DoE Energise Project DE-EE0008001

Integration of a DER Management System in Riverside

(Overview, Innovations, Challenges)

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

Washington, DC, May 16, 2019

Project Overview

Team:

- University of California, Riverside
- Riverside Public Utilities
- Smarter Grid Solutions
- Pacific Gas & Electric
- GridBright
- Lawrence Berkeley National Lab
- Lawrence Livermore National Lab

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

- Phase Identification
- Topology Identification
- Topology Reconfiguration
- Volt/VAR Control
- Load and Power Flow Balancing
- State Estimation

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

- Phase Identification
- Topology Identification
- Topology Reconfiguration
- Volt/VAR Control
- Load and Power Flow Balancing
- State Estimation

Monitoring Algorithms

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

- Phase Identification
- Topology Identification
- Topology Reconfiguration
- Volt/VAR Control
- Load and Power Flow Balancing
- State Estimation

Control Algorithms

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

Project Overview

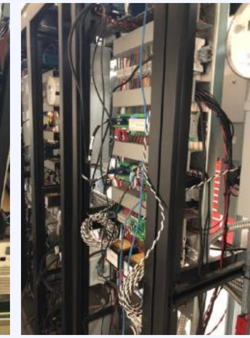
1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

SolarEdge and SMA Inverters

ANM Elements

Cap Bank and Switch Controller

Workstation



Micro-PMU

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

RPU Feeders

Model Conversion

Field Data

Model Validation

SolarEdge and SMA Inverters | ANM Elements | Cap Bank and Switch Controller | Workstation | Micro-PMU

