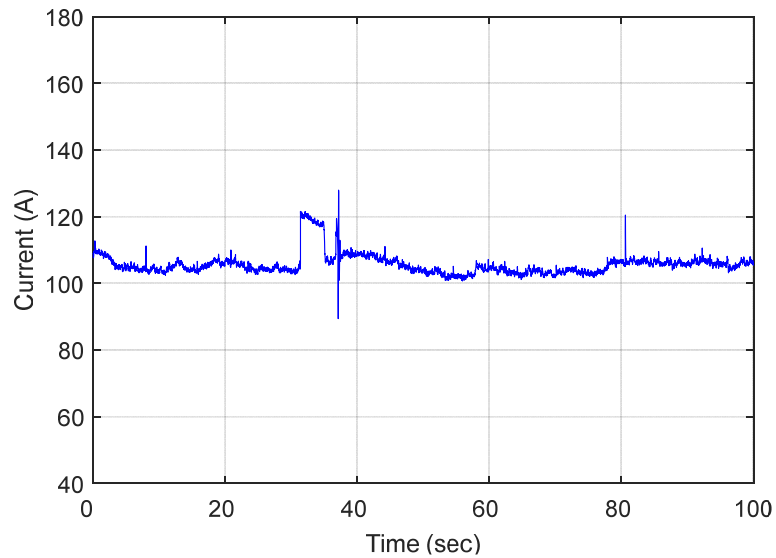
# Background: Events in Micro-PMU Data Streams



**On Average: 500 Events Per Day Per Feeder**

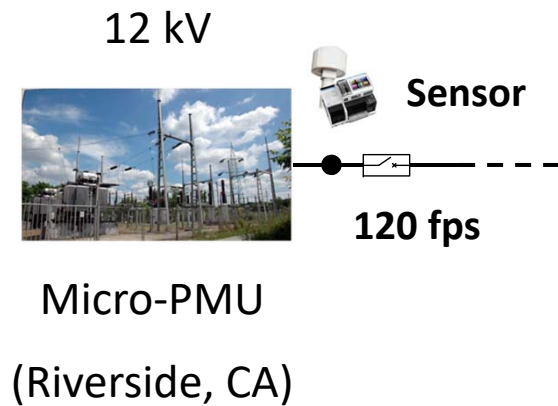


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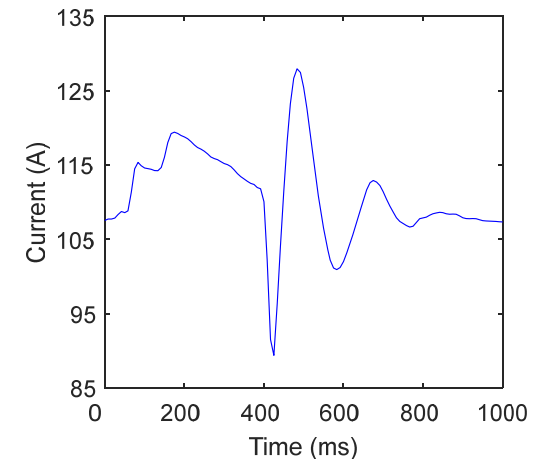
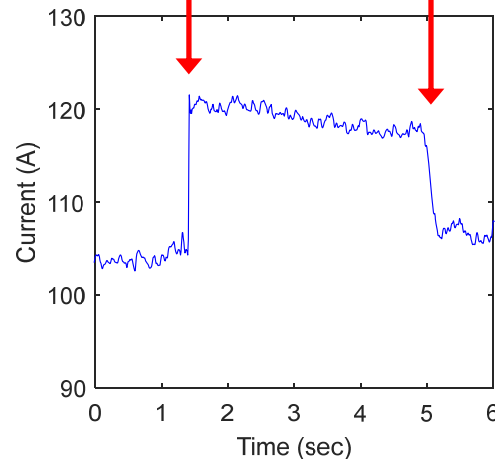


~~Data Stream~~

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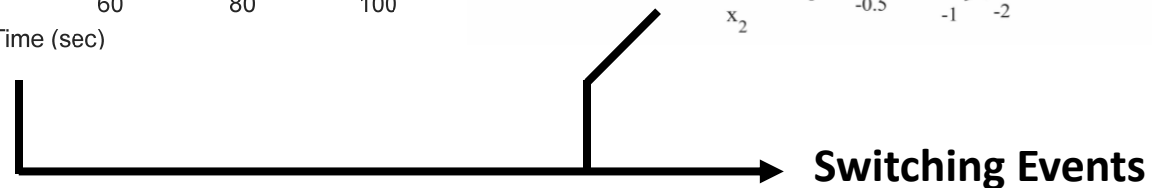
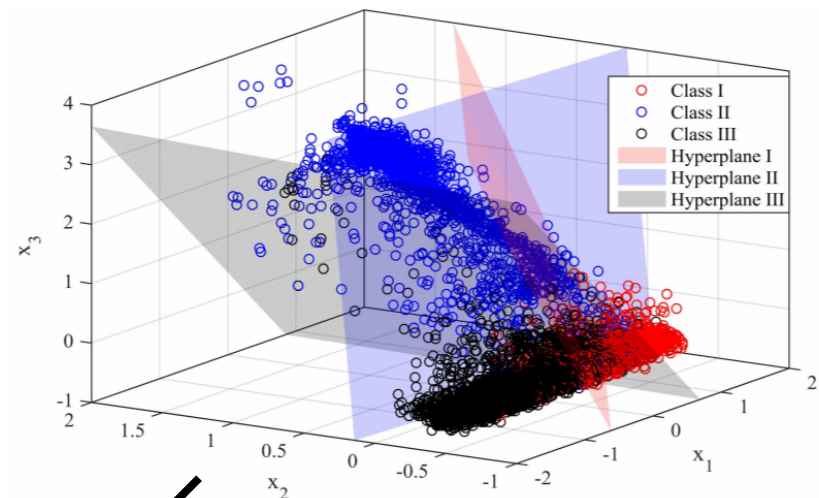
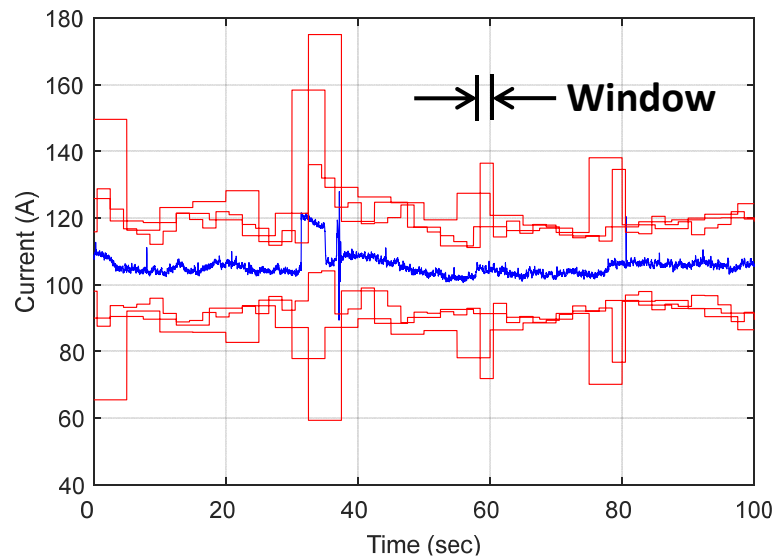


Switching



# Previous Results

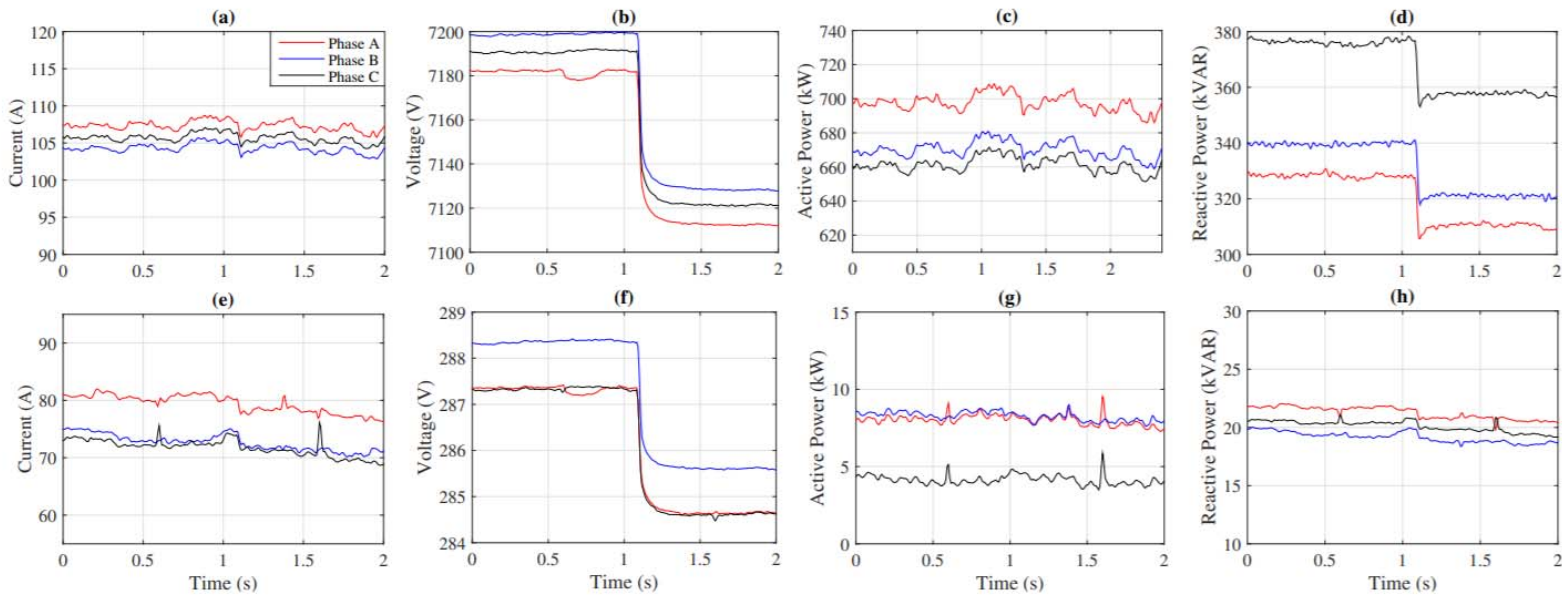
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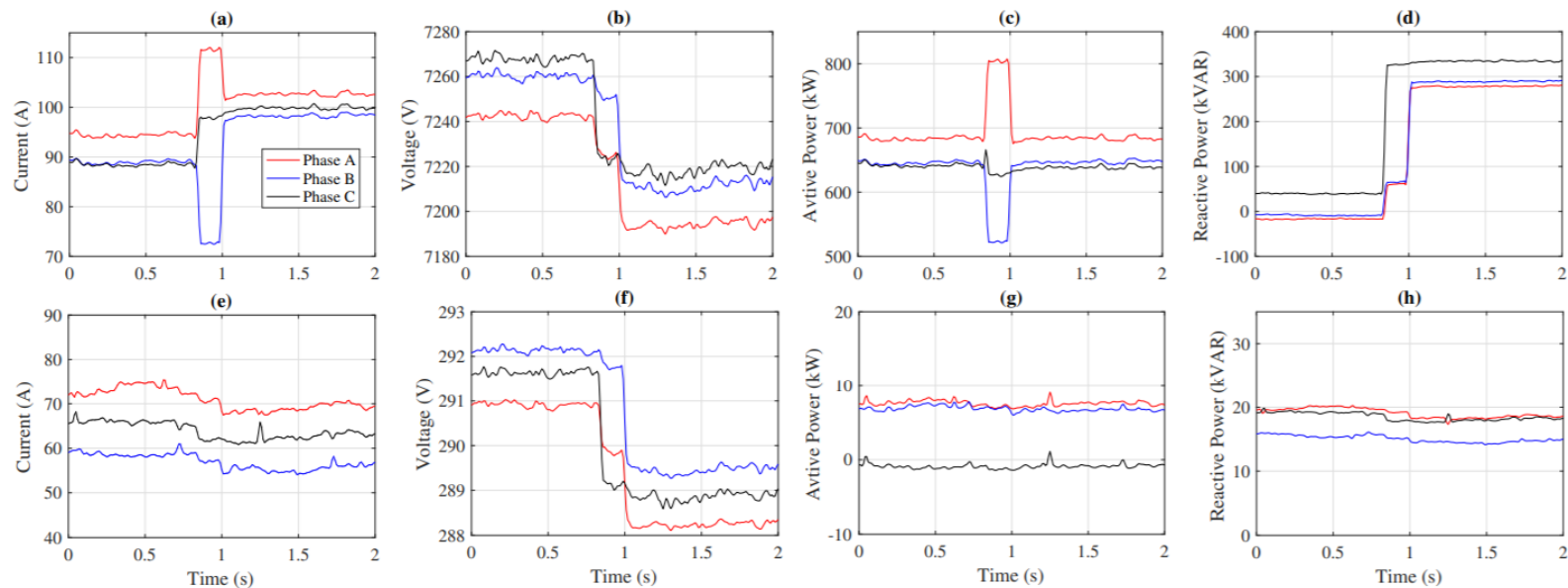


