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

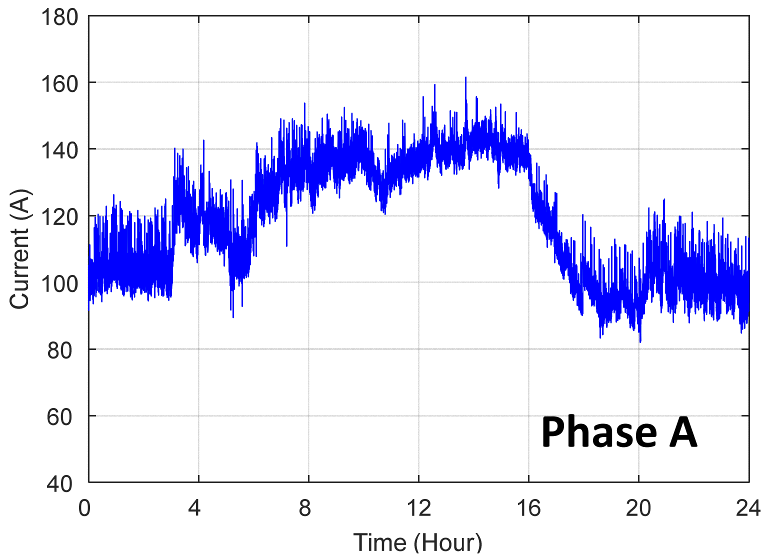
Smart Grid Comm 2019, Beijing, China

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

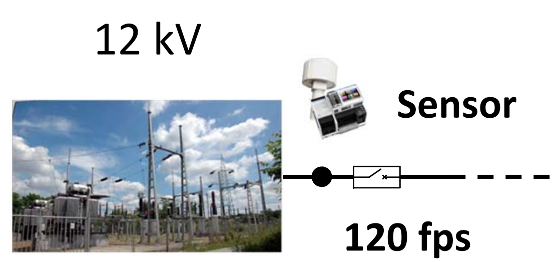
Acknowledgements: A. Shahsavari, M. Farajollahi, E. Stewart, E. Cortez,
A. von-Meier, L. Alvarez, C. Roberts, F. Megala, Z. Taylor

Background: Events in Micro-PMU Data Streams



Event Signature

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

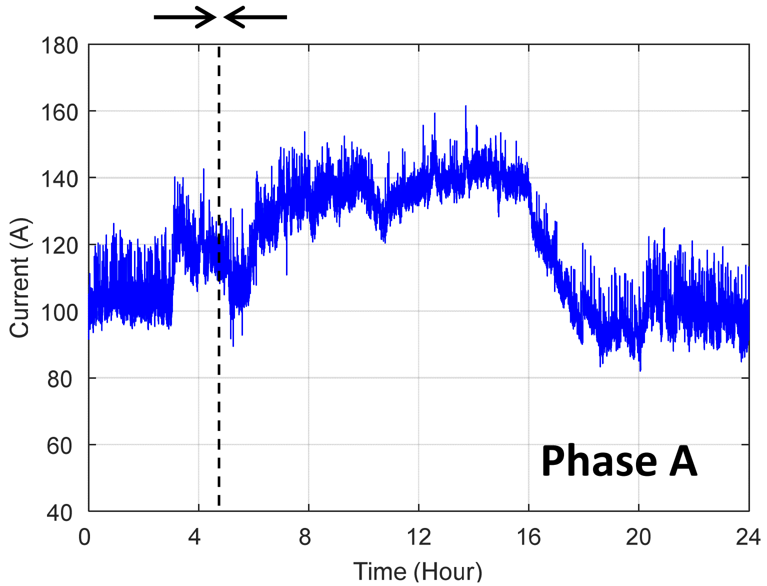


Micro-PMU

(Riverside, CA)

120 Million Data Points Per Day

Background: Events in Micro-PMU Data Streams



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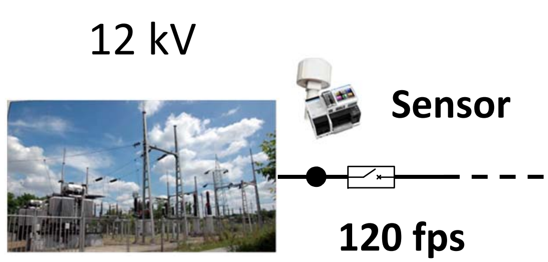

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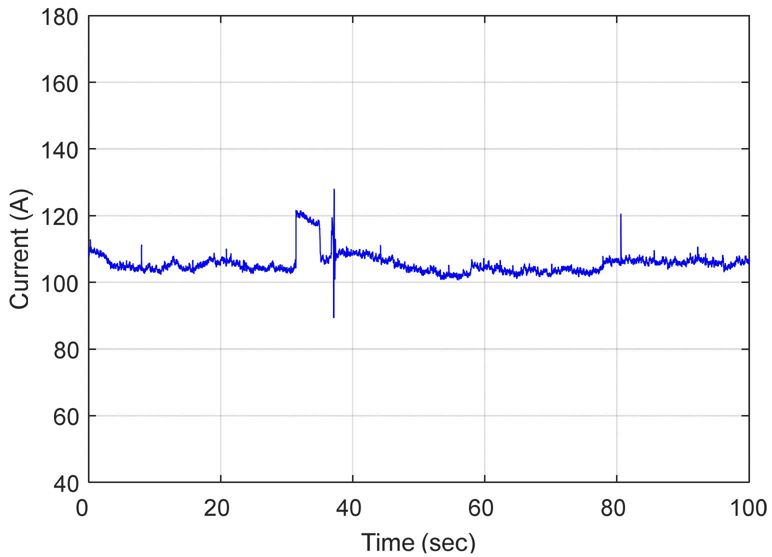

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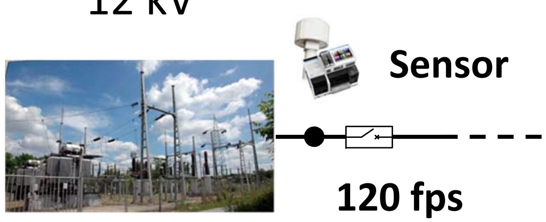
12 kV



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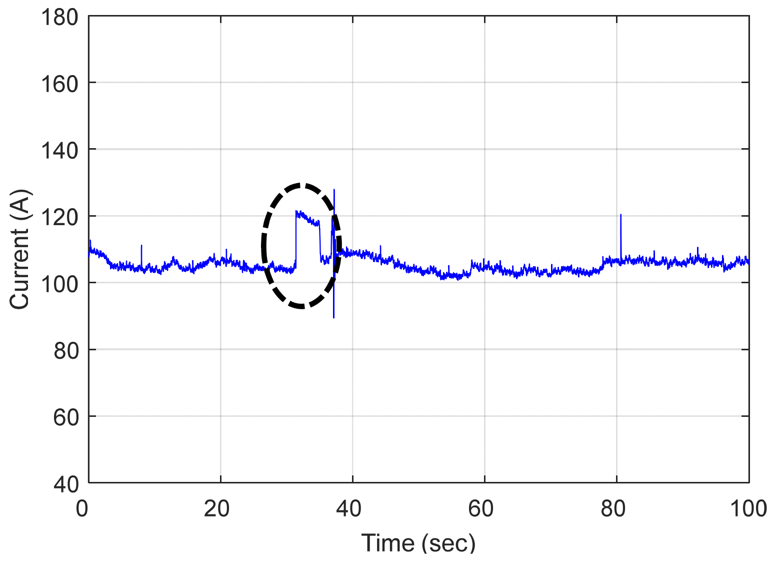

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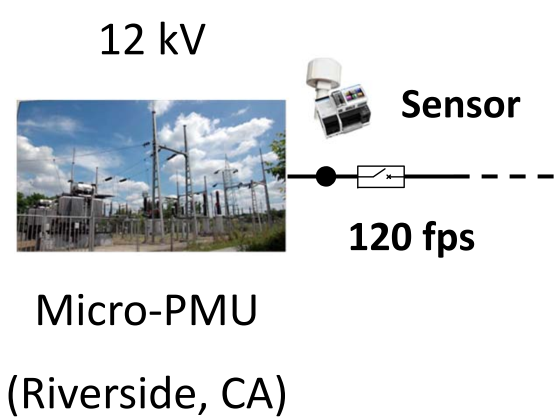

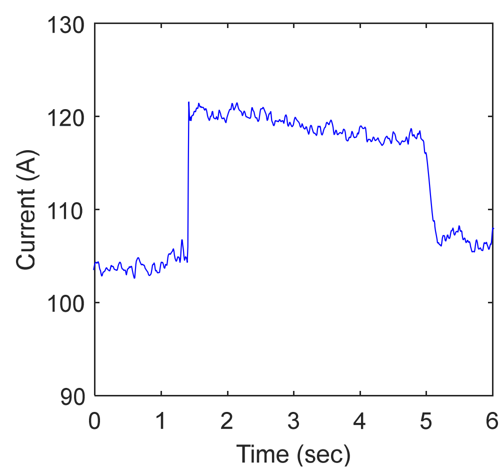

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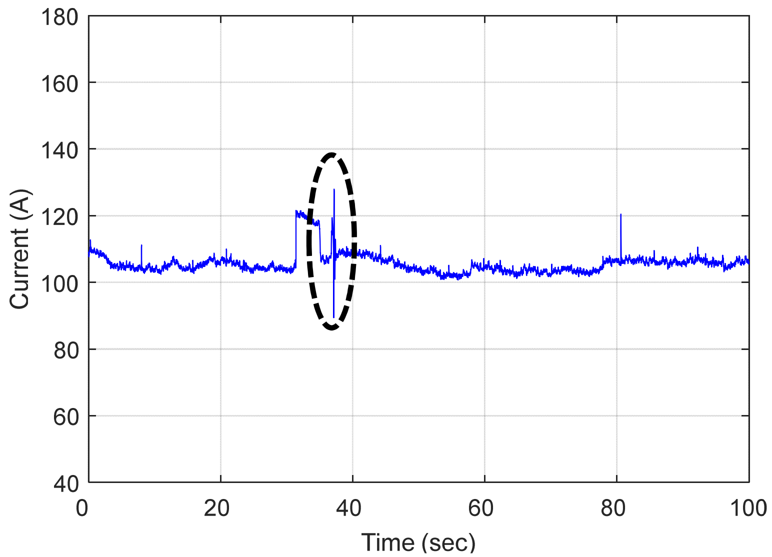

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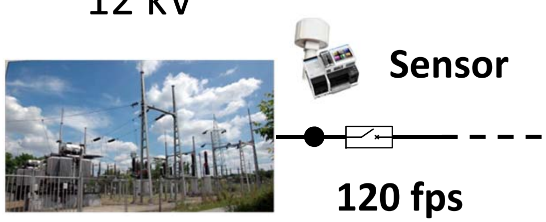

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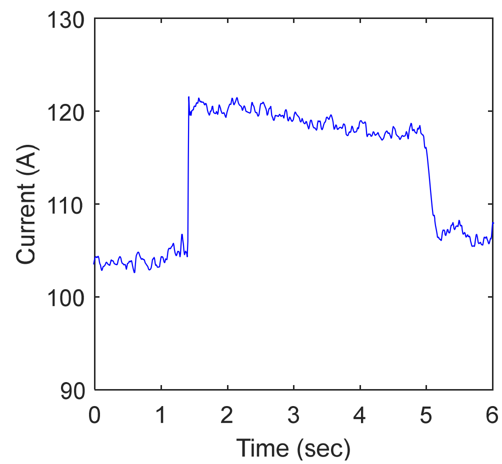