### Upstream Event (Sub-transmission or Transmission)

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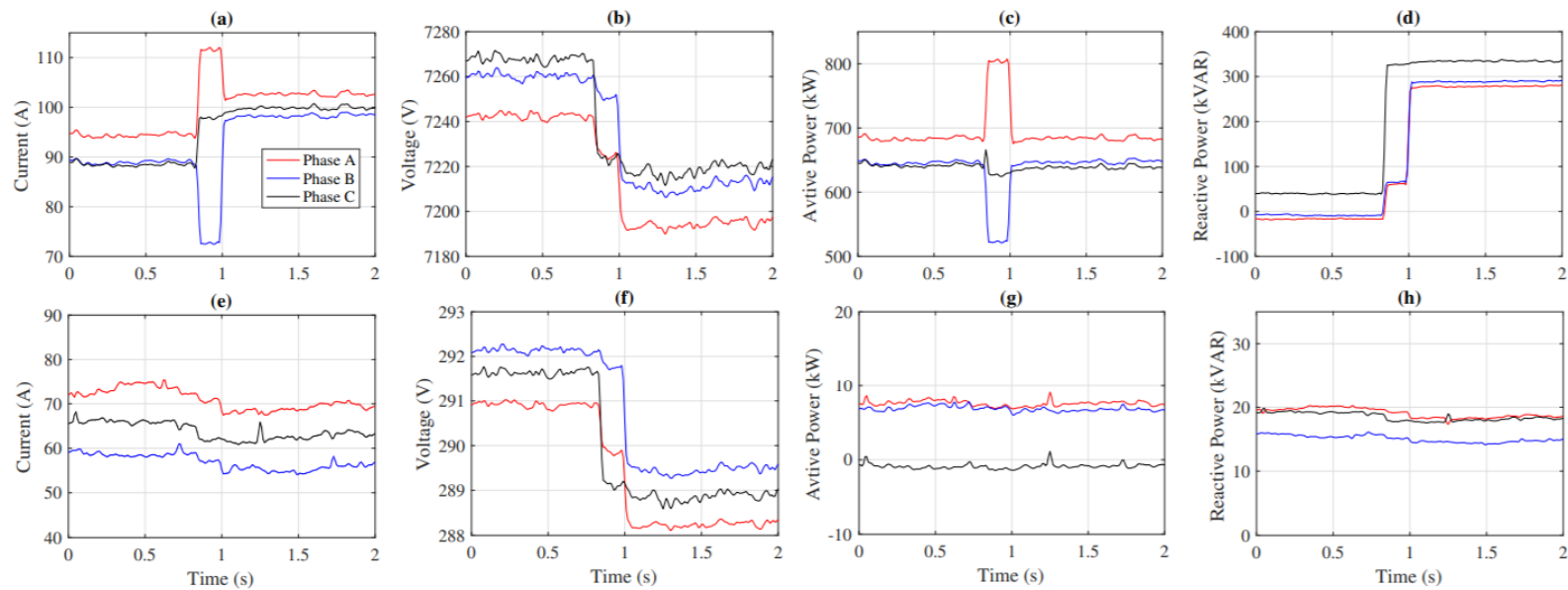


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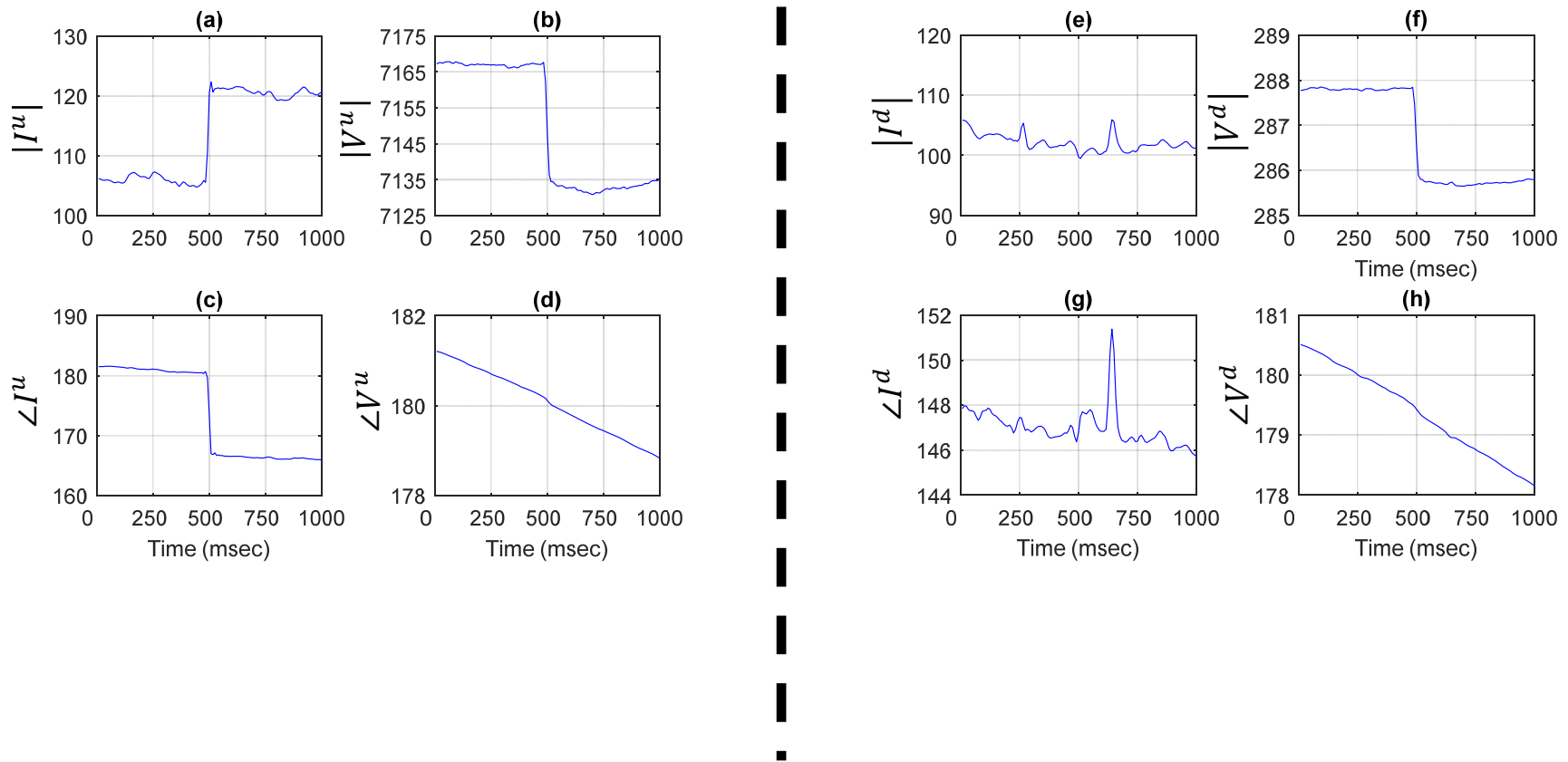