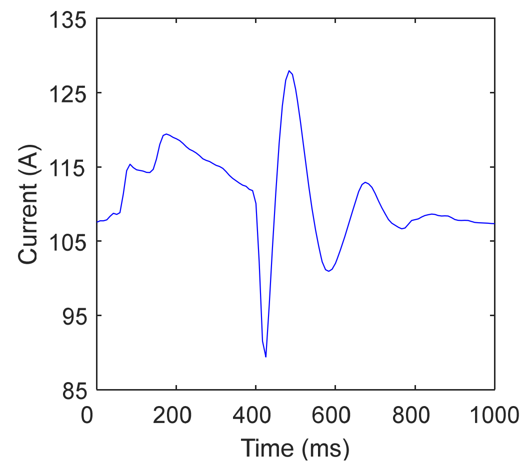

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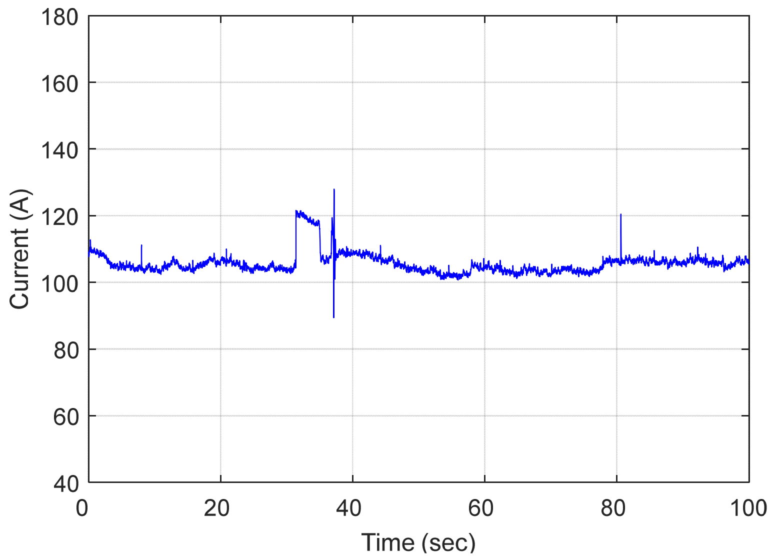

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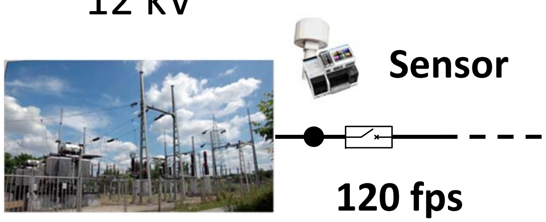
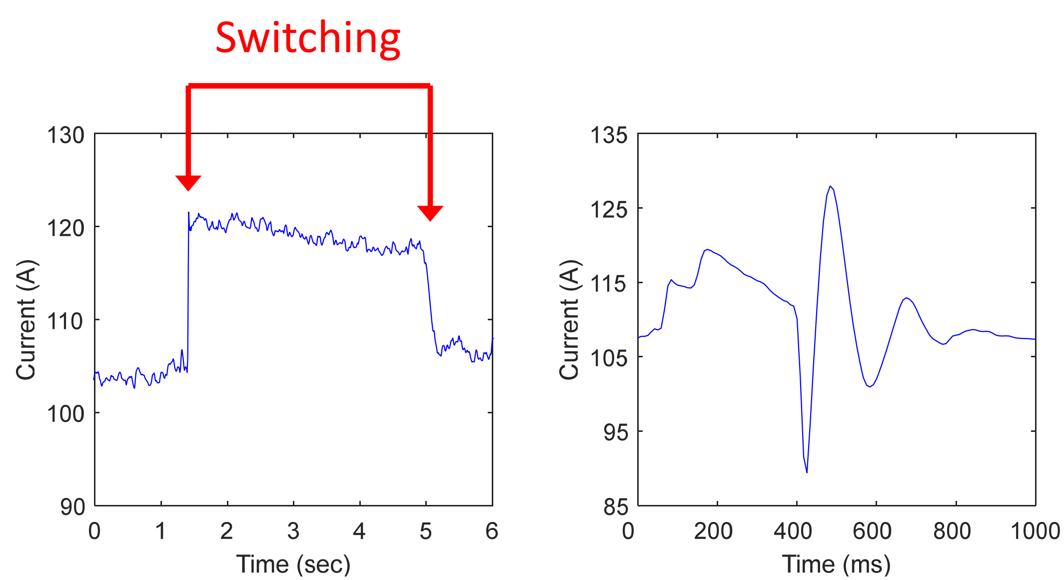


Micro-PMU

(Riverside, CA)



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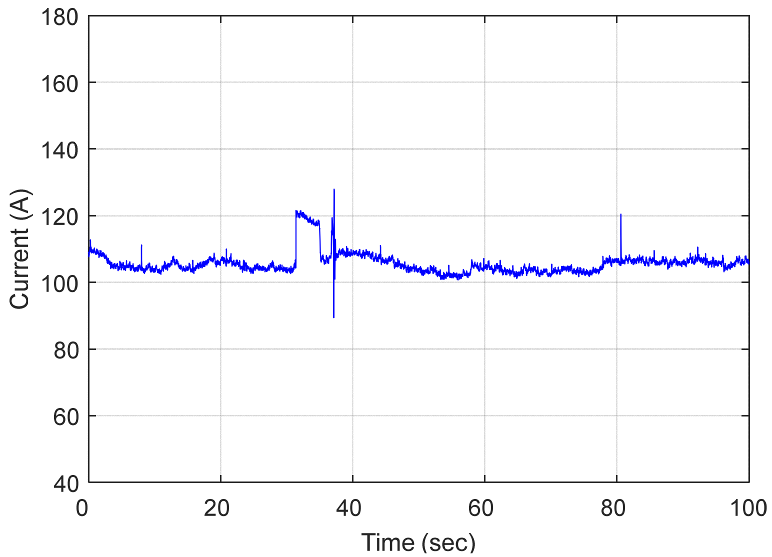
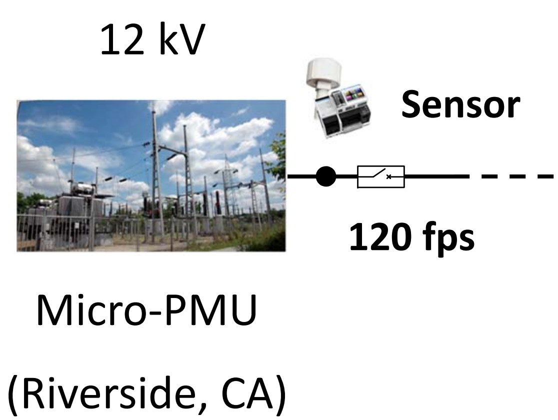
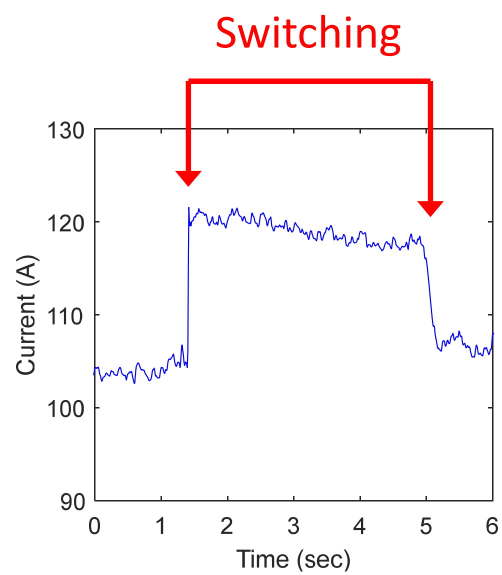
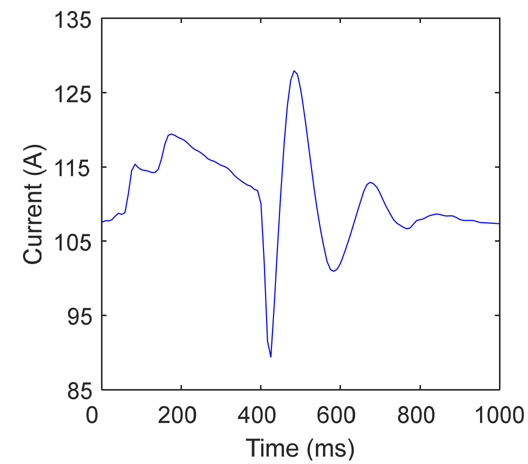


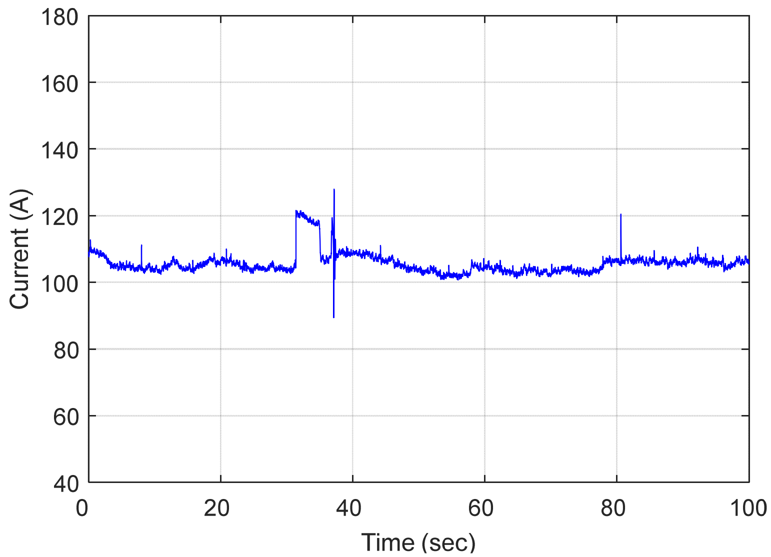
On Average: 500 Events Per Day Per Feeder





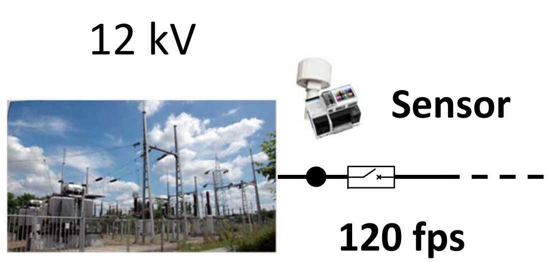


Background: Events in Micro-PMU Data Streams



~~Data Stream~~

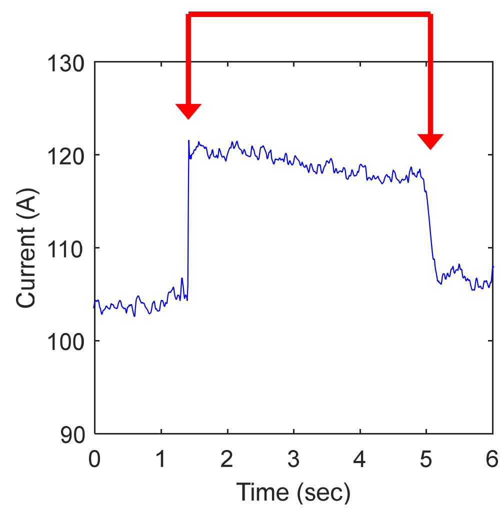
On Average: 500 Events Per Day Per Feeder

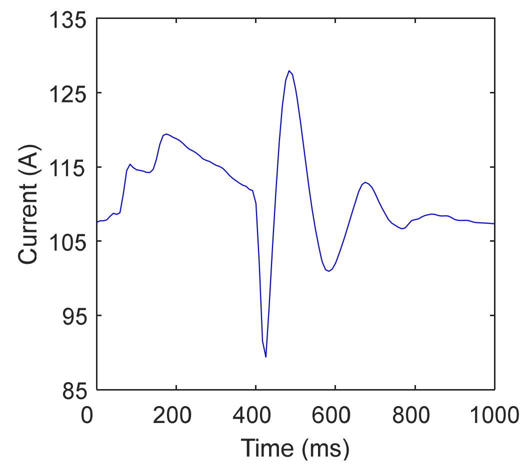


Micro-PMU

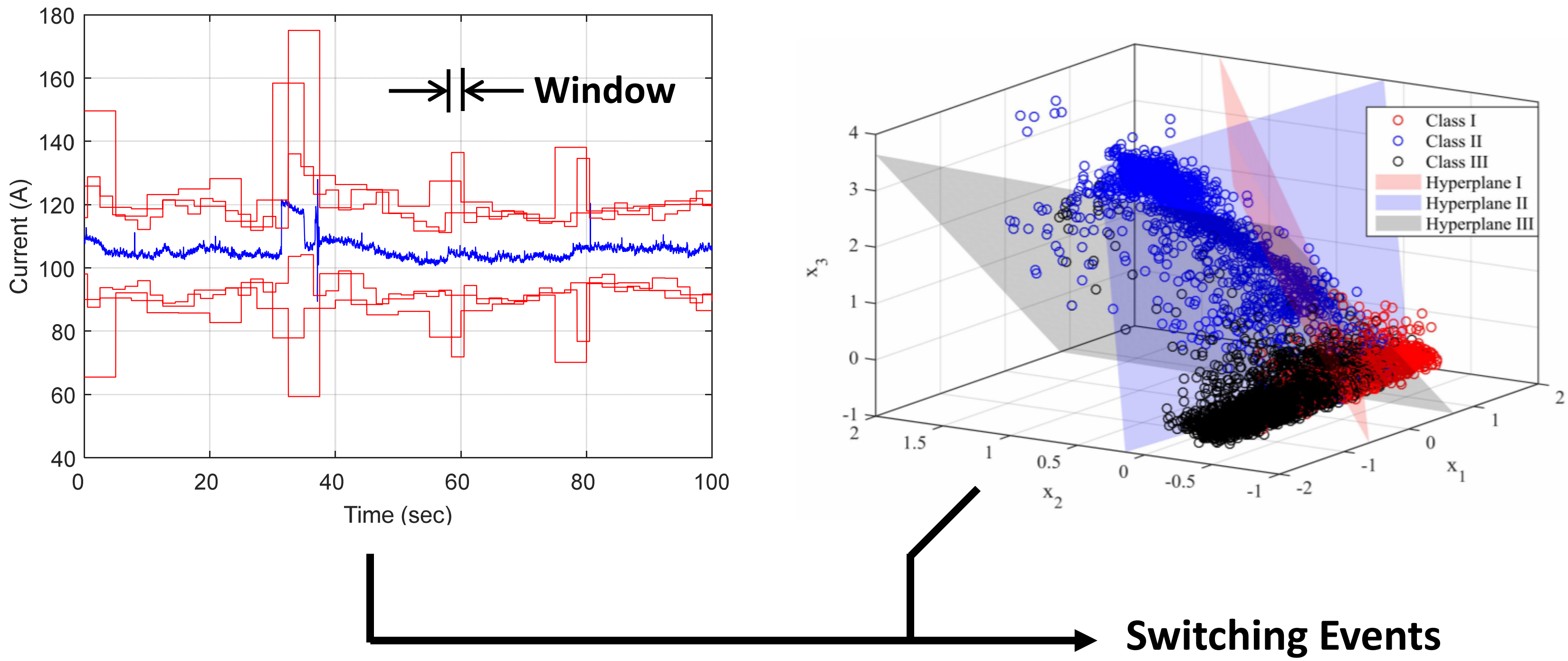
(Riverside, CA)

Switching





1. Event Detection and Event Classification (Machine Learning):



[1] A. Shahsavari, M. Farajollahi, E. Stewart, E. Cortez, H. Mohsenian-Rad, "Situational Awareness in Distribution Grid Using Micro-PMU Data: A Machine Learning Approach," *IEEE Trans. on Smart Grid*, Nov 2019.

Previous Results

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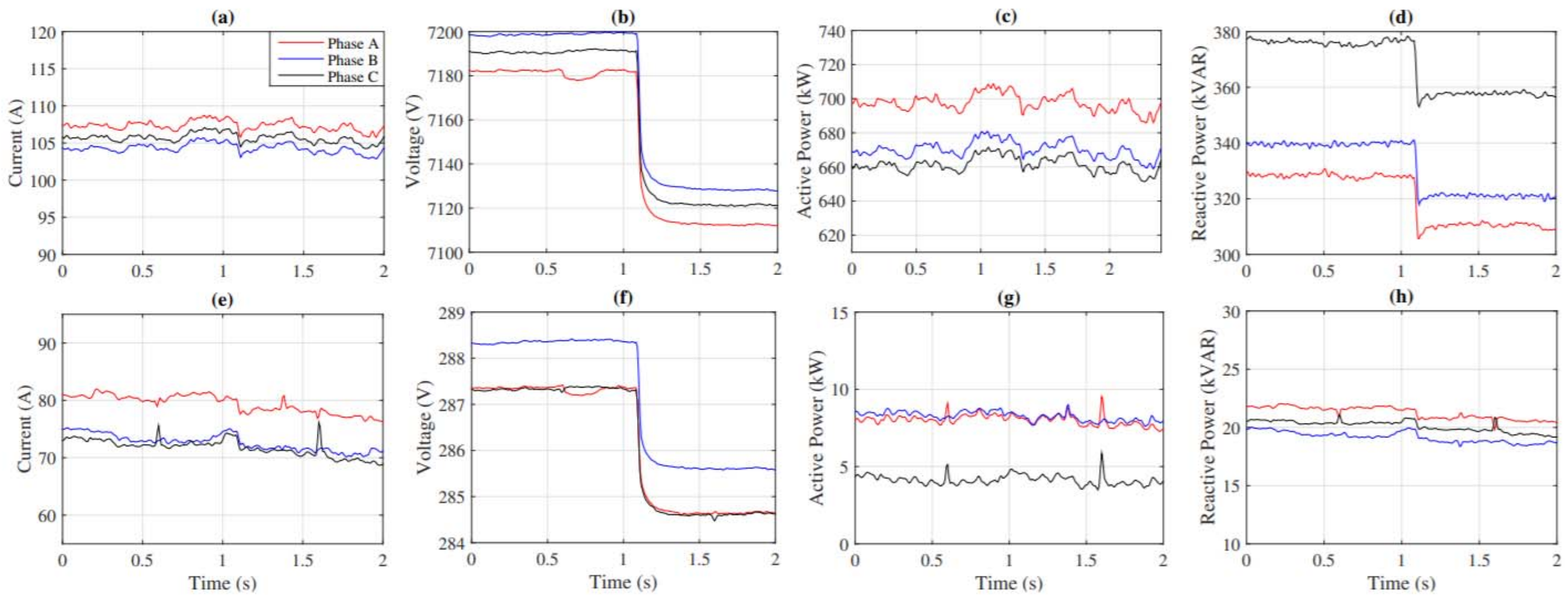

Upstream Event (Sub-transmission or Transmission)

[1] A. Shahsavari, M. Farajollahi, E. Stewart, E. Cortez, H. Mohsenian-Rad, "Situational Awareness in Distribution Grid Using Micro-PMU Data: A Machine Learning Approach," *IEEE Trans. on Smart Grid*, Nov 2019.

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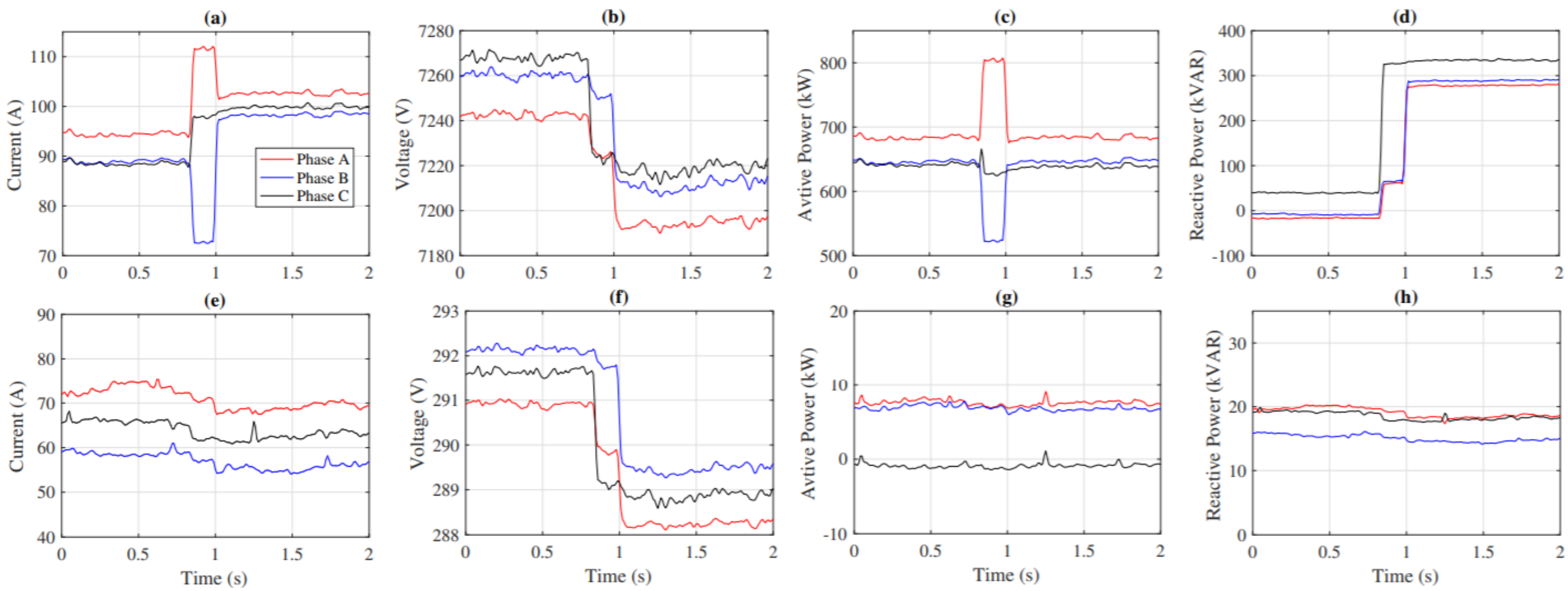

Switching Event (Distribution)

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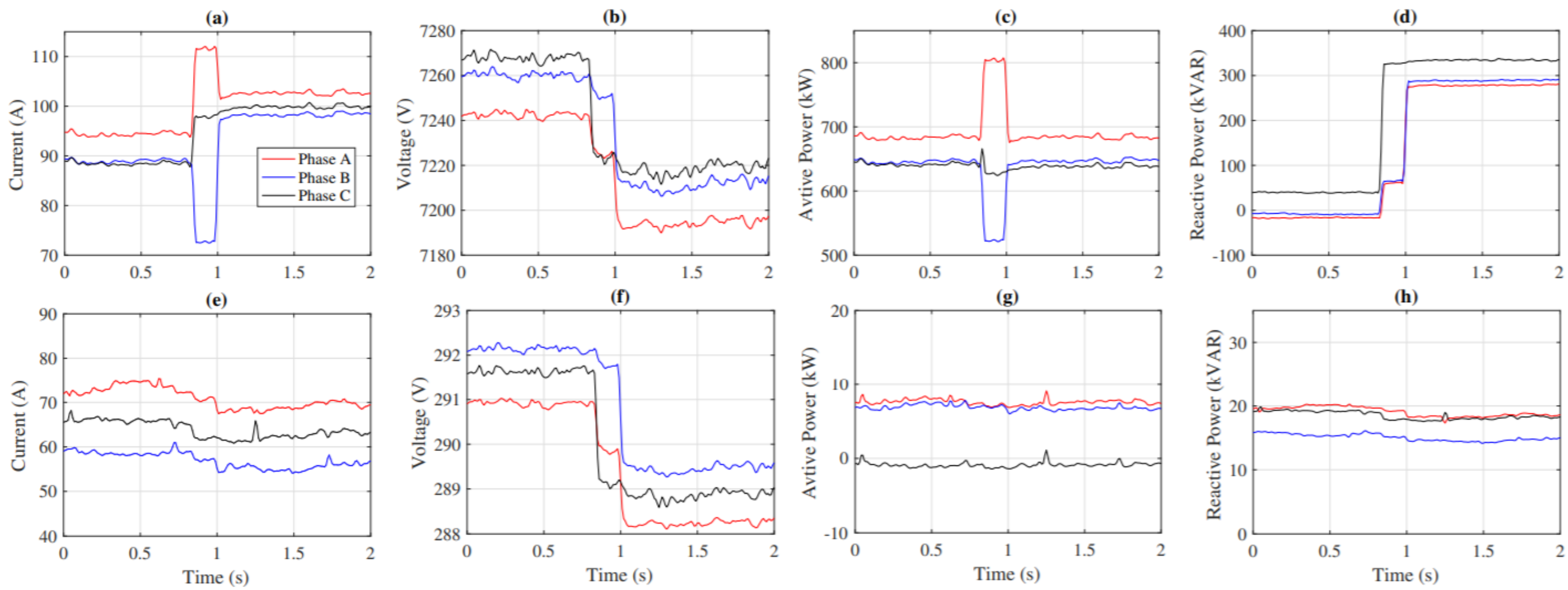