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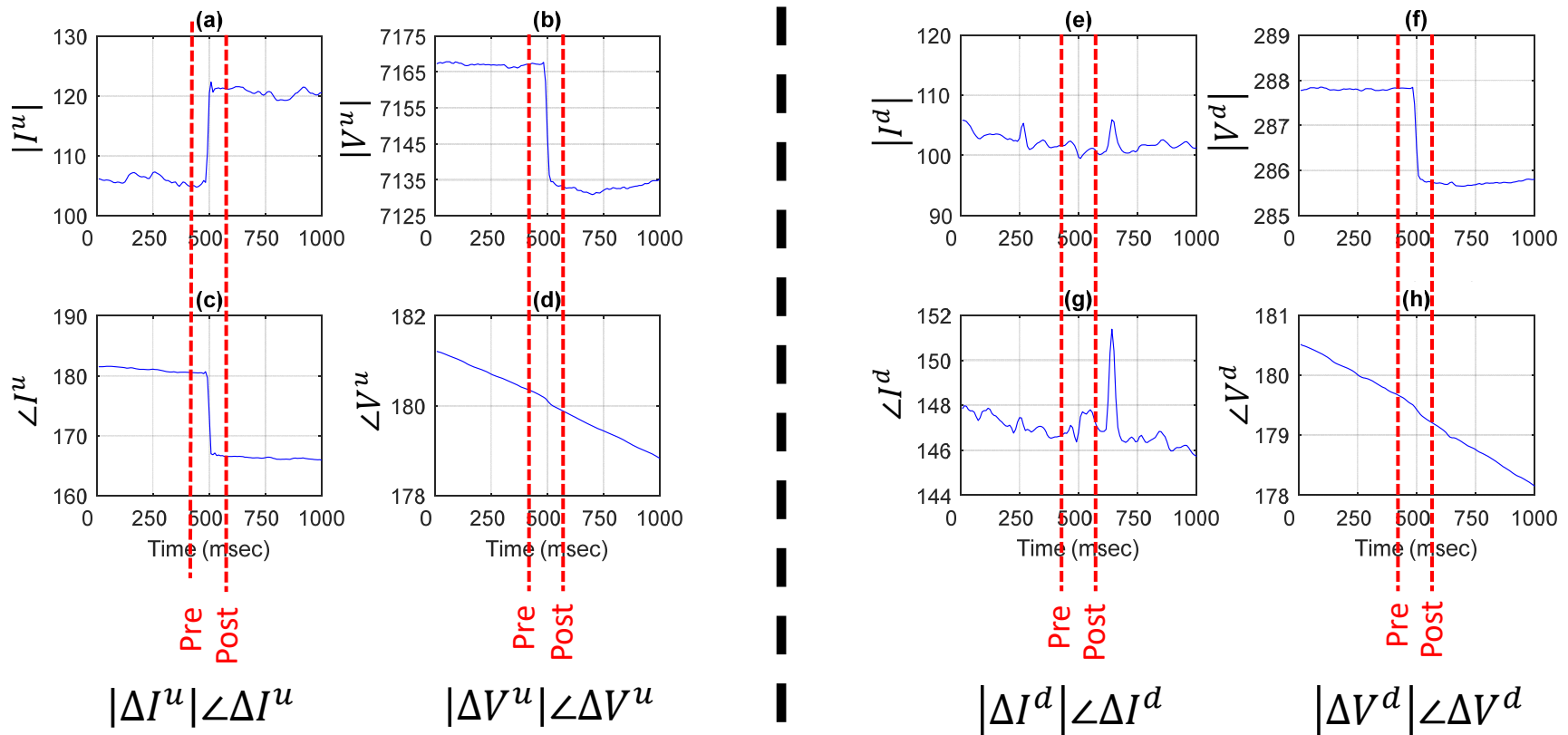
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[2] M. Farajollahi, A. Shahsavari, E. Stewart, H. Mohsenian-Rad, "Locating the Source of Events in Power Distribution Systems Using Micro-PMU Data," *IEEE Trans. on Power Systems* vol. 33, no. 6, Nov. 2018.

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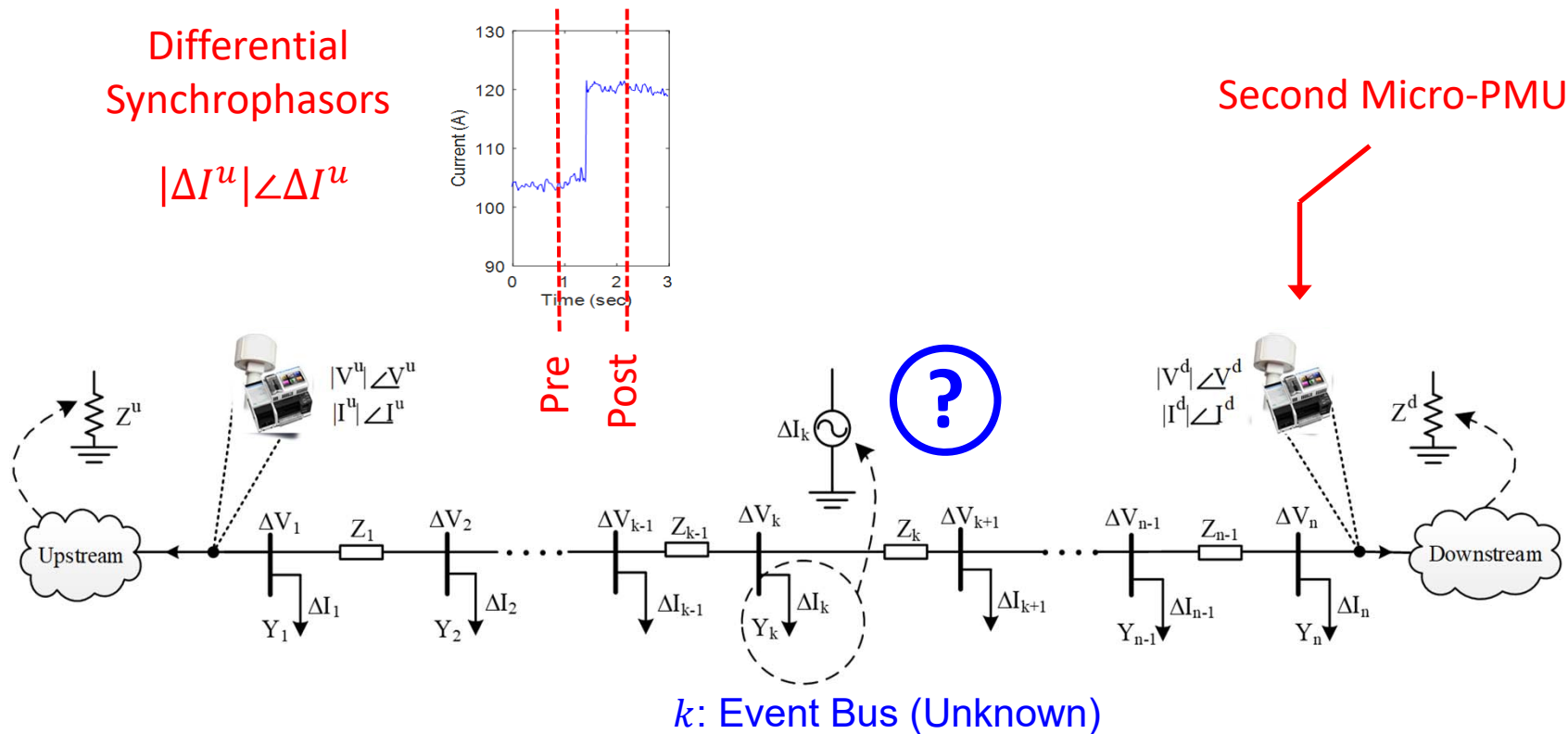


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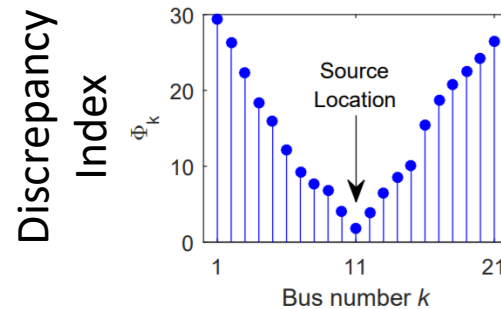
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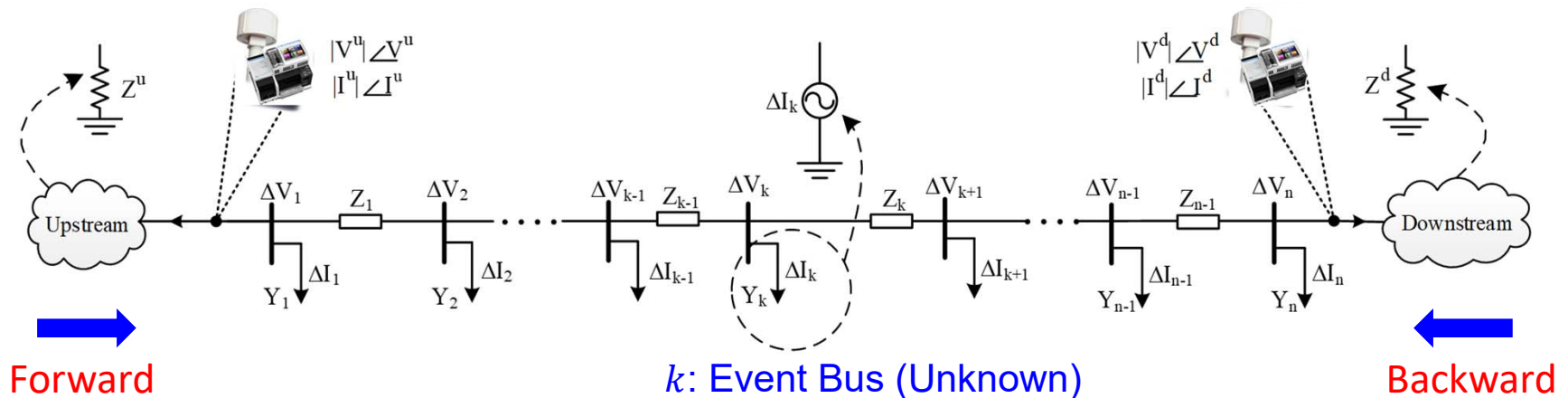
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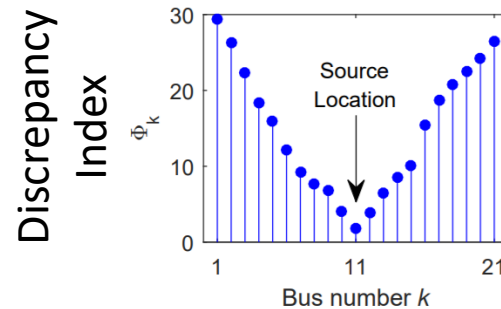
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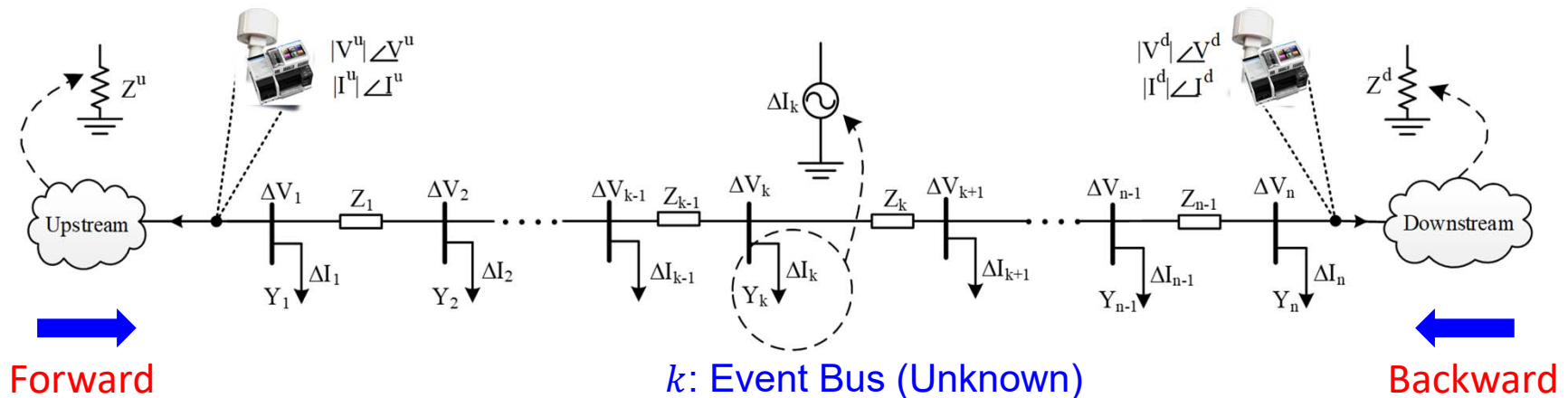
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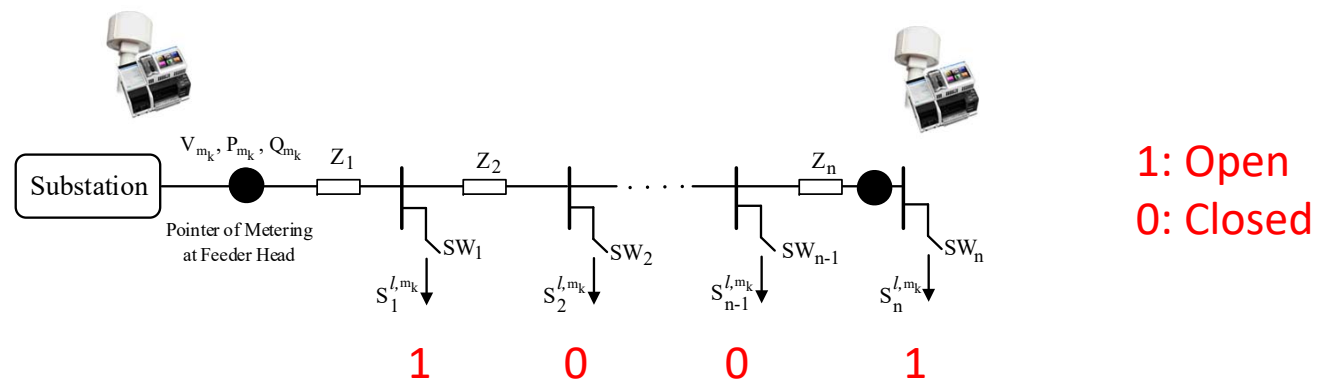
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# Observations

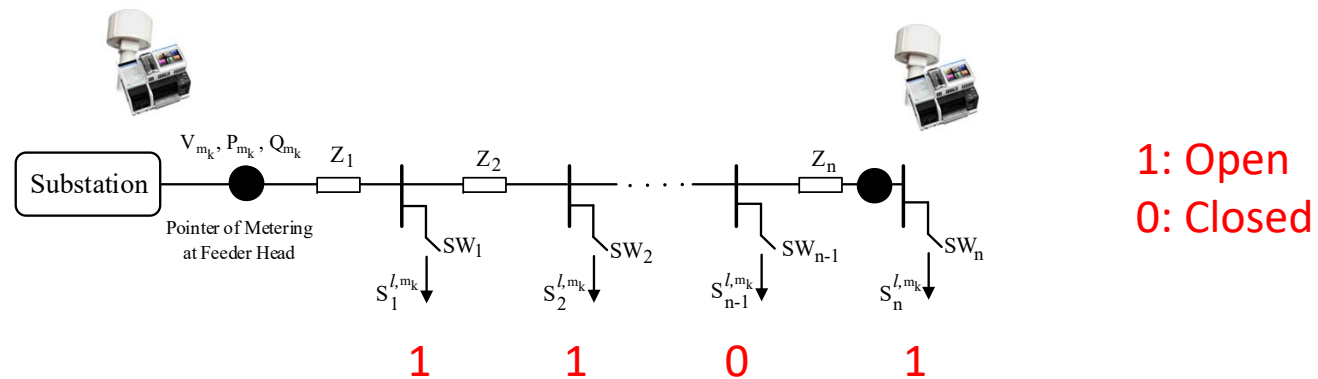
- We used only two micro-PMUs
- We can **remotely** and **automatically** monitor all **load switching events**



- Therefore, we can keep track of switching configurations.

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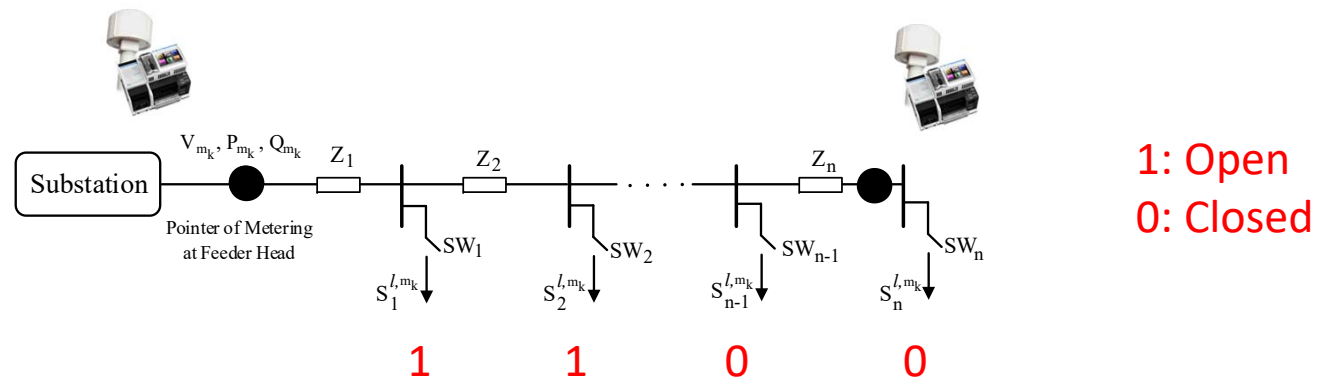
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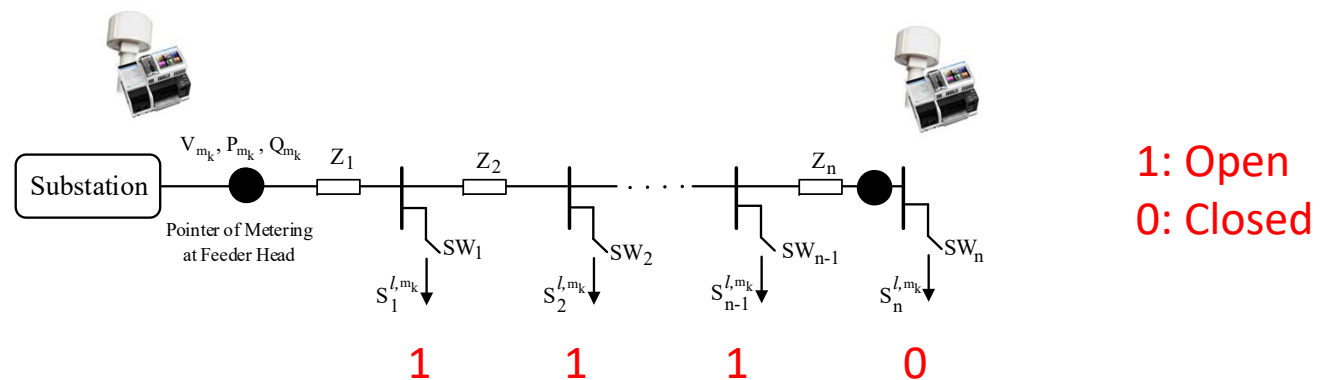
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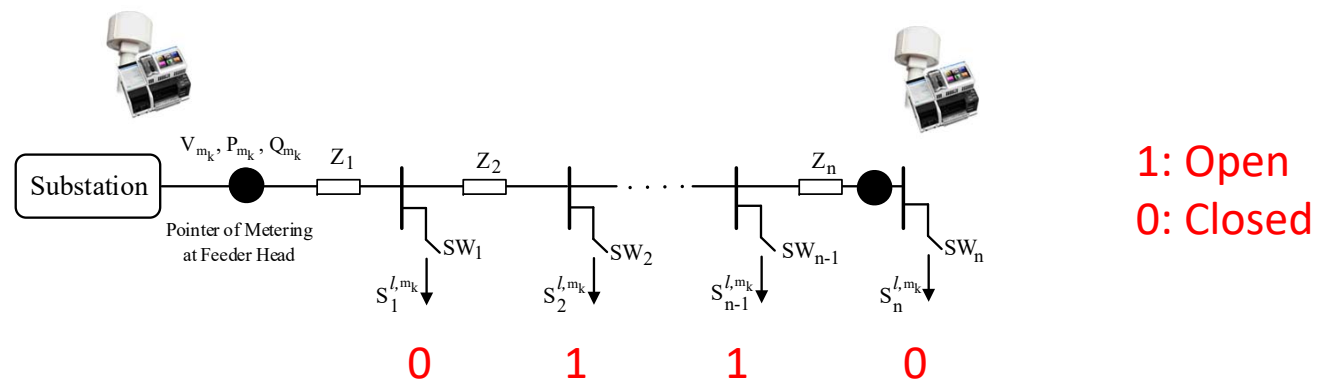
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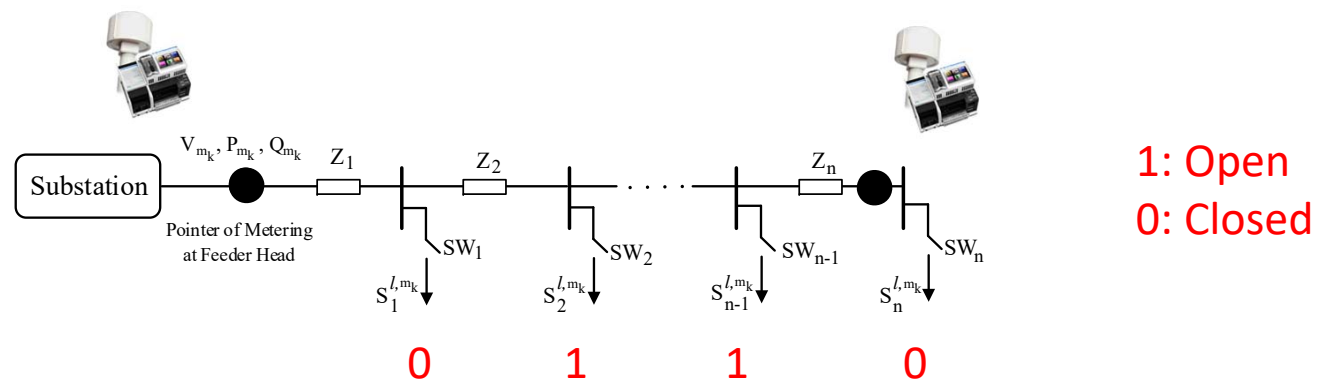