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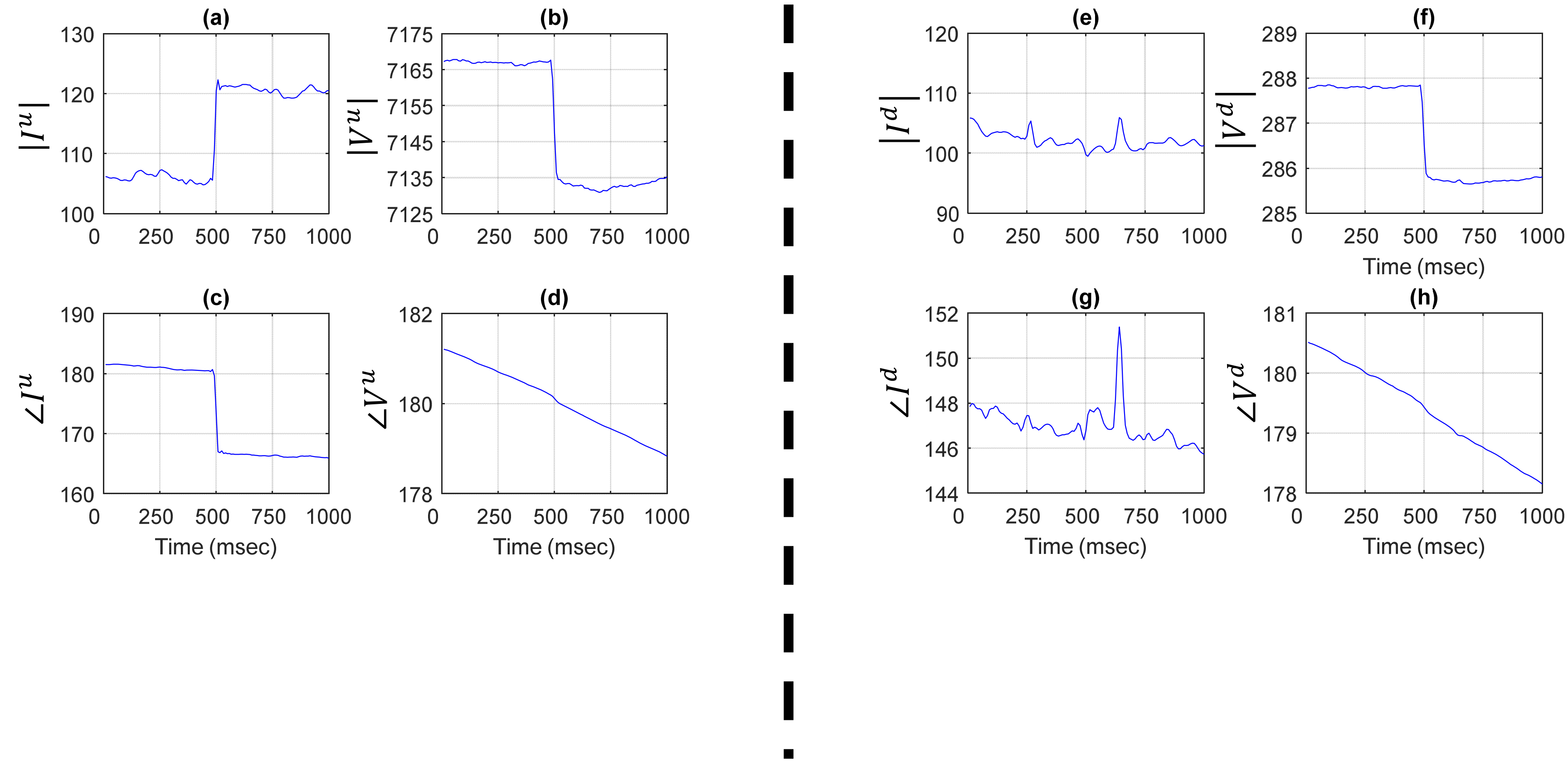

[2] M. Farajollahi, A. Shahsavari, E. Stewart, H. Mohsenian-Rad, "Locating the Source of Events in Power Distribution Systems Using Micro-PMU Data," *IEEE Trans. on Power Systems* vol. 33, no. 6, Nov. 2018.

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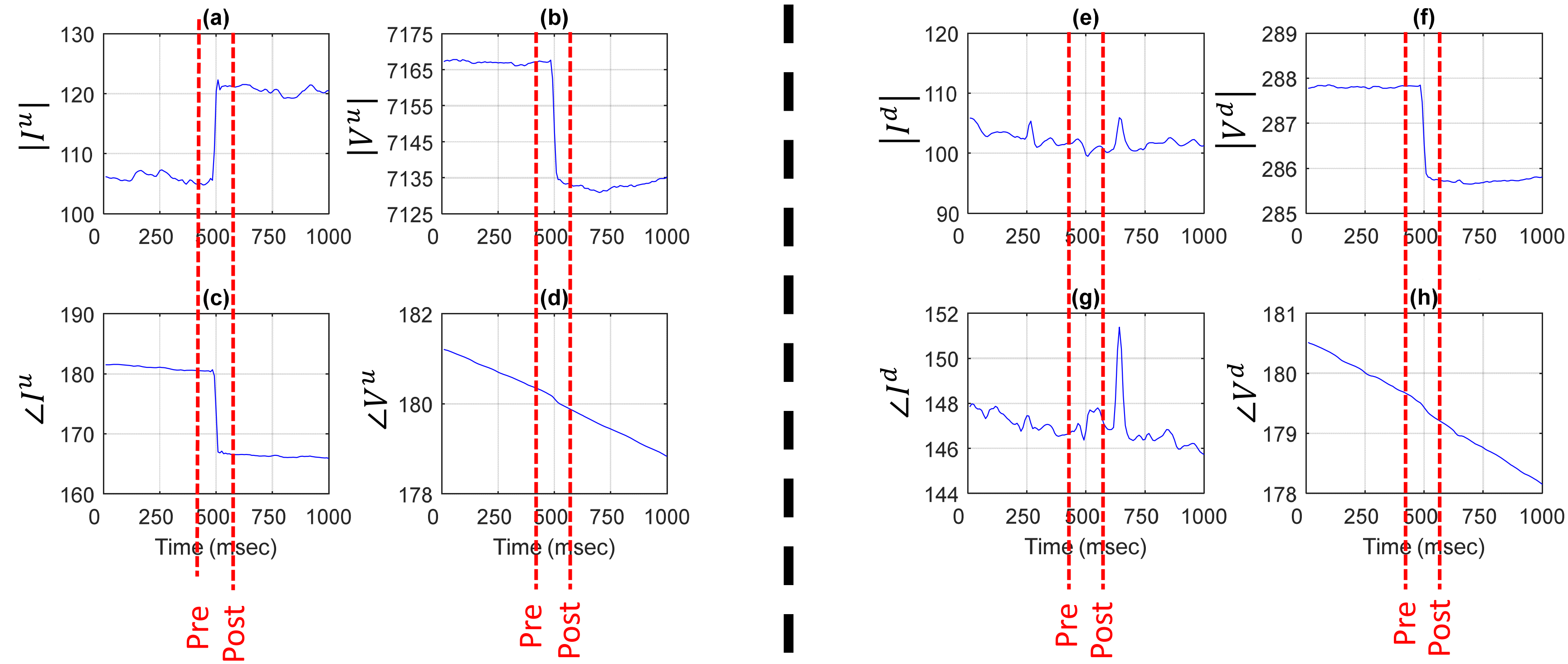

$|\Delta I^u|\angle\Delta I^u$ $|\Delta V^u|\angle\Delta V^u$ $|\Delta I^d|\angle\Delta I^d$ $|\Delta V^d|\angle\Delta V^d$

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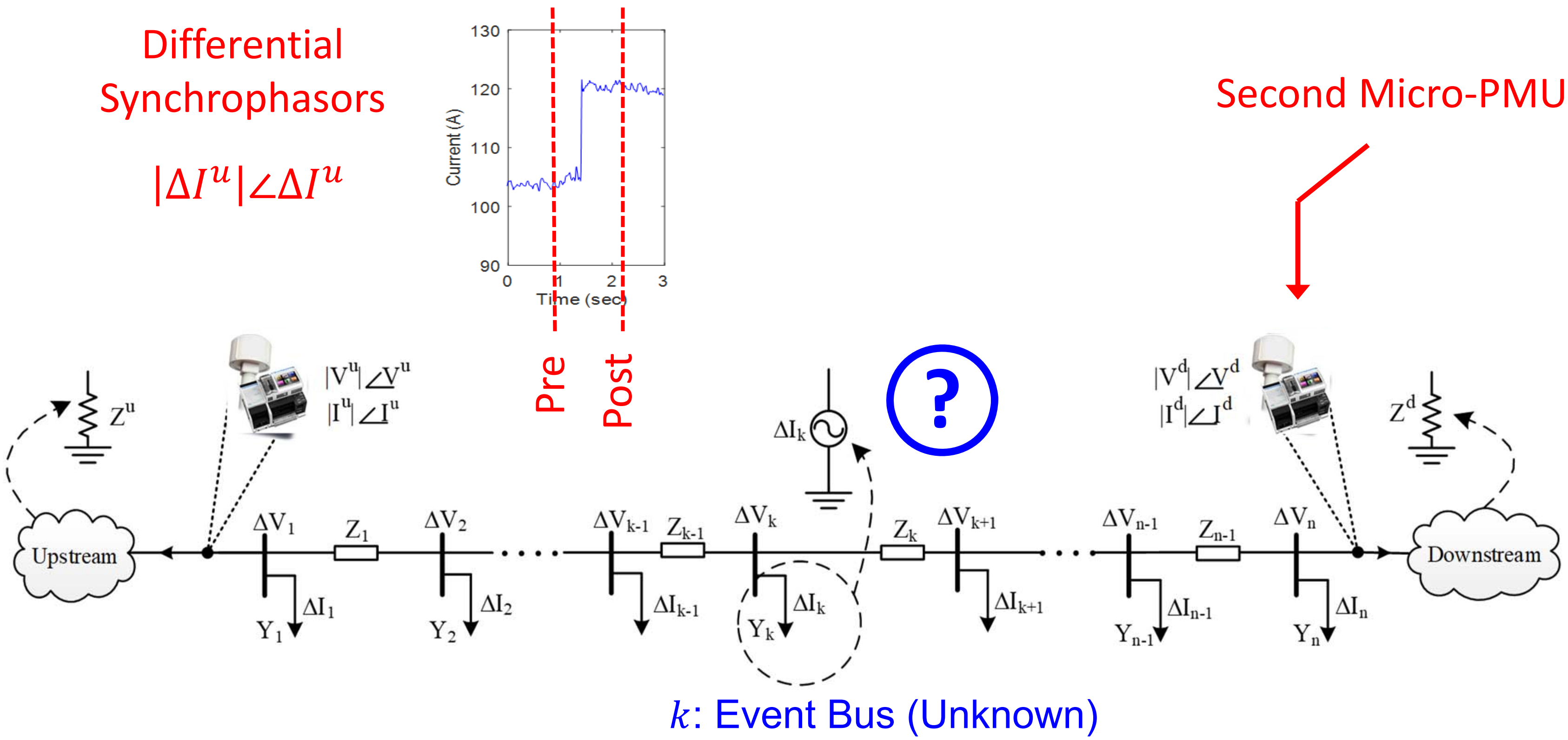

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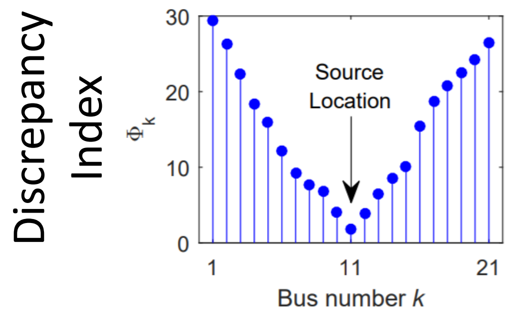
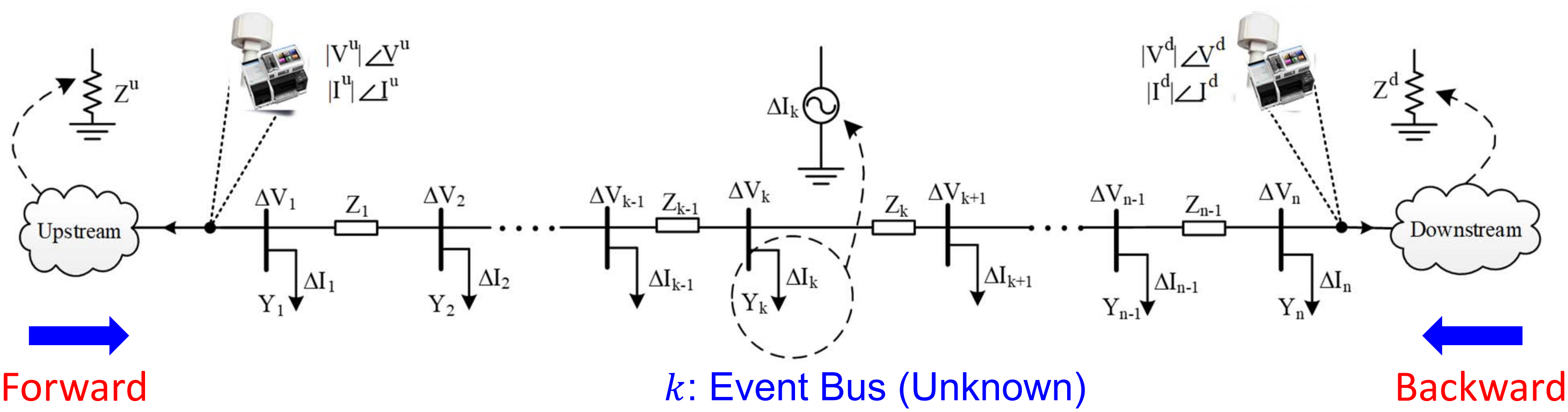


$$k = \underset{i}{\operatorname{argmin}} \left| \Delta V_i^f - \Delta V_i^b \right|$$



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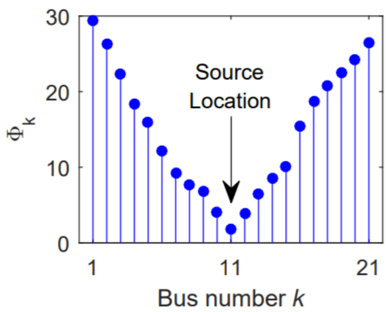
2. Event Location Identification (Hybrid Model-Based):

Discrepancy Index



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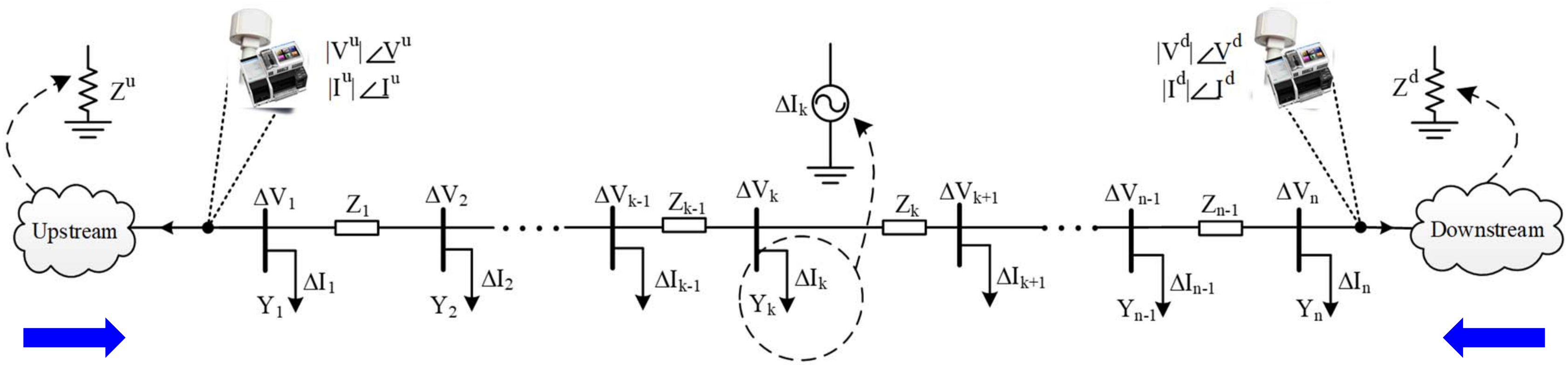


Forward

k: Event Bus (Unknown)

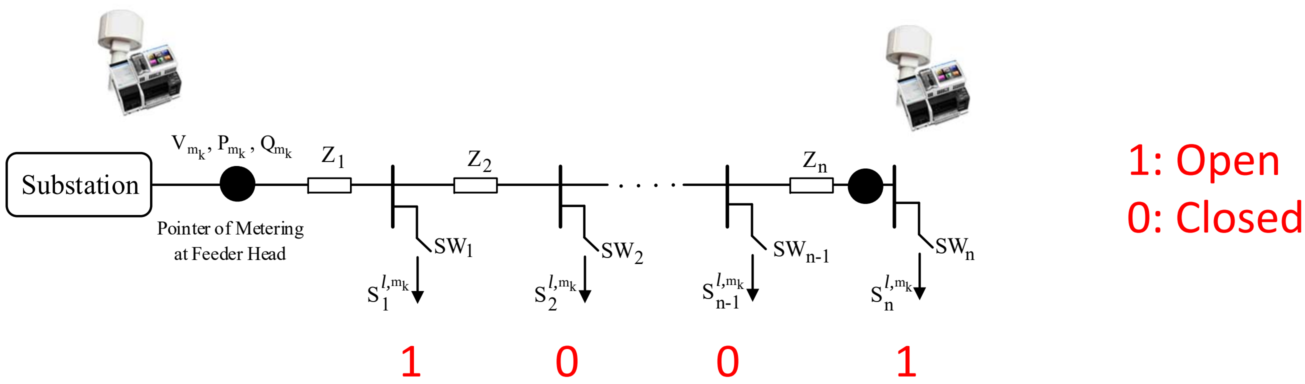
Backward

[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.

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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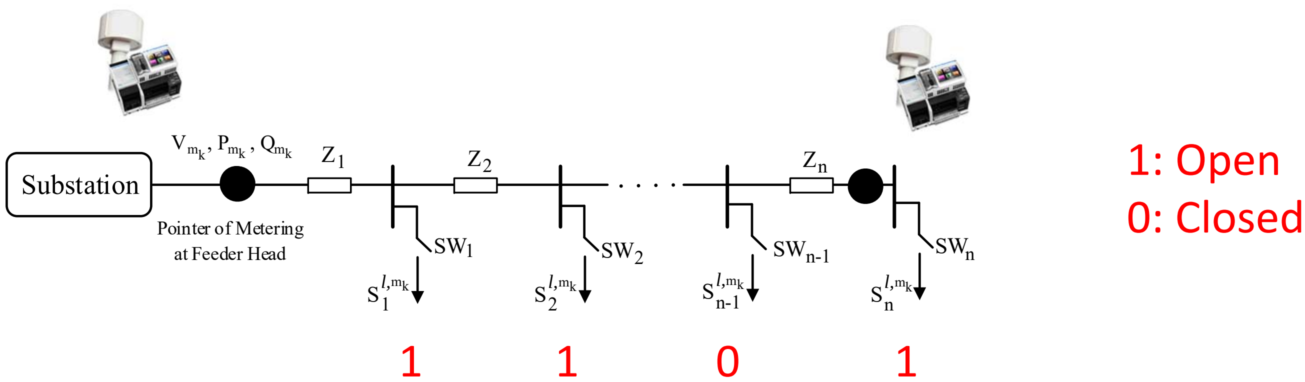

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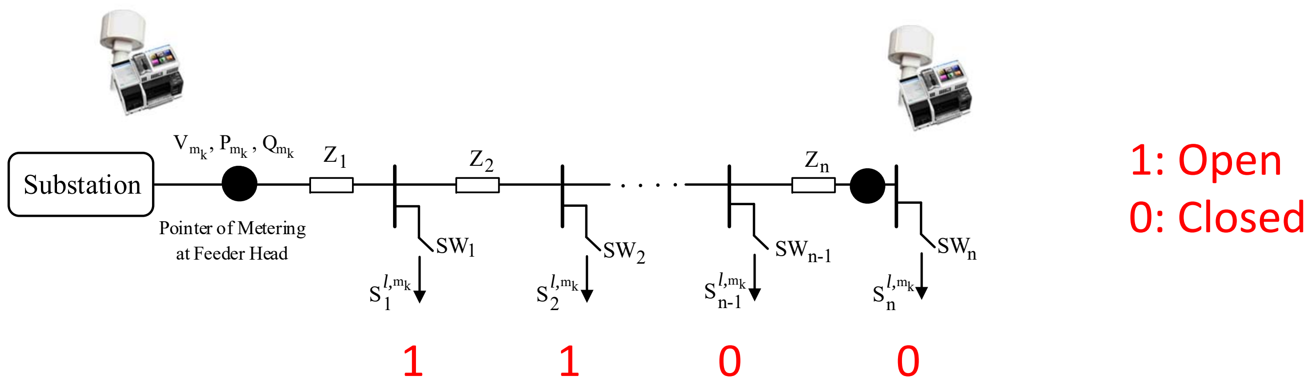

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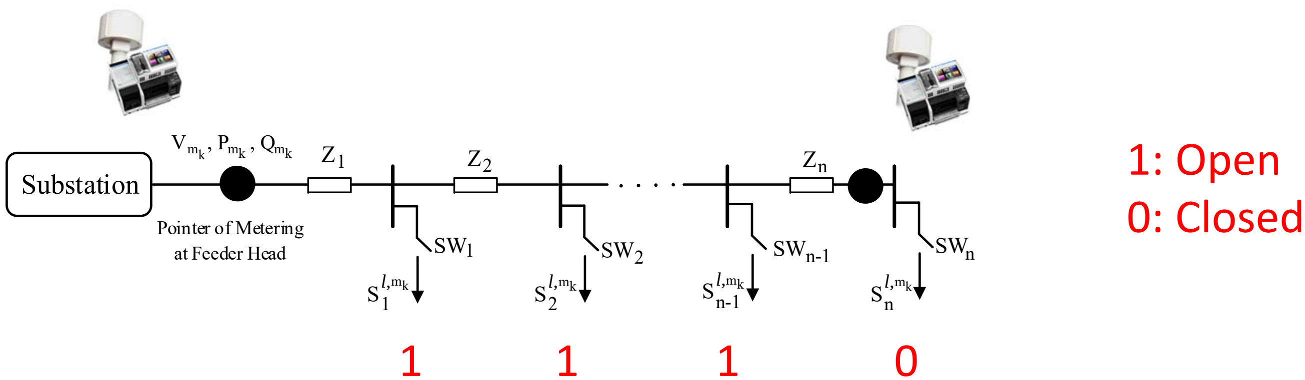

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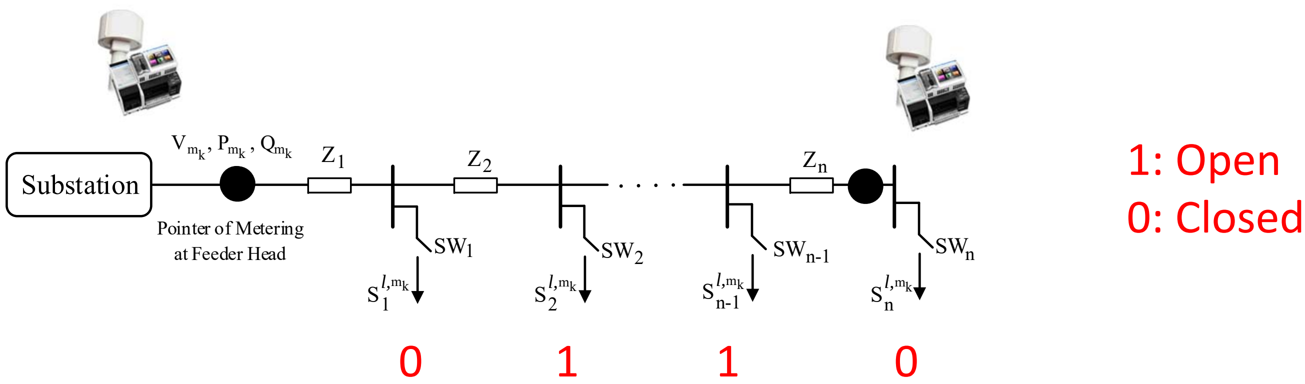