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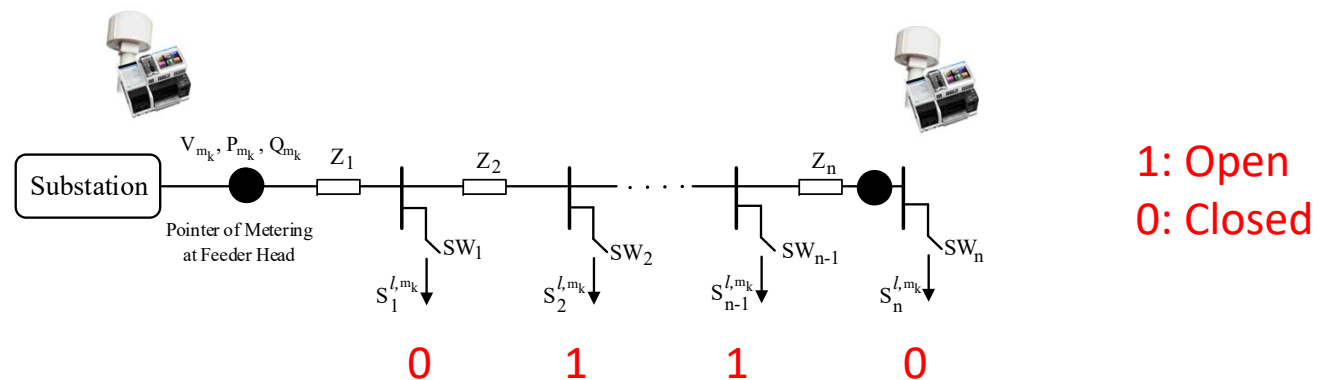


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**Q: What can we do with this?**

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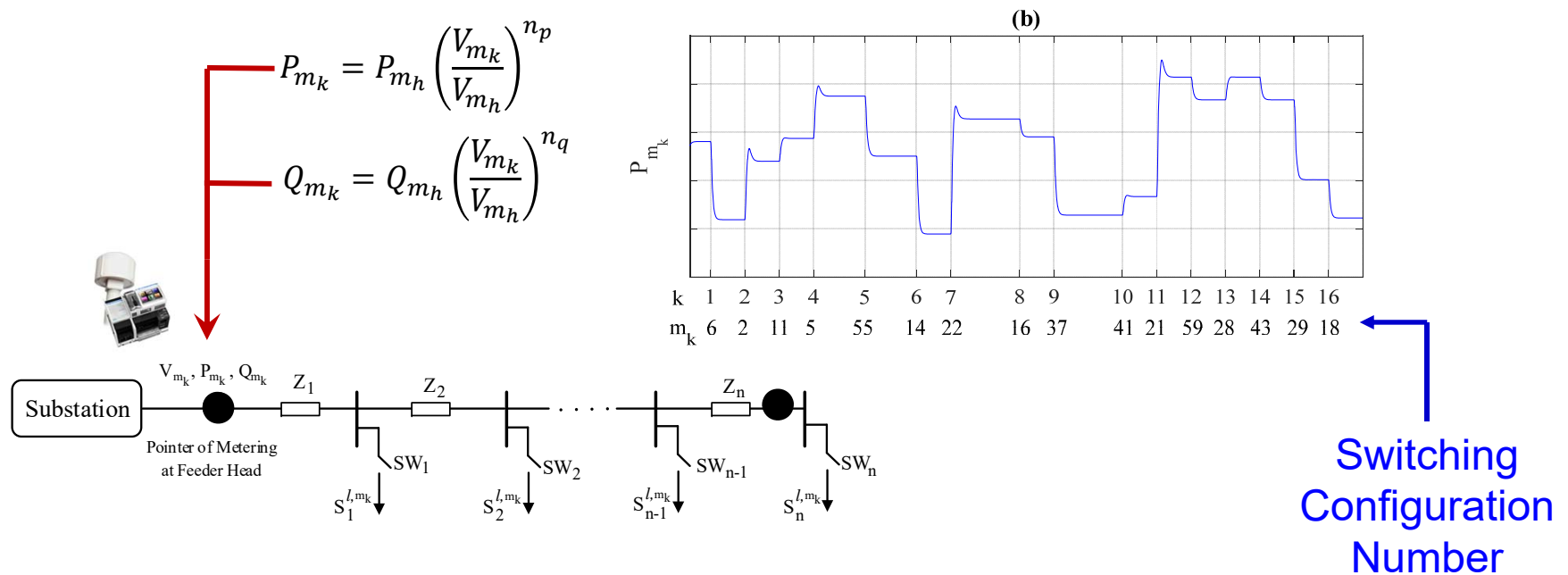
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**A: Nonintrusive Load Modeling**