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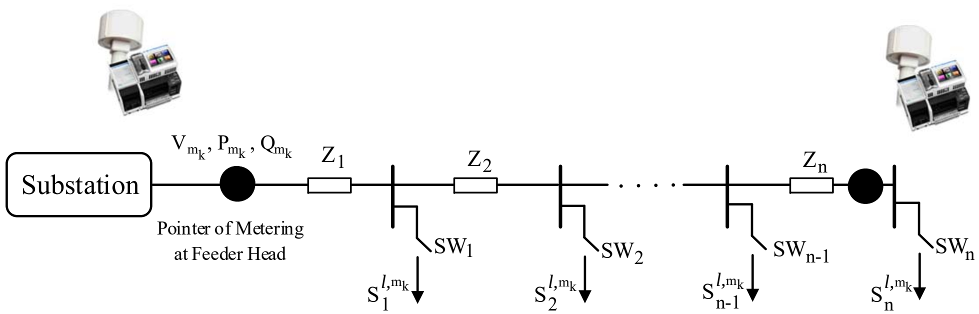

0 1 1 0

1: Open
0: Closed

- Therefore, we can keep track of switching configurations.

Q: What can we do with this?

Observations

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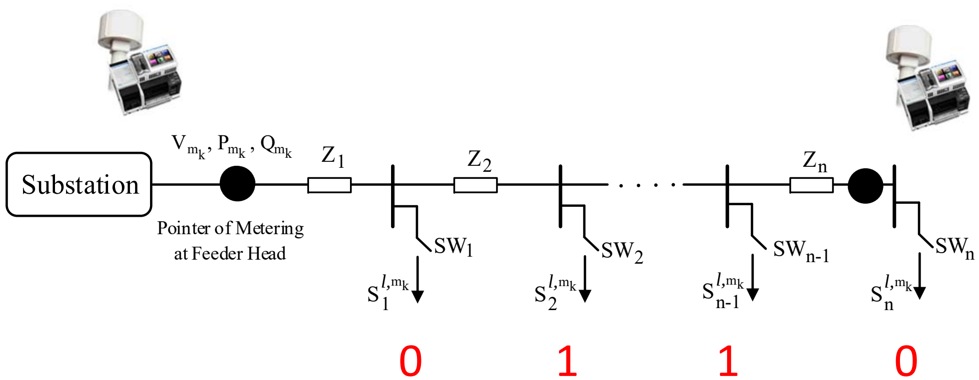
- We can **remotely** and **automatically** monitor all **load switching events**



1: Open
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- Therefore, we can keep track of switching configurations.

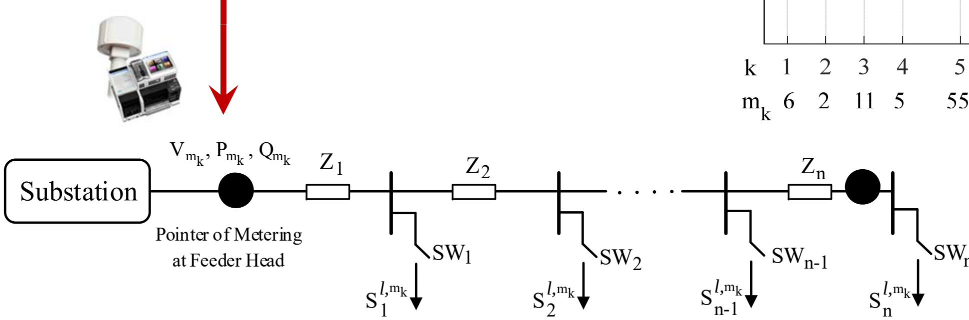
Q: What can we do with this?

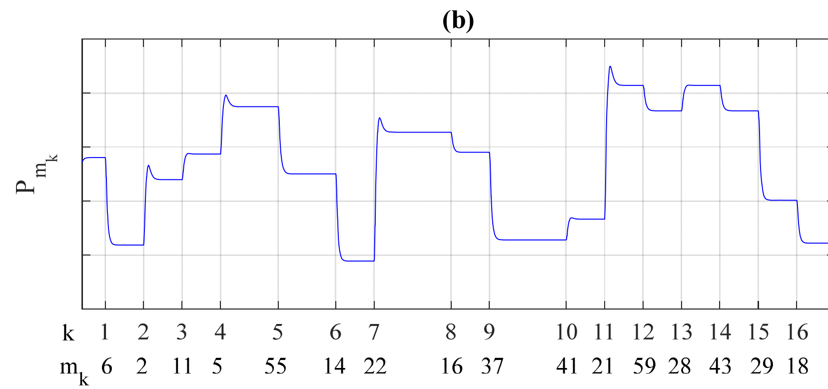
A: Nonintrusive Load Modeling

- **Feeder Aggregated Load Model:**

$$P_{m_k} = P_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_p}$$

$$Q_{m_k} = Q_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_q}$$





Switching Configuration Number

A Variation of the "<u>ZIP Model</u>".

Constant Impedance

Constant Current

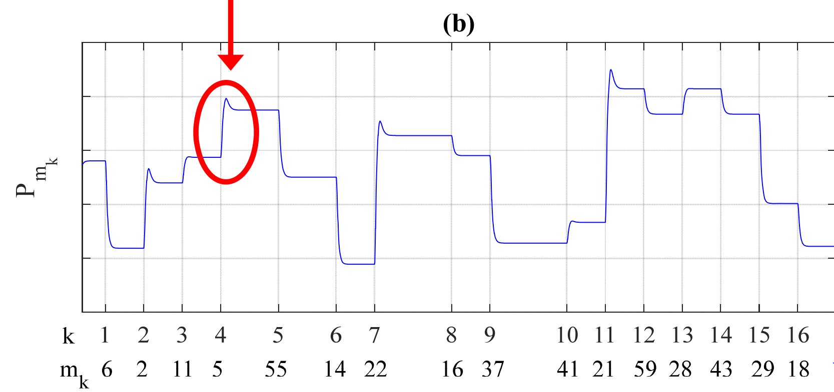
Constant Power

- **Individual Load Models:**

$$P_{m_k} = P_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_p}$$

$$Q_{m_k} = Q_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_q}$$

Switching Event



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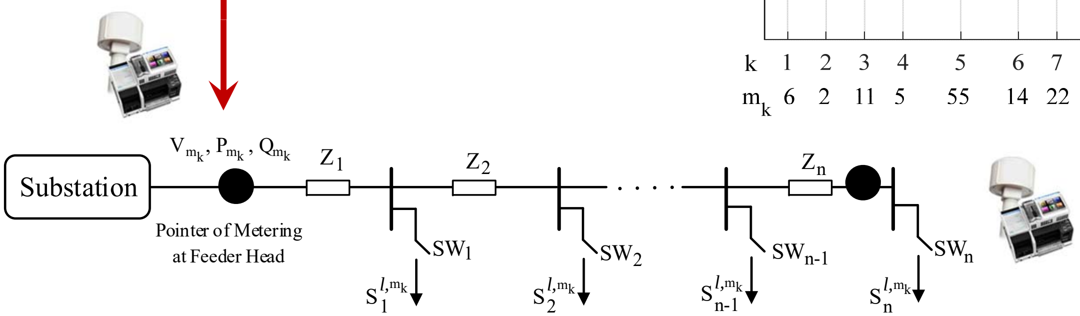

$$P_{m_k} = P_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_{p,i}}$$

$$Q_{m_k} = Q_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_{q,i}}$$

$$i = 1, 2, \dots, n$$

Nonintrusive Load Modeling

- **Individual Load Models:**

$$P_{m_k} = P_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_p}$$

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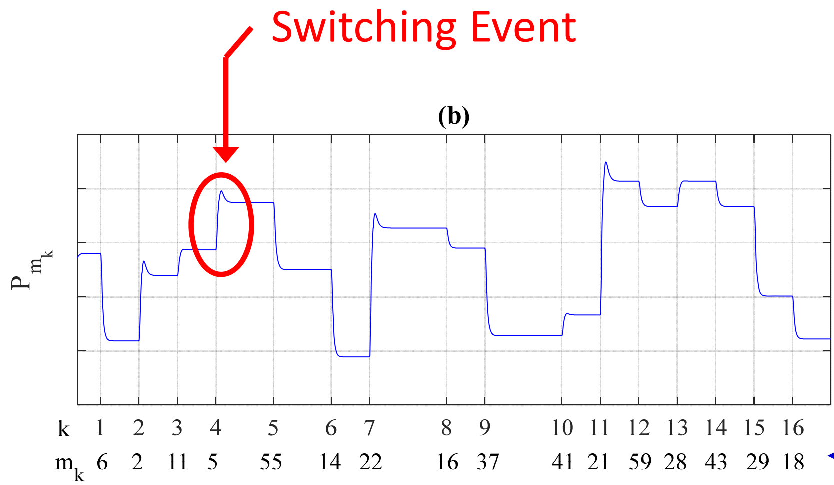

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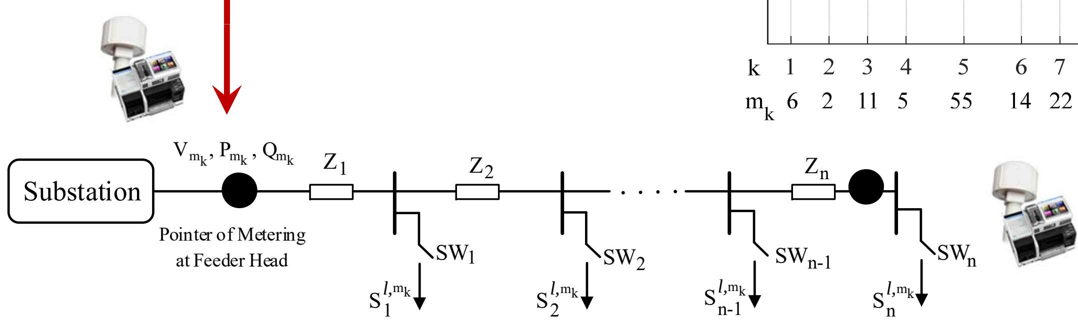

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$$i = 1, 2, \dots, n$$

Step 1: Circuit Model Equations

- **Complex Power Conservation:**

Current in Line j

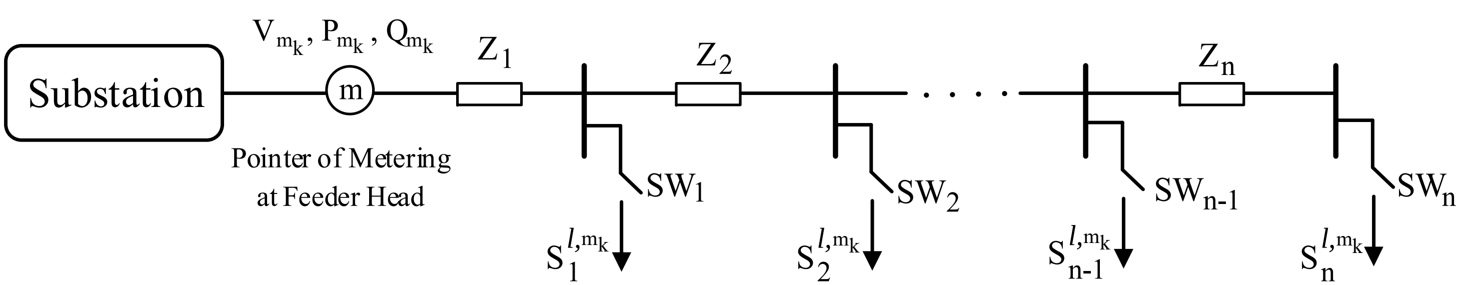
$$S_{m_k} = \sum_{i=1}^{n} \left(S_i^{l,m_k}\, SW_i^{m_k} \right) + \sum_{j=1}^{n} Z_j \left| \sum_{d=j}^{n} \left(\frac{S_d^{l,m_k}}{V_d^{l,m_k}} \right)^{*} \times SW_d^{m_k} \right|^{2}$$

Switching Configuration

Total Load

Total Loss

# of Equations = 1



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

Step 1: Circuit Model Equations

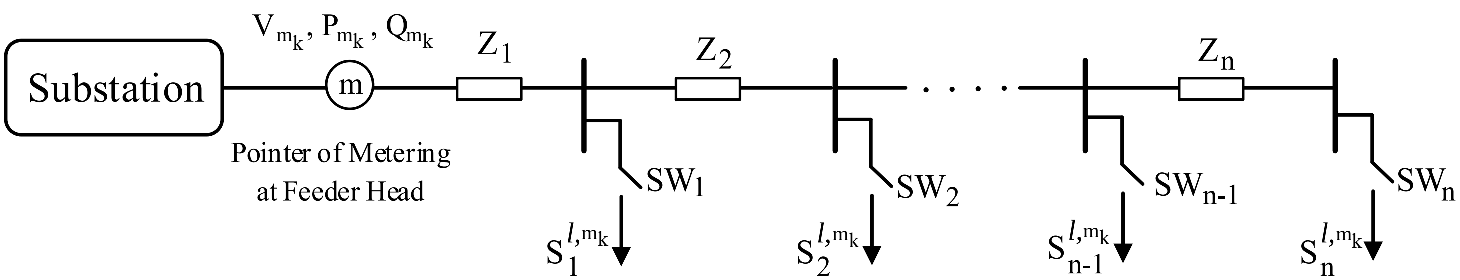
- **KVL:**

Voltage at Substation

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

Voltage Drop at Line j

# of Equations = n



Step 1: Circuit Model Equations

- **Combined Equations:**

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

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

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

- **For any switching configuration m_k:**

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

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:

$n_{s_i} = n_{p_i} + \mathrm{j}\, n_{q_i} \quad \text{for} \quad i = 1, \cdots, n$

Step 3: Solving the System of Equations

- **Given c distinct switching configurations**:

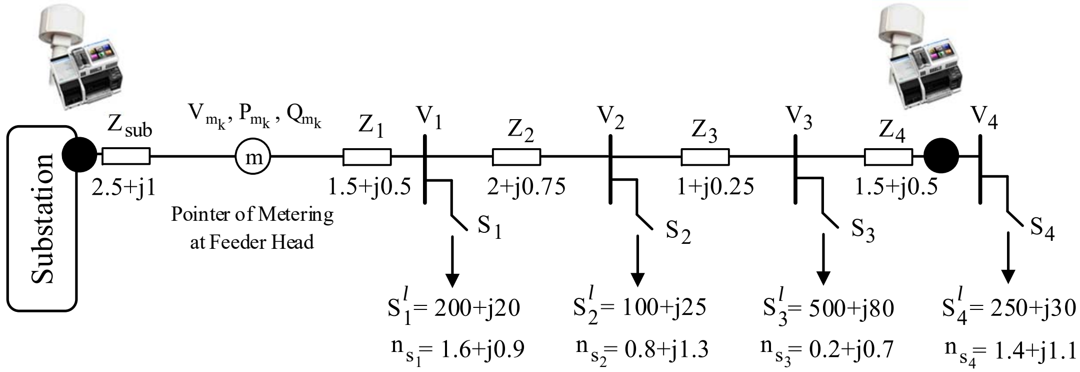
\# of Unknowns: $$n \times c + \sum_{k=1}^{c} \sum_{i=1}^{n} SW_i^{m_k} + n$$

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

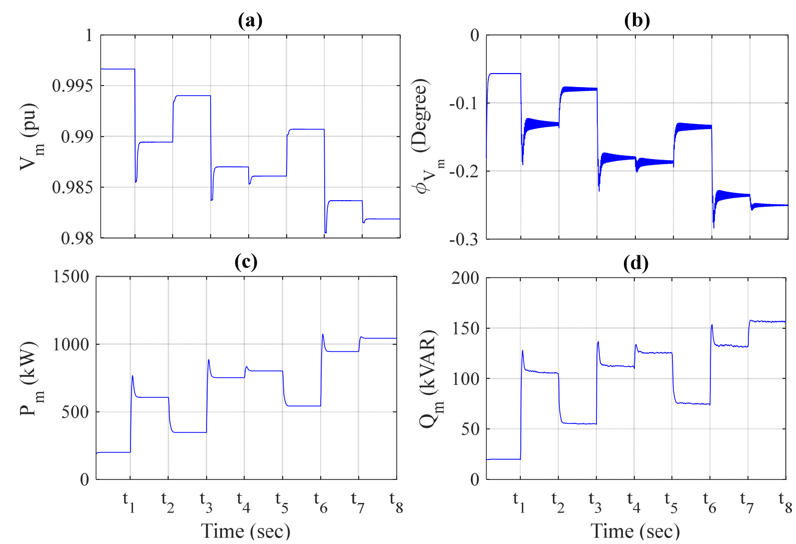
Theorem: We need to observe at least $c_{min} = 2n$ distinct switching configurations to solve the nonintrusive individual load modeling problem.

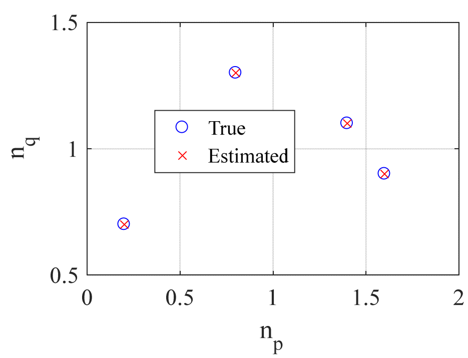
Illustrative Example

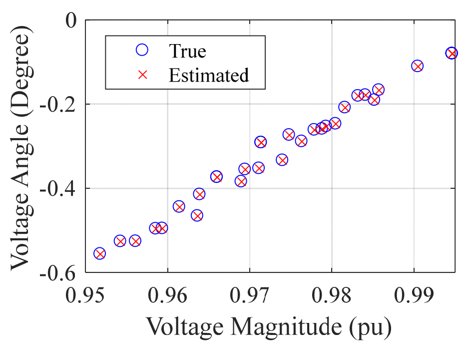
Configuration	SW_1	SW_2	SW_3	SW_4	Time
m_1	1	0	0	0	$[0\ ,\ t_1]$
m_2	0	1	1	0	$[t_1\ ,\ t_2]$
m_3	0	1	0	1	$[t_2\ ,\ t_3]$
m_4	0	0	1	1	$[t_3\ ,\ t_4]$
m_5	1	1	1	0	$[t_4\ ,\ t_5]$
m_6	1	1	0	1	$[t_5\ ,\ t_6]$
m_7	1	0	1	1	$[t_6\ ,\ t_7]$
m_8	1	1	1	1	$[t_7\ ,\ t_8]$



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

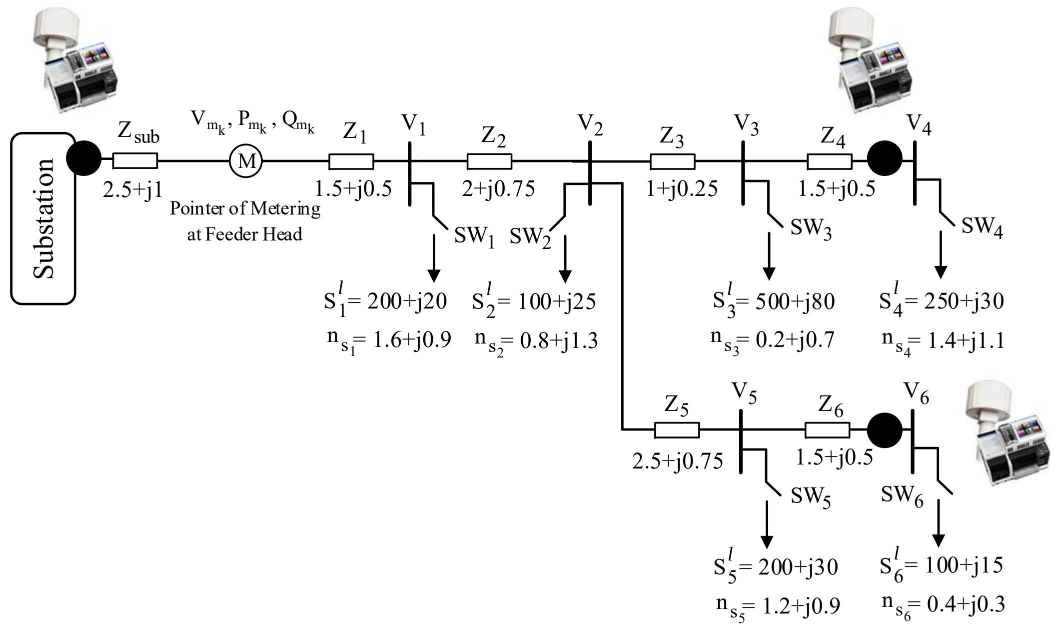




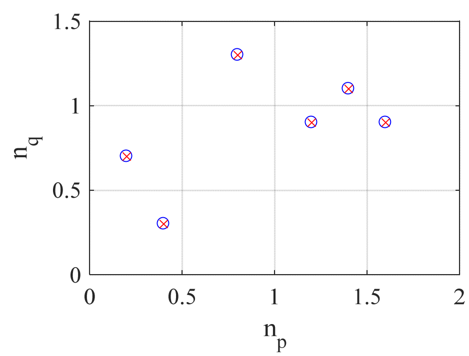


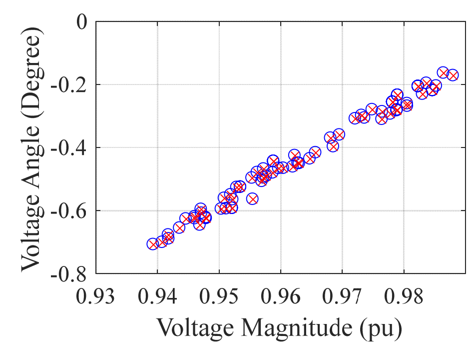
Extension 1: Distribution Feeder with Laterals