# Nonintrusive Load Modeling

- Feeder Aggregated Load Model:**

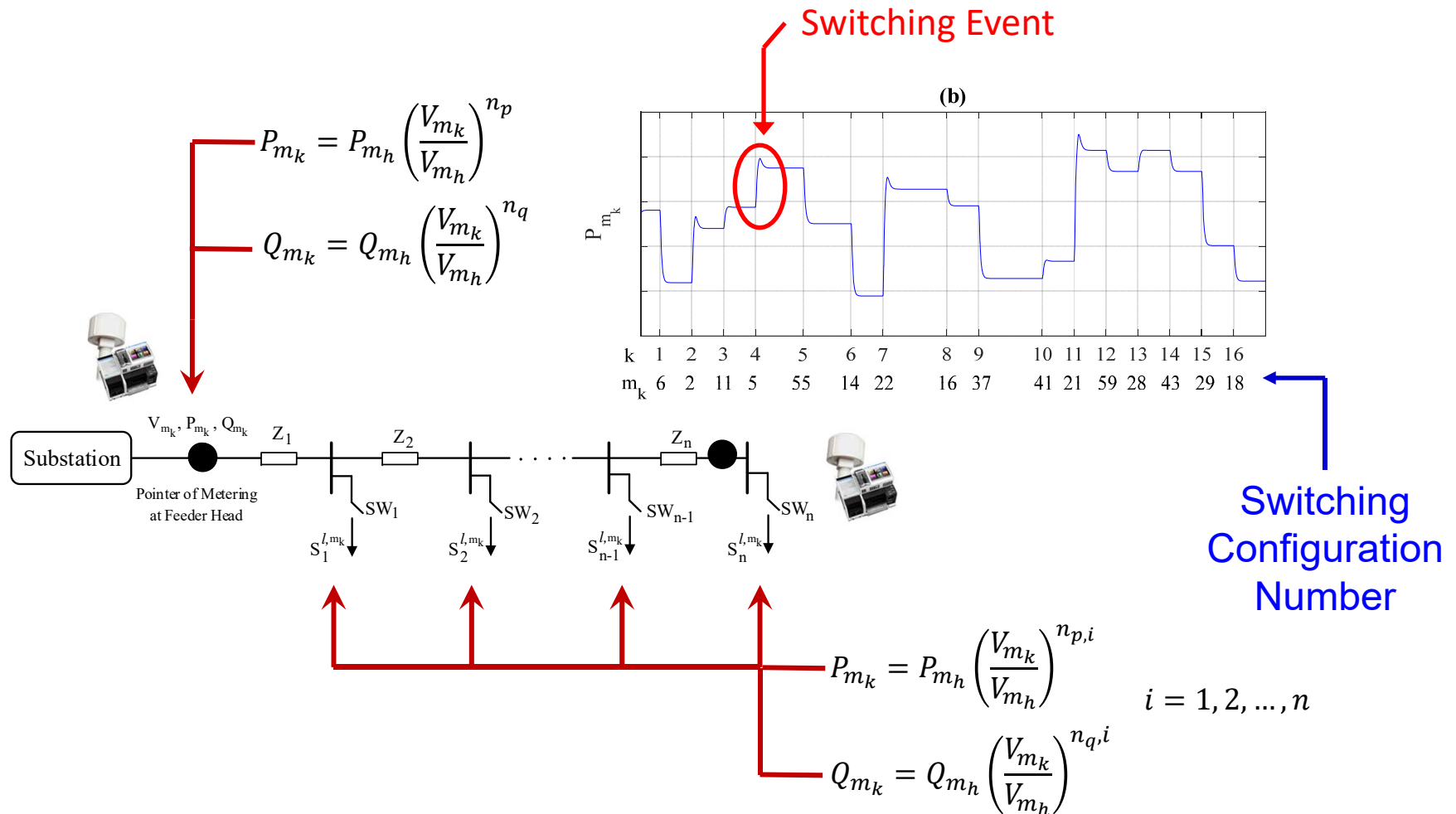


## A Variation of the “ZIP Model”.



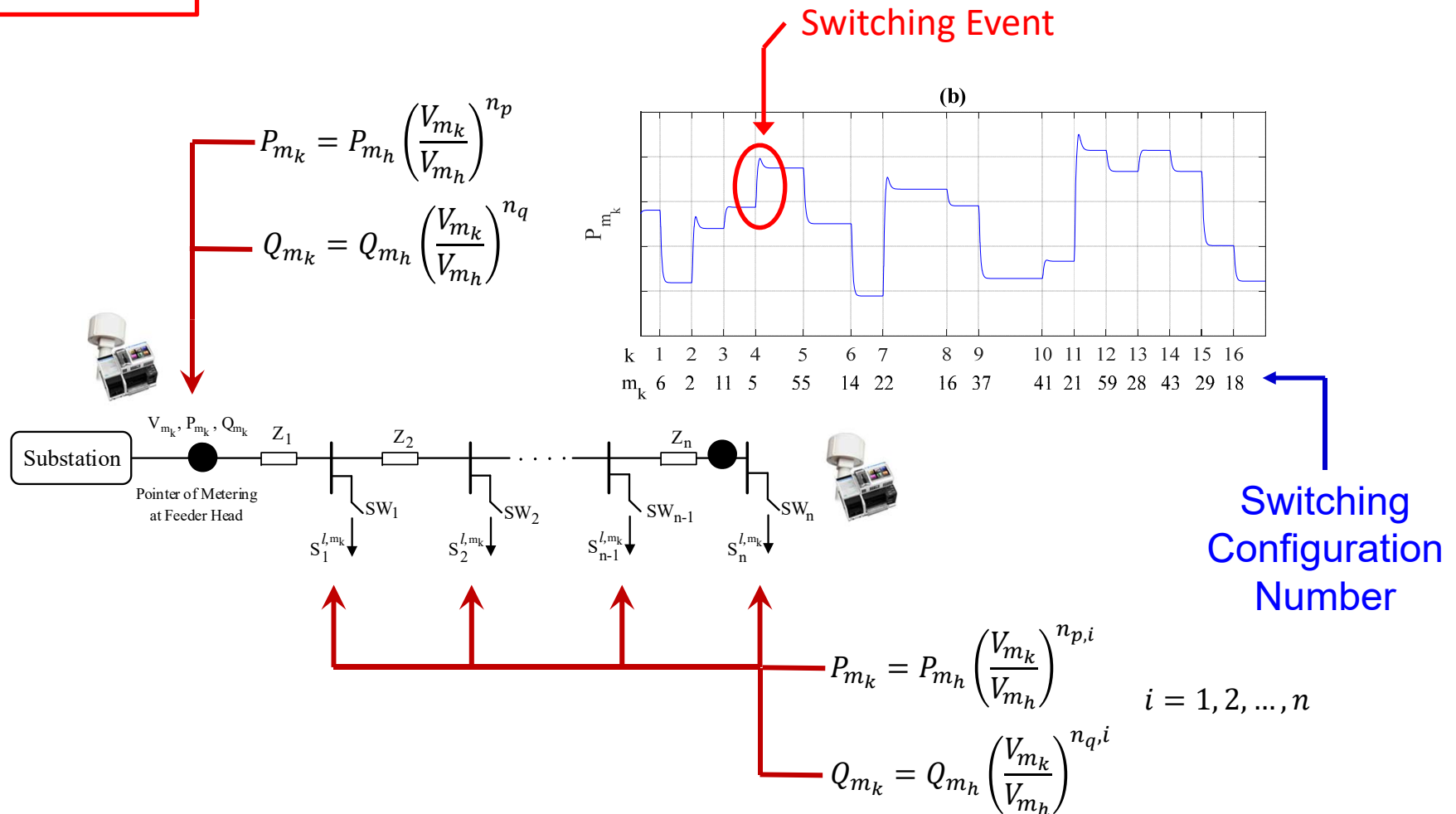
# Nonintrusive Load Modeling

- Individual Load Models:



# Nonintrusive Load Modeling

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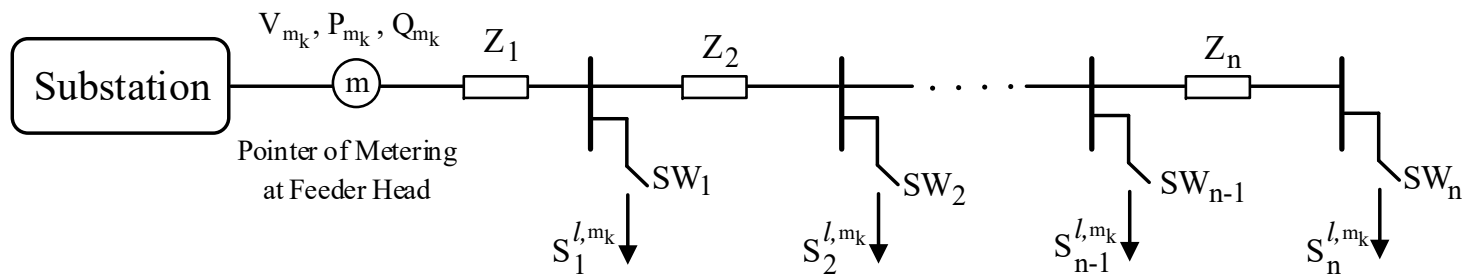
# Step 1: Circuit Model Equations

- Complex Power Conservation:**

$$S_{m_k} = \underbrace{\sum_{i=1}^n (S_i^{l,m_k} SW_i^{m_k})}_{\text{Total Load}} + \sum_{j=1}^n Z_j \left[ \underbrace{\sum_{d=j}^n \left( \frac{S_d^{l,m_k}}{V_d^{l,m_k}} \right)^* \times SW_d^{m_k}}_{\text{Current in Line } j} \right]^2$$

Switching Configuration  $\uparrow$

# of Equations = 1



Parameter  $SW_i^{m_k}$  is one if the individual load  $i$  is turned on during switching configuration  $m_k$ ; and zero otherwise

# Step 1: Circuit Model Equations

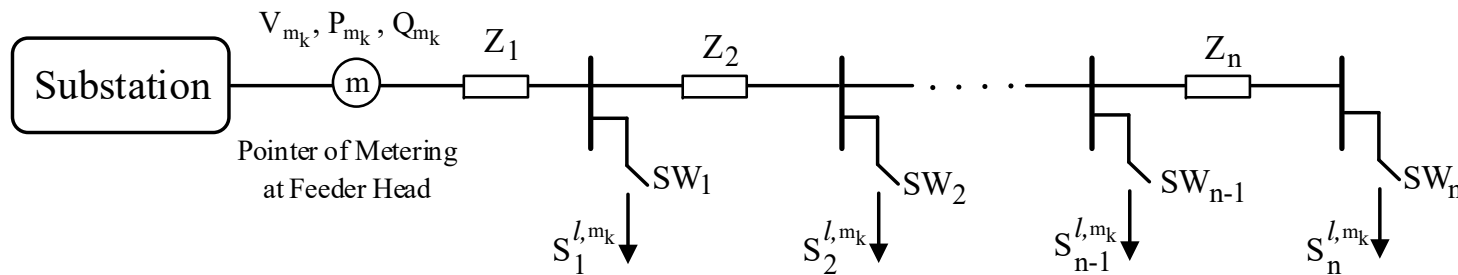
- KVL:**

Voltage at Substation

$$V_i^{m_k} = V_{m_k} - \sum_{j=1}^i Z_j \left( \sum_{d=j}^n \left( \frac{S_d^{l,m_k}}{V_d^{l,m_k}} \right)^* SW_d^{m_k} \right)$$

Voltage Drop at Line  $j$

# of Equations =  $n$



# Step 1: Circuit Model Equations

- **Combined Equations:**

$$S_{m_k} = \sum_{i=1}^n (S_i^{l,m_k} SW_i^{m_k}) + \sum_{j=1}^n Z_j \left| \sum_{d=j}^n \left( \frac{S_d^{l,m_k}}{V_d^{l,m_k}} \right)^* \times SW_d^{m_k} \right|^2$$

$$V_i^{m_k} = V_{m_k} - \sum_{j=1}^i Z_j \left( \sum_{d=j}^n \left( \frac{S_d^{l,m_k}}{V_d^{l,m_k}} \right)^* SW_d^{m_k} \right), i = 1, \dots, n$$

**Unknowns:**  $S_i^{l,m_k}$  and  $V_i^{m_k}$  for  $i = 1, \dots, n$

- **For any switching configuration  $m_k$ :**

<u>Number of Equations:</u>		<u>Number of Unknowns :</u>
$n + 1$	$<$	$n + \sum_{i=1}^n SW_i^{m_k}$



## Step 2: Load Model Equations

- For any two distinct switching configurations  $m_k$  and  $m_h$ :

$$S_i^{l,m_k} = P_i^{l,m_h} \left( \frac{|V_i^{m_k}|}{|V_i^{m_h}|} \right)^{n_{p_i}} + j Q_i^{l,m_h} \left( \frac{|V_i^{m_k}|}{|V_i^{m_h}|} \right)^{n_{q_i}}$$

**Necessary Condition:**  $\sum_{k=1}^c SW_i^{m_k} \geq 2$

**Additional Unknowns:**  
 $n_{s_i} = n_{p_i} + j n_{q_i}$  for  $i = 1, \dots, n$

## Step 3: Solving the System of Equations

- **Given  $c$  distinct switching configurations:**

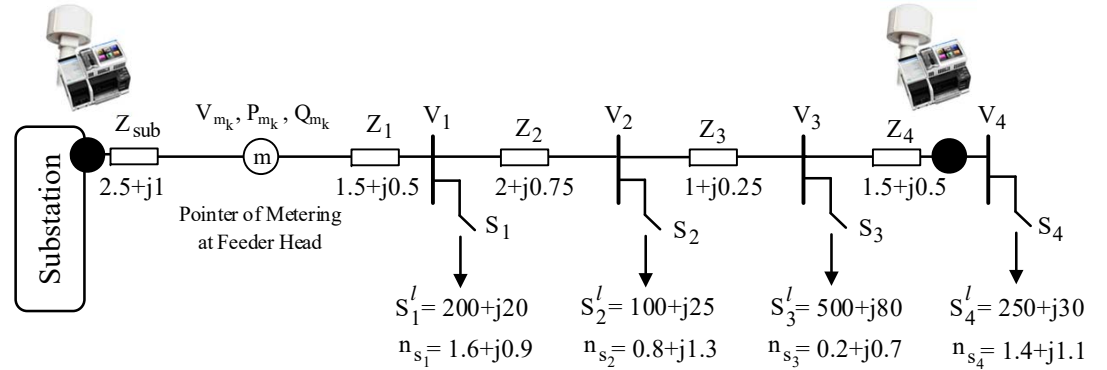
# of Unknowns: 
$$n \times c + \sum_{k=1}^c \sum_{i=1}^n SW_i^{m_k} + n$$

# of Equations: 
$$c \times (n + 1) + \sum_{i=1}^n \sum_{k=1}^c SW_i^{m_k} - n$$

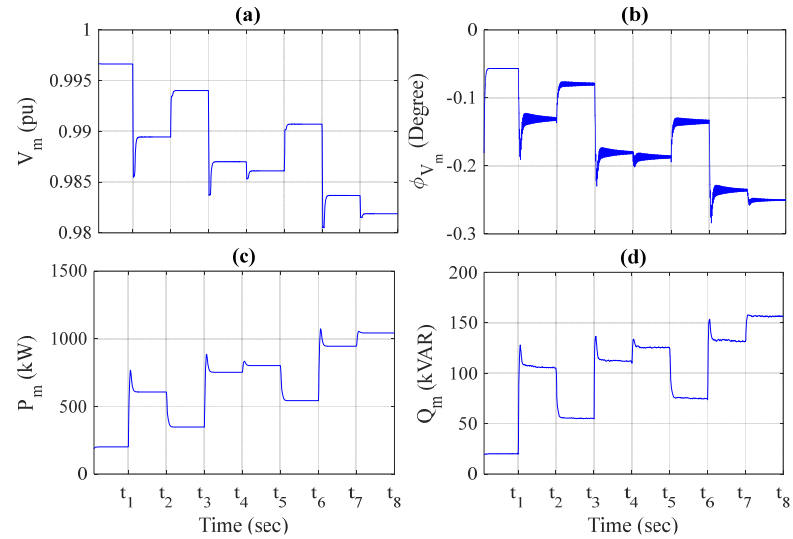
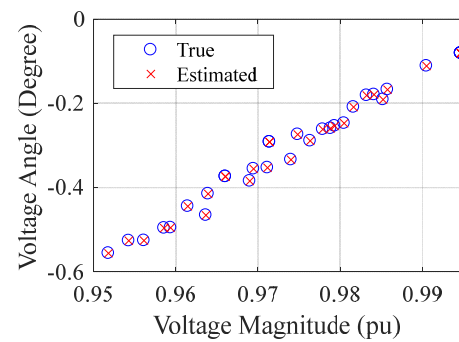
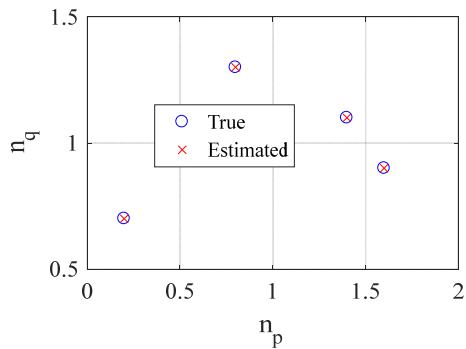
**Theorem:** We need to observe at least  $c_{min} = 2n$  distinct switching configurations to solve the nonintrusive individual load modeling problem.