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	$[t_{11}\ ,\ t_{12}]$

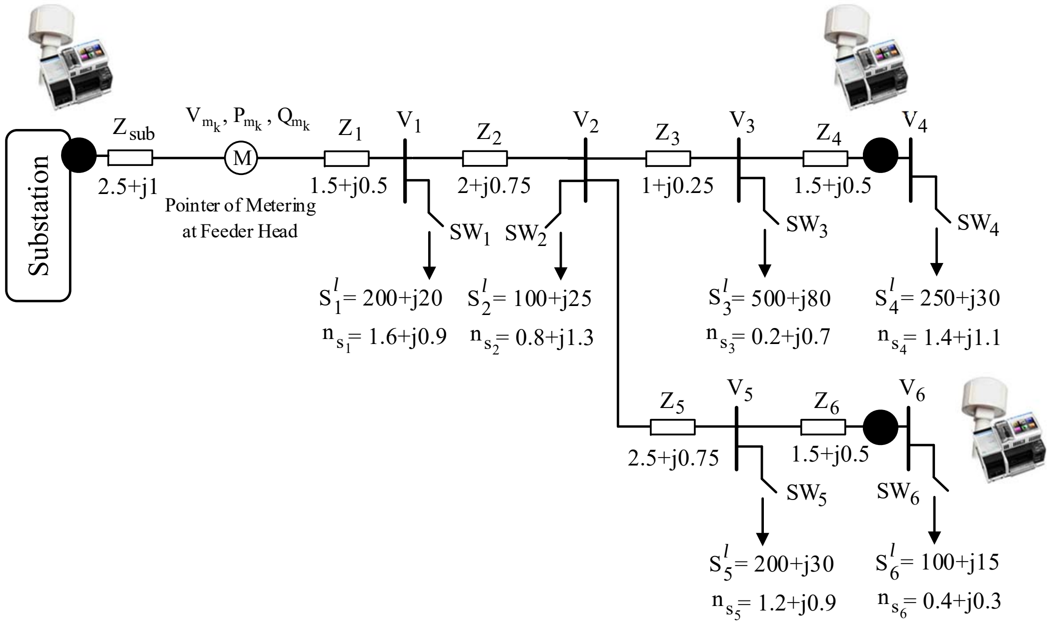


	# of Equations	# of Unknowns
Circuit Model	84	120
Load Model	42	6
Combined	126	126





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

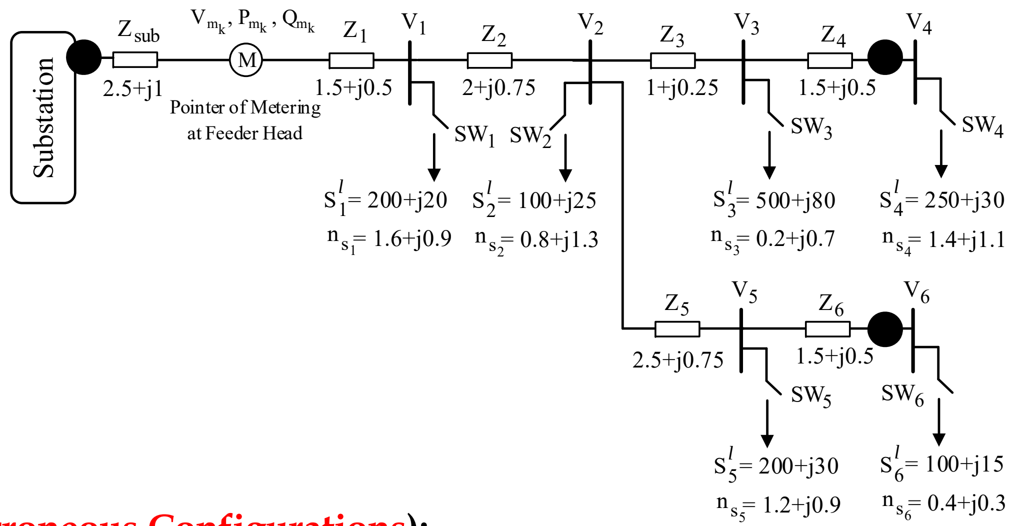
Error in Line Impedance	5%	10%	15%	20%	25%	30%
Error in Estimating n_p	0.09	0.93	1.30	1.98	2.54	3.38
Error in Estimating n_q	0.78	1.95	3.23	5.34	9.16	11.87

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

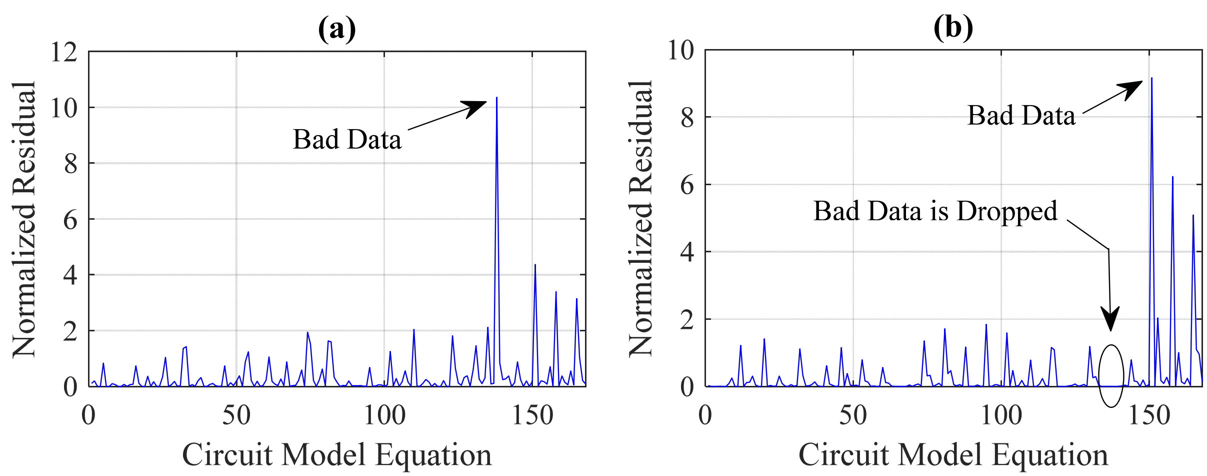
In Presence of Error in Measurements

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

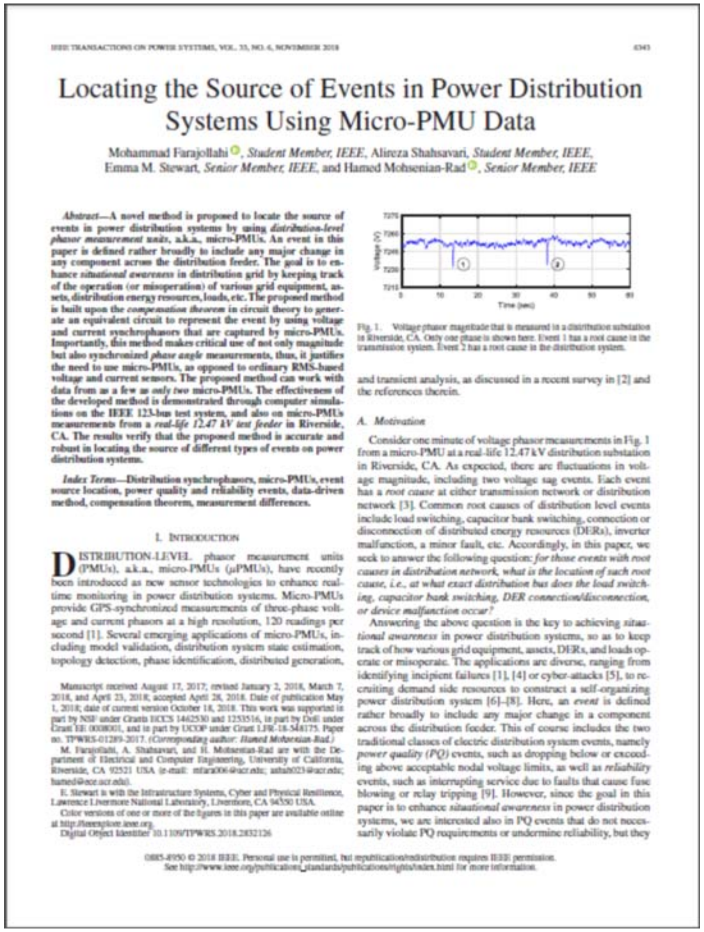
- Install a few micro-PMUs at feeder head and end buses.

- 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
    - …

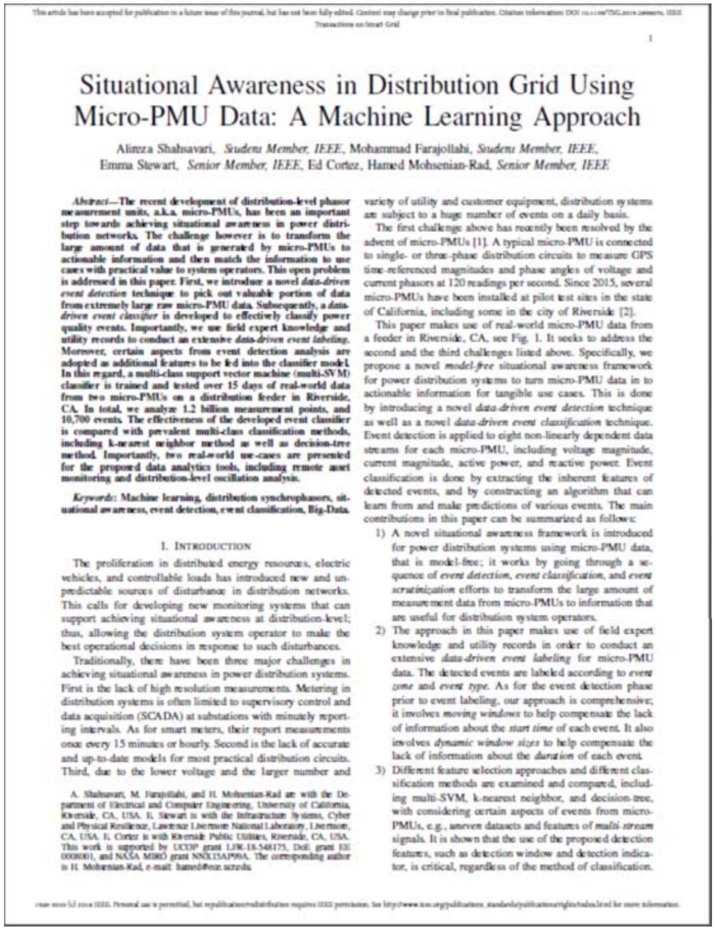
Further Reading



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

IEEE T. on Power Systems 2018



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

IEEE T. on Smart Grid 2019

Further Reading (Cont.)

1

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

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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 prameters 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 *upstream* 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].

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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.

Intuitively, the basic idea in this paper is as follows: once a load switches, the switching event changes the voltage in the rest of the loads on the same feeder, and this causes variation in their active and reactive power consumption; thus allowing us to estimate their load parameters. However, the challenge in implementing this idea is that such variations *cannot* be measured directly unless there is a meter at each load bus; which in that case individual load modeling is trivial. Thus, we assume that individual load meters are *not* available. Instead, we seek to achieve individual load models by using only the measurements at the feeder-head.

II. ILLUSTRATIVE EXAMPLE

Consider a distribution feeder with $n = 3$ buses[1] 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 $m_1, \ldots, m_7$, 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,

[1] 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.

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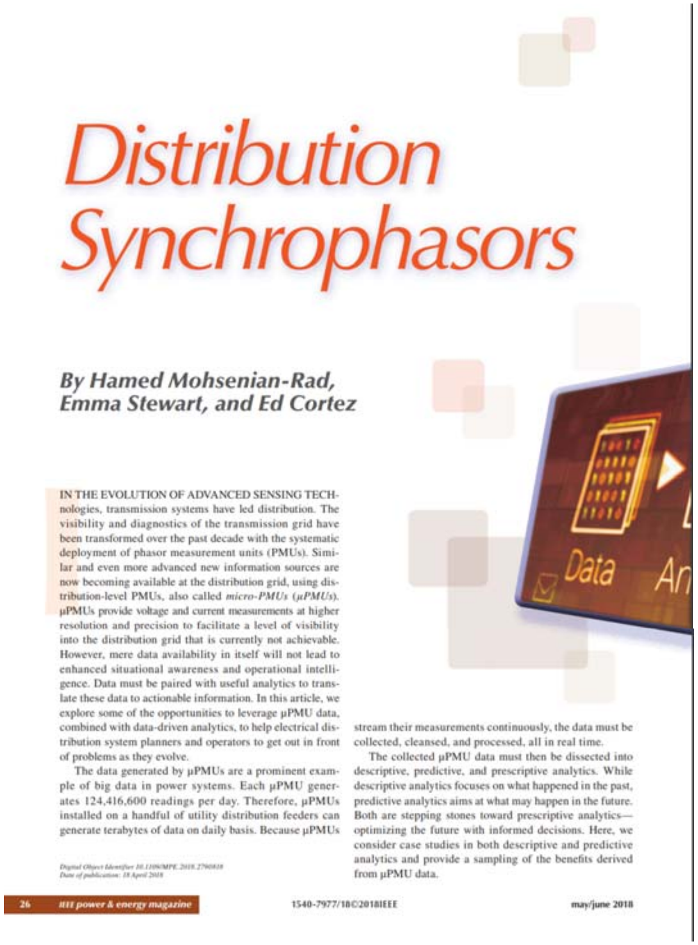

Distribution Synchrophasors

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* (*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 analytics to translate these data to actionable information. In this article, we explore some of the opportunities to leverage μPMU 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 μPMUs are a prominent 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 feeders can generate terabytes of data on daily basis. Because μPMUs stream their measurements continuously, the data must be collected, cleansed, 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.

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