# Illustrative Example

Configuration	SW <sub>1</sub>	SW <sub>2</sub>	SW <sub>3</sub>	SW <sub>4</sub>	Time
<i>m</i> <sub>1</sub>	1	0	0	0	[0, <i>t</i> <sub>1</sub> ]
<i>m</i> <sub>2</sub>	0	1	1	0	[ <i>t</i> <sub>1</sub> , <i>t</i> <sub>2</sub> ]
<i>m</i> <sub>3</sub>	0	1	0	1	[ <i>t</i> <sub>2</sub> , <i>t</i> <sub>3</sub> ]
<i>m</i> <sub>4</sub>	0	0	1	1	[ <i>t</i> <sub>3</sub> , <i>t</i> <sub>4</sub> ]
<i>m</i> <sub>5</sub>	1	1	1	0	[ <i>t</i> <sub>4</sub> , <i>t</i> <sub>5</sub> ]
<i>m</i> <sub>6</sub>	1	1	0	1	[ <i>t</i> <sub>5</sub> , <i>t</i> <sub>6</sub> ]
<i>m</i> <sub>7</sub>	1	0	1	1	[ <i>t</i> <sub>6</sub> , <i>t</i> <sub>7</sub> ]
<i>m</i> <sub>8</sub>	1	1	1	1	[ <i>t</i> <sub>7</sub> , <i>t</i> <sub>8</sub> ]

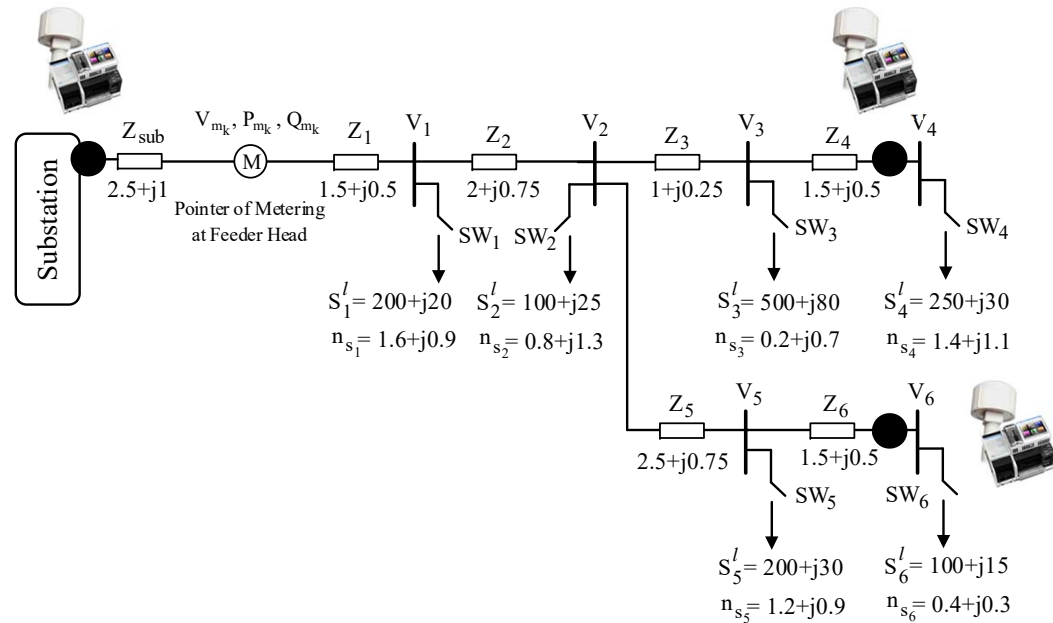


	# of Equations	# of Unknowns
Circuit Model	40	52
Load Model	16	4
Combined	56	56

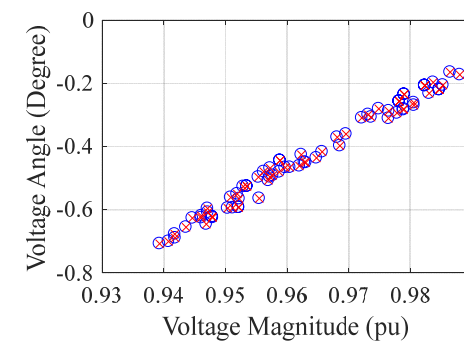
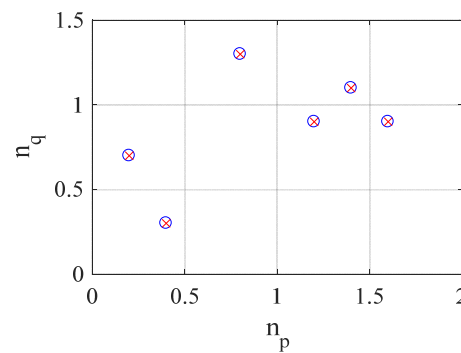


# Extension 1: Distribution Feeder with Laterals

Configuration	$SW_1$	$SW_2$	$SW_3$	$SW_4$	$SW_5$	$SW_6$	Time
$m_1$	1	0	0	1	0	0	$[0, t_1]$
$m_2$	1	0	0	1	0	1	$[t_1, t_2]$
$m_3$	1	1	0	0	1	0	$[t_2, t_3]$
$m_4$	0	0	1	1	0	1	$[t_3, t_4]$
$m_5$	0	1	1	1	0	1	$[t_4, t_5]$
$m_6$	1	1	0	0	1	1	$[t_5, t_6]$
$m_7$	0	1	1	0	1	1	$[t_6, t_7]$
$m_8$	1	0	1	1	1	0	$[t_7, t_8]$
$m_9$	0	1	1	1	1	1	$[t_8, t_9]$
$m_{10}$	1	1	1	0	1	1	$[t_9, t_{10}]$
$m_{11}$	1	1	1	1	1	0	$[t_{10}, t_{11}]$
$m_{12}$	1	1	1	1	1	1	$[t_{11}, t_{12}]$

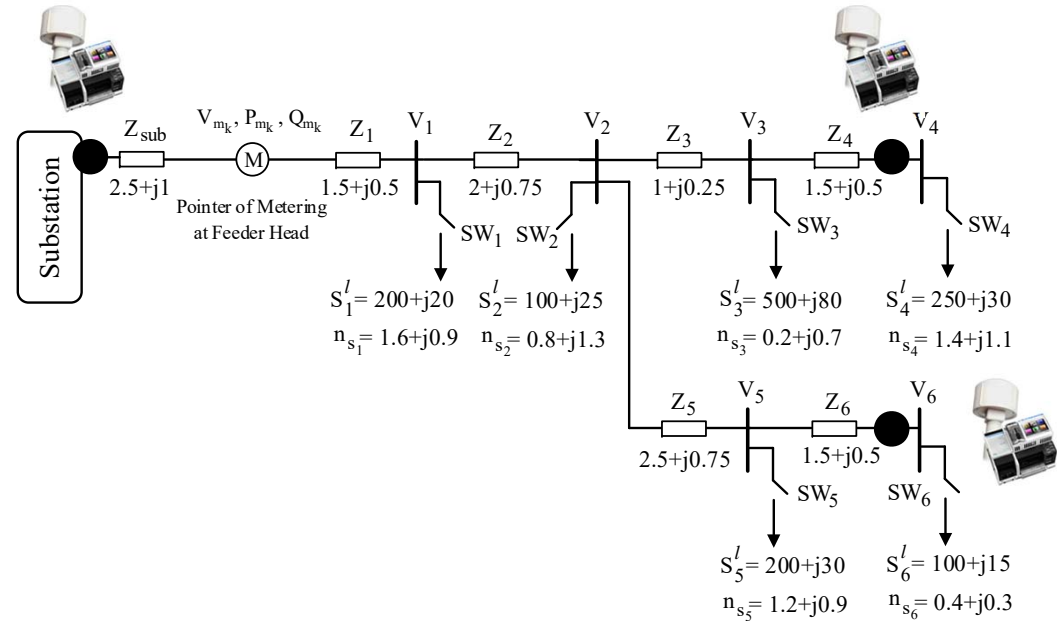


	# of Equations	# of Unknowns
Circuit Model	84	120
Load Model	42	6
Combined	126	126



# Extension 2: Redundant Switching Configurations

Configuration	$SW_1$	$SW_2$	$SW_3$	$SW_4$	$SW_5$	$SW_6$	Time
$m_1$	1	0	0	1	0	0	$[0, t_1]$
$m_2$	1	0	0	1	0	1	$[t_1, t_2]$
$m_3$	1	1	0	0	1	0	$[t_2, t_3]$
$m_4$	0	0	1	1	0	1	$[t_3, t_4]$
$m_5$	0	1	1	1	0	1	$[t_4, t_5]$
$m_6$	1	1	0	0	1	1	$[t_5, t_6]$
$m_7$	0	1	1	0	1	1	$[t_6, t_7]$
$m_8$	1	0	1	1	1	0	$[t_7, t_8]$
$m_9$	0	1	1	1	1	1	$[t_8, t_9]$
$m_{10}$	1	1	1	0	1	1	$[t_9, t_{10}]$
$m_{11}$	1	1	1	1	1	0	$[t_{10}, t_{11}]$
$m_{12}$	1	1	1	1	1	1	$[t_{11}, t_{12}]$



- We solve an “**estimation**” problem.

Error in Line Impedances

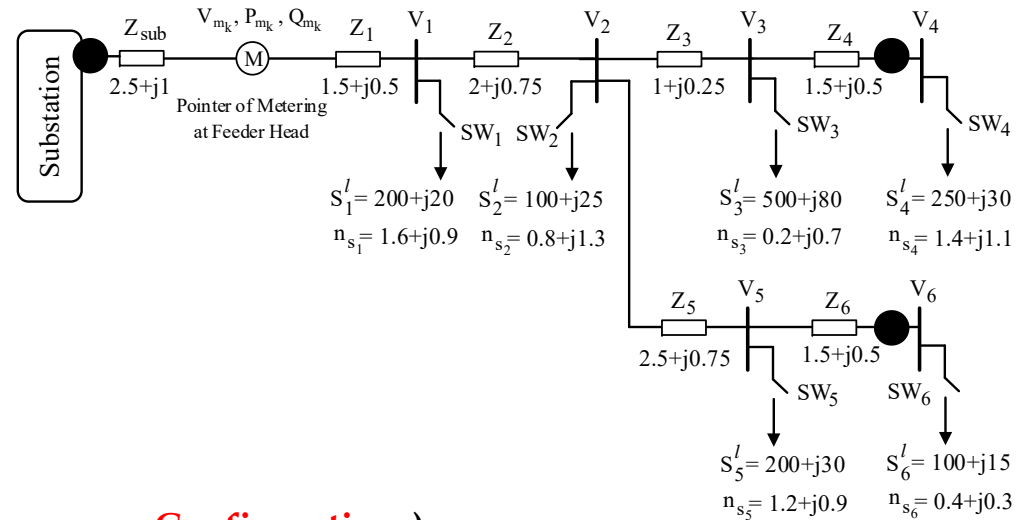
Error in Line Impedance	5%	10%	15%	20%	25%	30%
Error in Estimating $n_p$	0.09	0.93	1.30	1.98	2.54	3.38
Error in Estimating $n_q$	0.78	1.95	3.23	5.34	9.16	11.87

- # of Equations: 258
- # of unknowns: 246

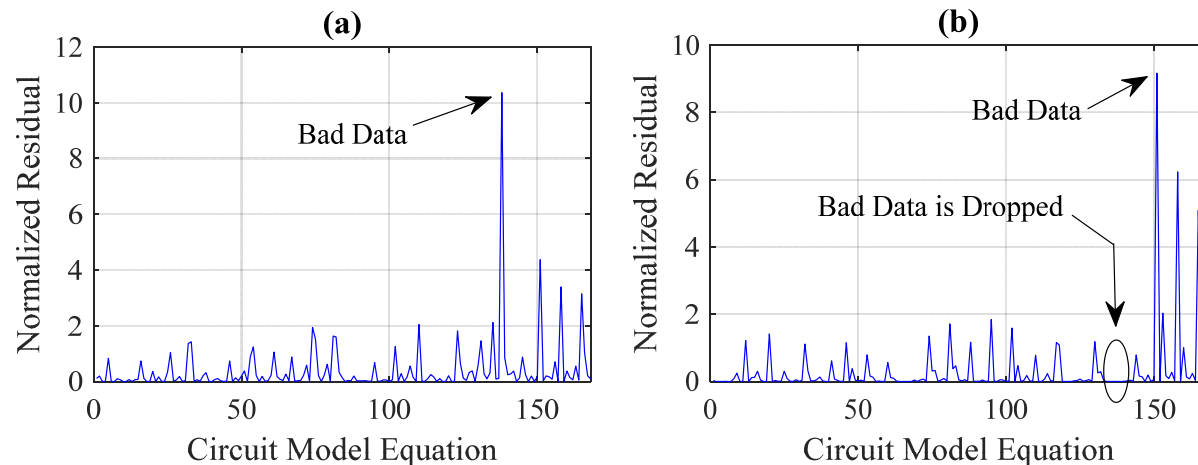
In Presence of Error in Measurements

# Extension 3: Identifying Erroneous Switching Status

Configuration	$SW_1$	$SW_2$	$SW_3$	$SW_4$	$SW_5$	$SW_6$	Time
$m_1$	1	0	0	1	0	0	$[0, t_1]$
$m_2$	1	0	0	1	0	1	$[t_1, t_2]$
$m_3$	1	1	0	0	1	0	$[t_2, t_3]$
$m_4$	0	0	1	1	0	1	$[t_3, t_4]$
$m_5$	0	1	1	1	0	1	$[t_4, t_5]$
$m_6$	1	1	0	0	1	1	$[t_5, t_6]$
$m_7$	0	1	1	0	1	1	$[t_6, t_7]$
$m_8$	1	0	1	1	1	0	$[t_7, t_8]$
$m_9$	0	1	1	1	1	1	$[t_8, t_9]$
$m_{10}$	1	1	1	0	1	1	$[t_9, t_{10}]$
$m_{11}$	1	1	1	1	1	0	$[t_{10}, t_{11}]$
$m_{12}$	1	1	1	1	1	1	$[t_{11}, t_{12}]$



- Residual Test (In Presence of Two **Erroneous Configurations**):



# Conclusions

- Install a few micro-PMUs at feeder head and end buses.

- Remotely and automatically Identify:

- ZIP Model for all individual loads across the distribution feeder.

Non-Intrusive

- AMI / Smart Meters:

- Not Available: Our Approach is a Replacement

- Available: Our Approach is an Oversight

- AMI Failure
    - Electricity Theft
    - Cybersecurity
    - ...

# Further Reading

IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 33, NO. 6, NOVEMBER 2018 4343

## 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 synchronized 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 a 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-PMUs 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 (PMUs), 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, ...

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CiteSeer versions of one or more of the figures in this paper are available online at <http://dx.doi.org/10.1109/TPWRS.2018.2832126>

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Transactions on Smart Grid 1

## 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 analysis are adopted as additional features to be fed into the classifier model. In this regard, a multi-class support vector machine (multi-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 1.2 billion measurement points, and 10,700 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 oscillation analysis.

**Keywords**: Machine learning, distribution synchrophasors, situational awareness, event detection, event classification, Big-Data.

### I. INTRODUCTION

The proliferation in 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 minute reporting intervals. As for smart meters, their report measurements occur 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 ...

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IEEE T. on Smart Grid 2019



# Further Reading (Cont.)

**Application of Load Switching Events in Steady-State Load Modeling in Power Distribution Networks**

Alireza Shahsavari, Mohammad Farajollahi, and Hamed Mohsenian-Rad  
Department of Electrical and Computer Engineering, University of California, Riverside, CA, USA

**Abstract**—A novel event-oriented method is proposed to conduct steady-state load modeling in power distribution systems. It has two fundamental differences with the comparable methods in the literature. First, the type of events are different. Specifically, the existing event-oriented load modeling methods use upstream voltage events as the main enabler for load modeling. In contrast, here we use the load switching events across the distribution feeder itself. Second, the objective of the analysis is different. The existing event-oriented load modeling methods are intended to obtain a ZIP model for the aggregate load of the entire distribution feeder. The application of such feeder-aggregated load models is in analysis of sub-transmission and transmission systems. In contrast, here we seek to obtain a ZIP model for each individual load across the feeder. The application of such individual load models is in the analysis of the distribution system itself, such as with respect to the operation of distributed energy resources. The performance of the proposed method is examined on a test-feeder under various operating scenarios by considering the impact of errors in feeder-head measurements.

**Keywords**: Event-oriented method, steady-state load modeling, distribution system analysis, load switching events.

**I. INTRODUCTION**

A recent CIGRE report in [1] has found that the majority of the utilities use measurement-based methods to estimate the parameters of their load models. Measurement-based load modeling can be classified static and dynamic. Our focus in this paper is on static load modeling, where the goal is to estimate the parameters of the so-called ZIP load models.

An important class of measurement-based static load modeling methods is *event-oriented*, i.e., they analyze certain events and the responses of the loads to those events in order to estimate the load modeling parameters. When it comes to event-oriented static load modeling at distribution-level, one can identify two common features for the existing methods. First, they are concerned with obtaining a ZIP model for the *entire* load of the feeder as seen by the distribution substation, such as the methods in [2]–[7]. Second, they use the *aperture* events to enable load modeling, such as voltage events that are initiated from outside the distribution feeder, e.g., see [2]–[7].

In this paper, we explore making use of a different type of events and seek to achieve a different load modeling objective. Specifically, we seek to investigate the load switching events on the distribution feeder itself in order to obtain models for the individual loads that exist across the feeder that is being studied. Accordingly, the methodology in this paper is inherently different compared to the existing event-oriented static load modeling approaches, such as those in [2]–[7].

This work was supported by NSF grants 1462530 and 1253516; DoE grant EE-000800; and NASA MBRO grant NNX15AP99A. The corresponding author is H. Mohsenian-Rad, e-mail: hamed@ece.ucr.edu.

Fig. 1. A distribution feeder with three loads, corresponding to the illustrative example in Section II. (a) the single line diagram of the feeder; (b) and (c) the measured voltage and active power at the feeder-head, respectively.

**II. ILLUSTRATIVE EXAMPLE**

Consider a distribution feeder with  $n = 3$  buses<sup>1</sup> as shown in Fig. 1(a). Depending on which individual loads are *turned on* and which individual loads are *turned off*, there can be a total of  $2^n - 1 = 7$  possible load configurations in this feeder, excluding the no load situation. Figs. 1(b) and (c) show the voltage and active power that are measured at the feeder-head during load configuration  $m_1, \dots, m_7$ , respectively. The switches status corresponding to each load configuration is given in Table I. Our goal in this paper is to model each of the three individual loads in Fig. 1(a) by studying the sequences of measurements at the feeder-head in Fig. 1(b) and (c).

**A. System of Equations and Unknowns**

In order to achieve the above goal, we need to solve a system of equations that comprises circuit models and load models. We start with writing the law of complex power conservation,

<sup>1</sup>As we will see in Theorem 1(b) in Section III, the minimum number of buses to conduct the proposed event-oriented load modeling problem is three.

## Distribution Synchrophasors

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

IN THE EVOLUTION OF ADVANCED SENSING TECHNOLOGIES, transmission systems have led 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* ( $\mu$ PMUs).  $\mu$ PMUs 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 analytics to translate these data to actionable information. In this article, we explore some of the opportunities to leverage  $\mu$ PMU data, combined with data-driven analytics, to help electrical distribution system planners and operators to get out in front of problems as they evolve.

The data generated by  $\mu$ PMUs are a prominent example of big data in power systems. Each  $\mu$ PMU generates 124,416,600 readings per day. Therefore,  $\mu$ PMUs installed on a handful of utility distribution feeders can generate terabytes of data on daily basis. Because  $\mu$ PMUs

stream their measurements continuously, the data must be collected, cleansed, and processed, all in real time.

The collected  $\mu$ PMU 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  $\mu$ PMU data.

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