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

Project Overview

1) Algorithm Development
2) HIL Simulation
3) Field Demonstration

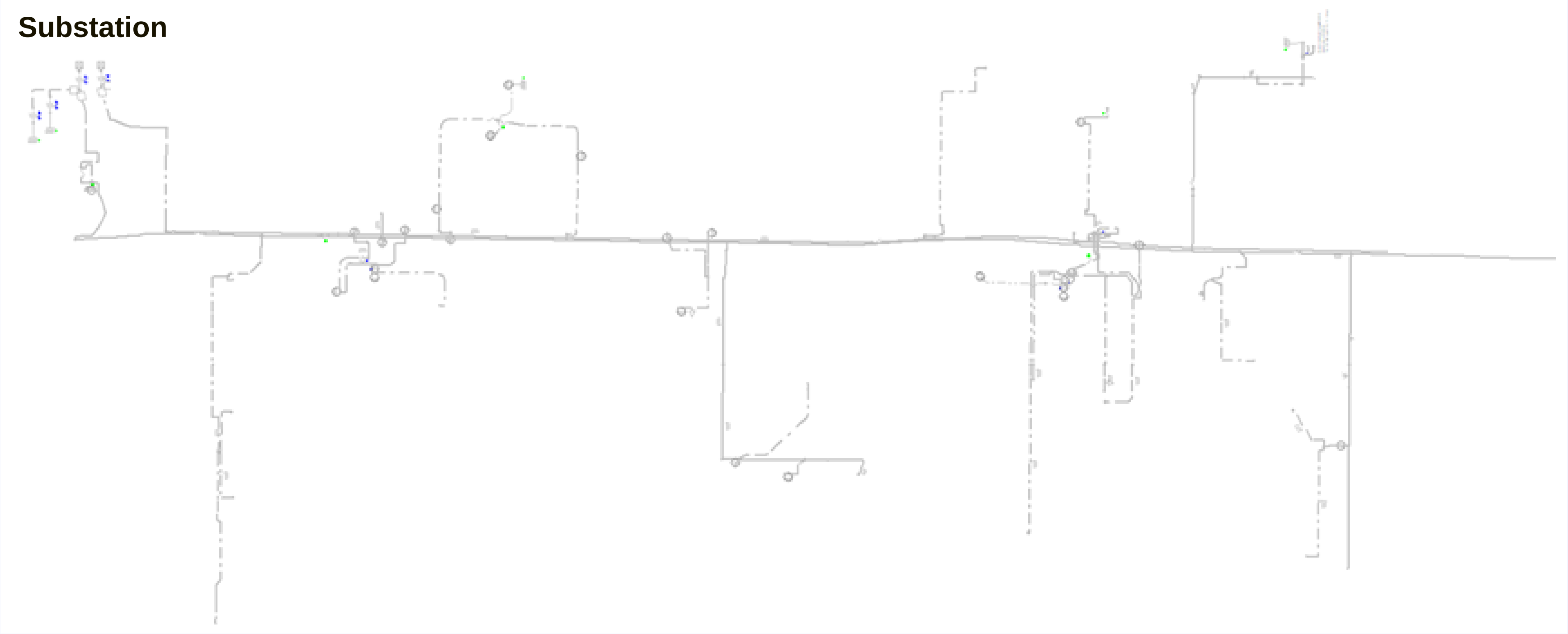
- DERs



- Advanced Sensors

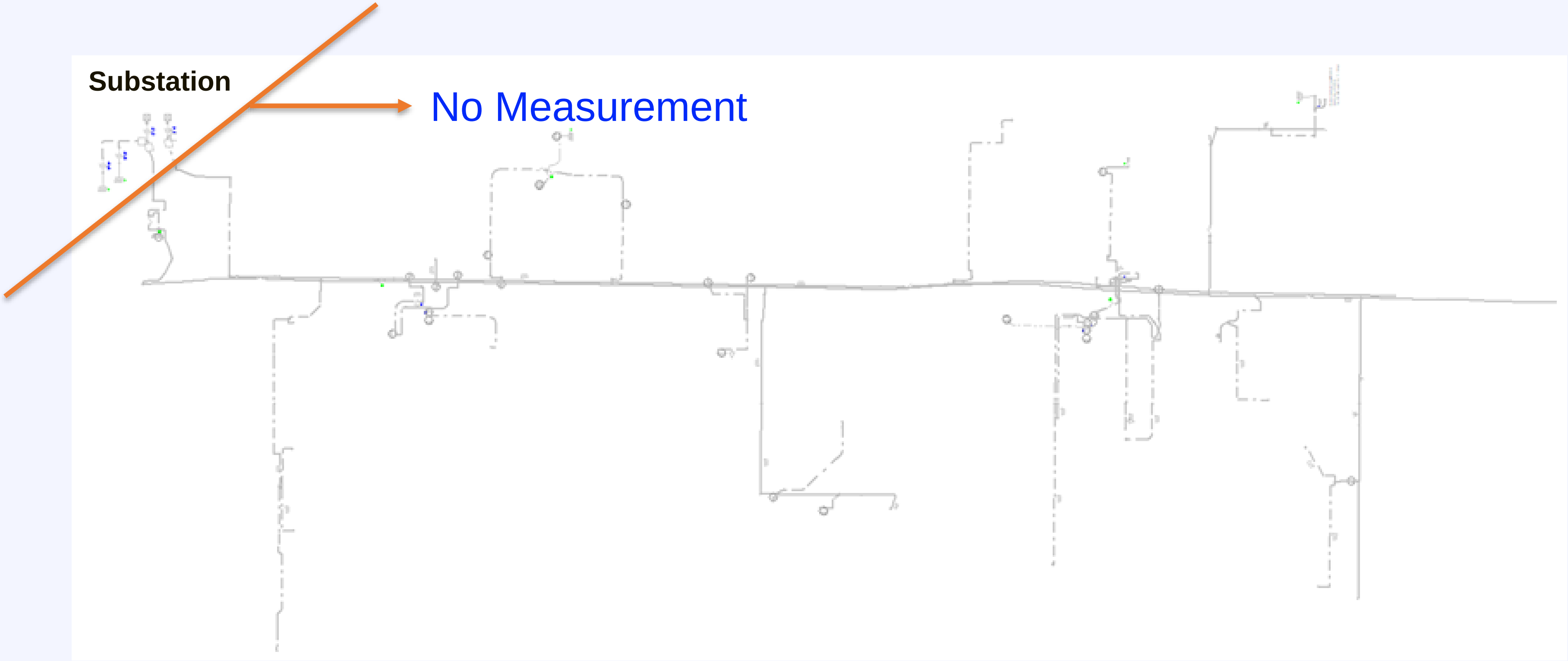
Micro-PMU and Line Sensor

One of the Feeders:



Innovations and Challenges

One of the Feeders:



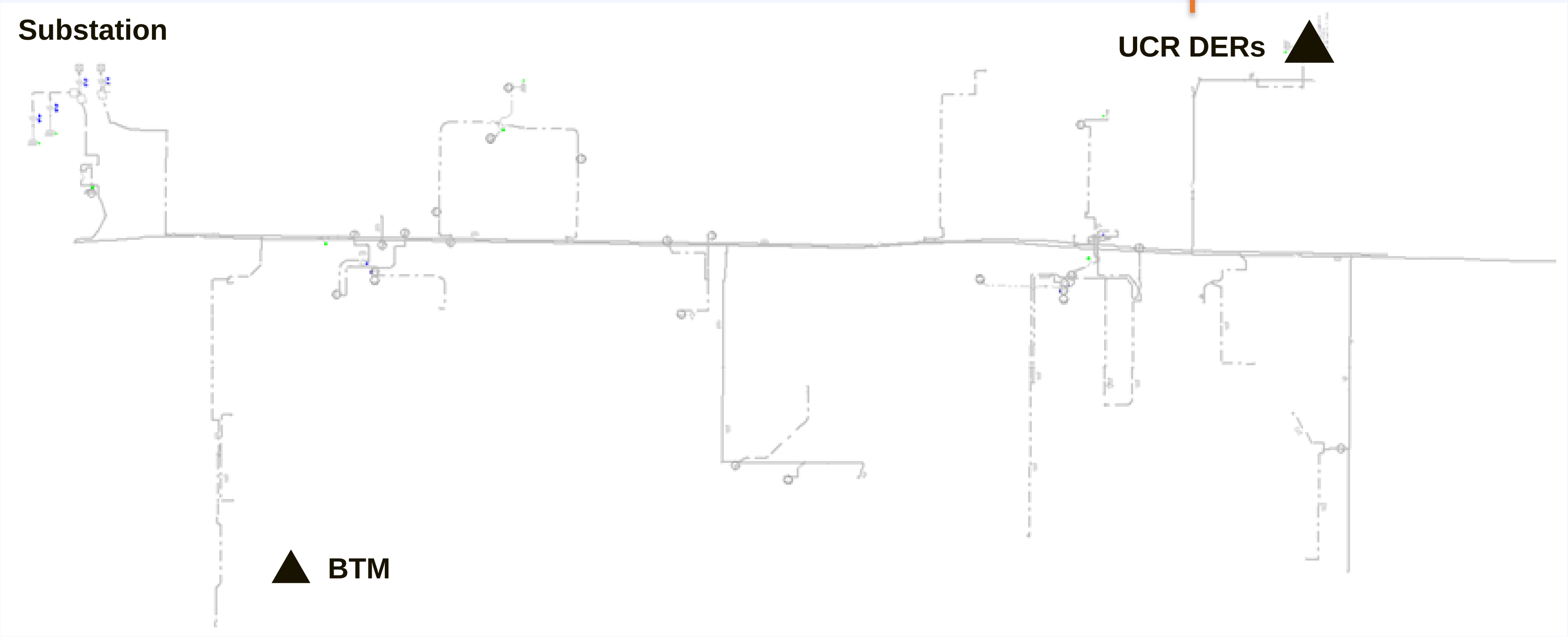
SunShot U.S. Department of Energy

UNIVERSITY OF CALIFORNIA UC RIVERSIDE

Innovations and Challenges

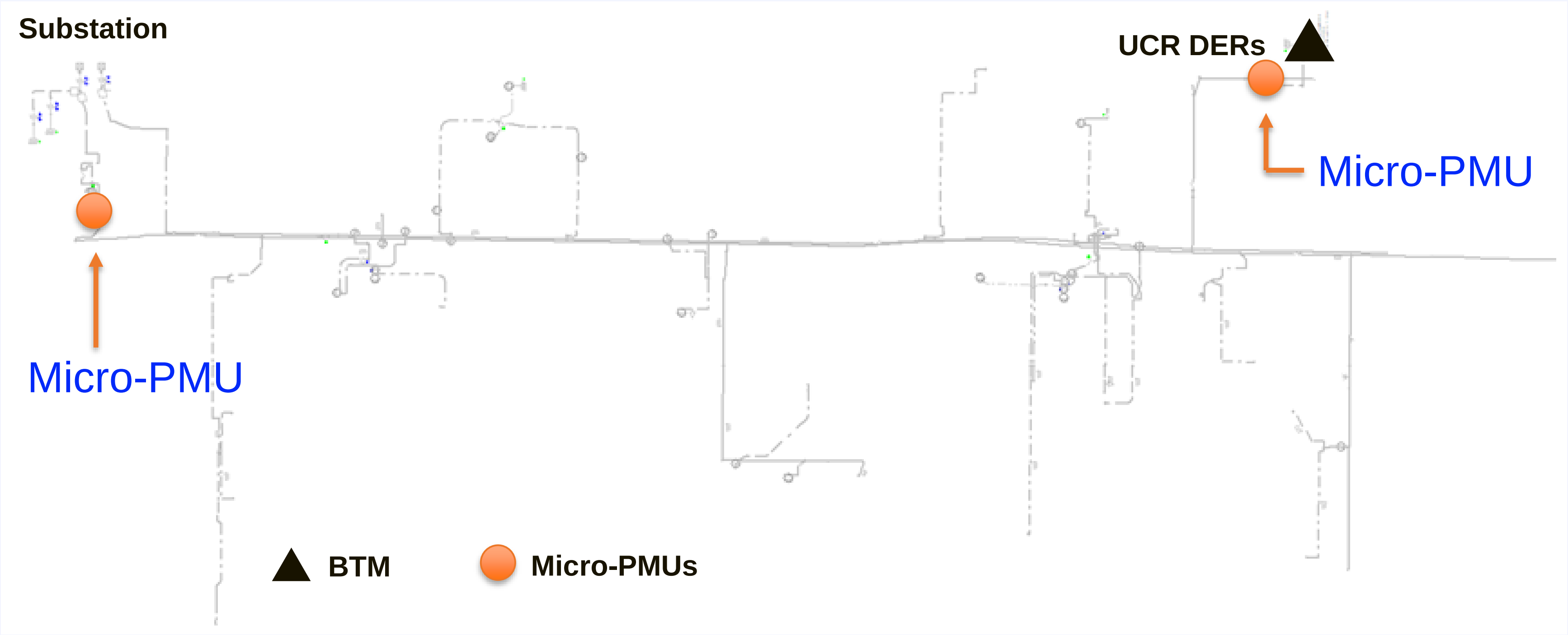
One of the Feeders:

BTM Measurements



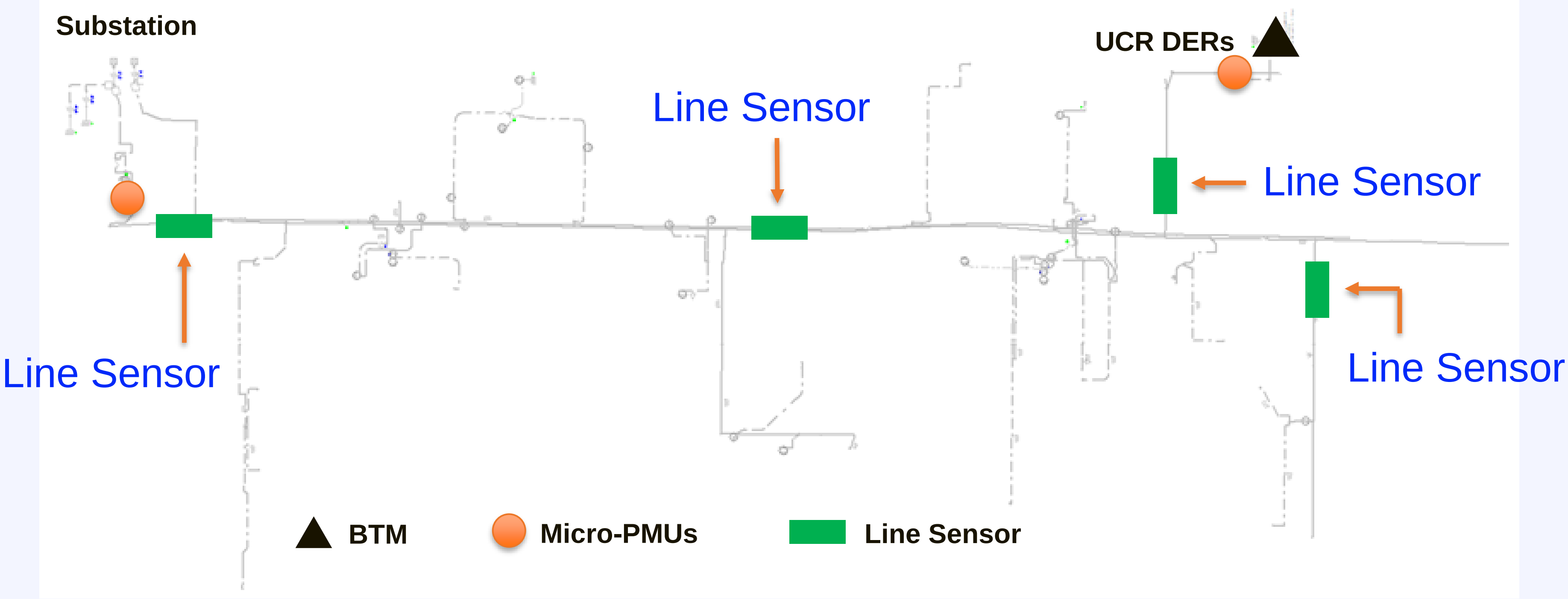
Innovations and Challenges

One of the Feeders:



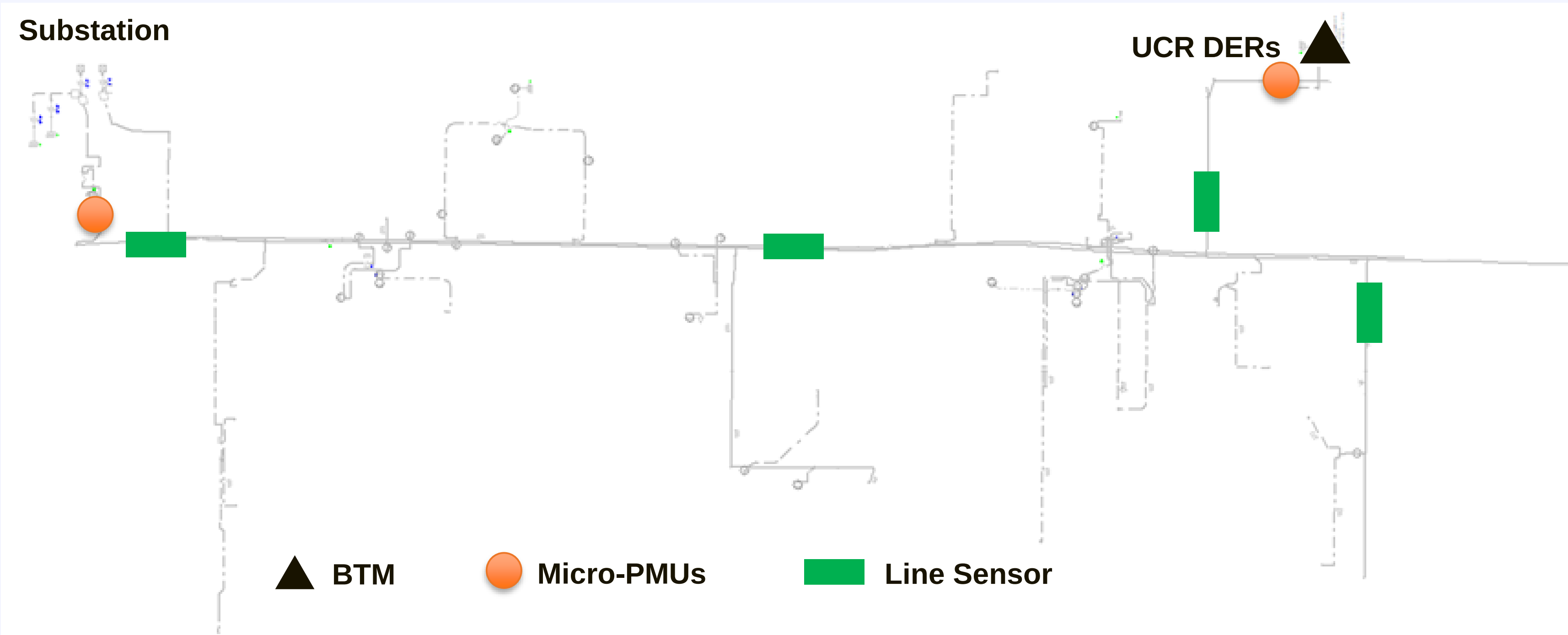
Innovations and Challenges

One of the Feeders:



Innovations and Challenges

One of the Feeders:



Innovations and Challenges

With Two Micro-PMUs:

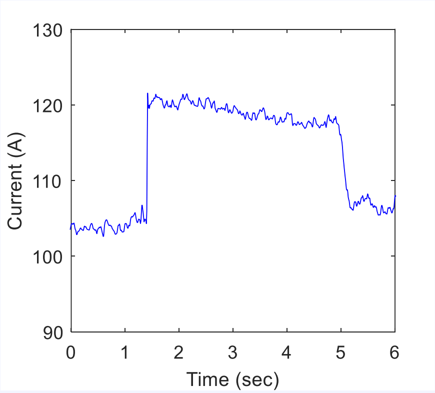
Micro-PMU Data Analytics Package

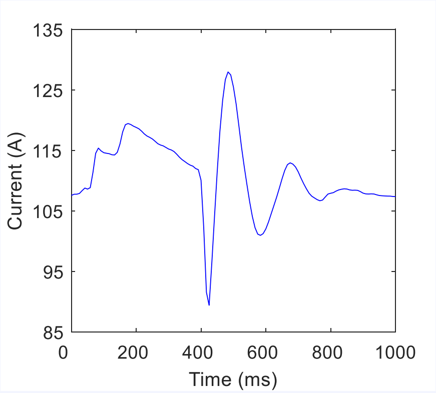
- Event Detection
- Event Classification
- Event Identification

With Two Micro-PMUs:

Micro-PMU Data Analytics Package

- Event Detection → 500 Events Per Day Per Feeder
- Event Classification
- Event Identification





Innovations and Challenges

With Two Micro-PMUs:

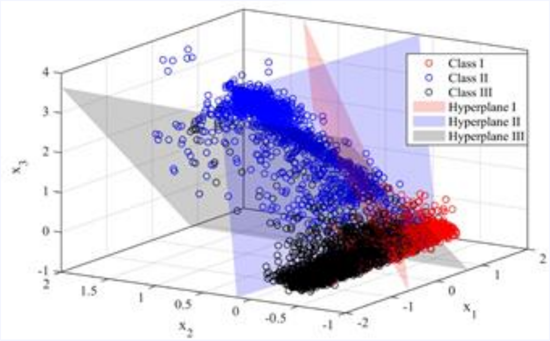
Micro-PMU Data Analytics Package

- Event Detection
- Event Classification
- Event Identification

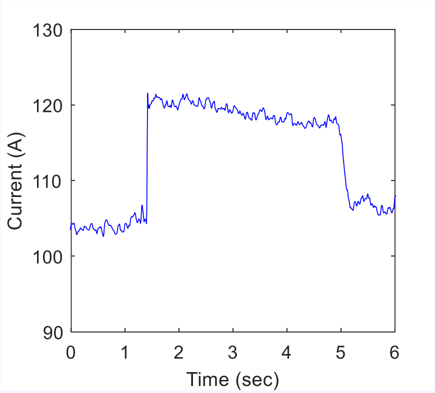
Feature Selection

Event Labeling

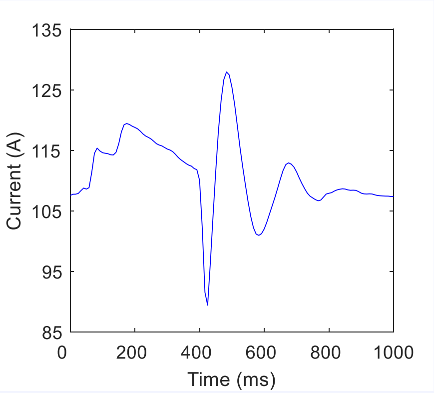
Machine Learning



Test Data



Step Change



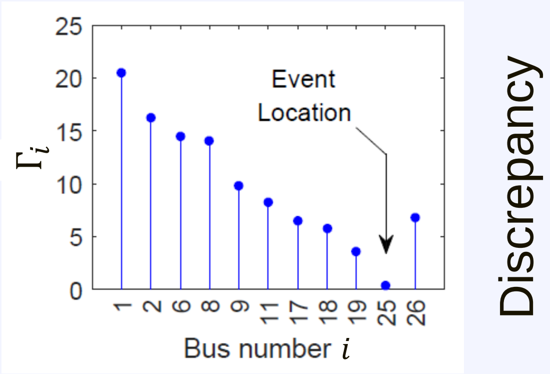
Dynamic

Innovations and Challenges

With Two Micro-PMUs:

Micro-PMU Data Analytics Package

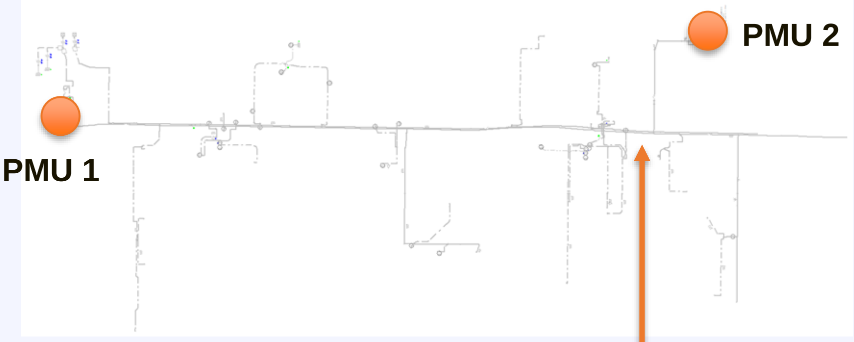
- Event Detection
- Event Classification
- Event Identification



Differential Synchrophasors

Compensation Theorm

Equivalent Circuit



Event Location

Innovations and Challenges

With Two Micro-PMUs:

Micro-PMU Data Analytics Package

- Event Detection
- Event Classification
- Event Identification

Remote Asset and DER Monitoring

Static and Transient Load Modeling

Protection System Diagnostics

Situational Awareness

Cybersecurity

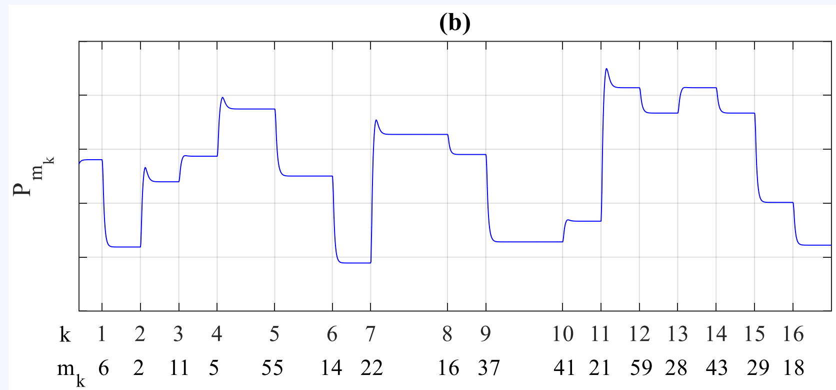
⋮

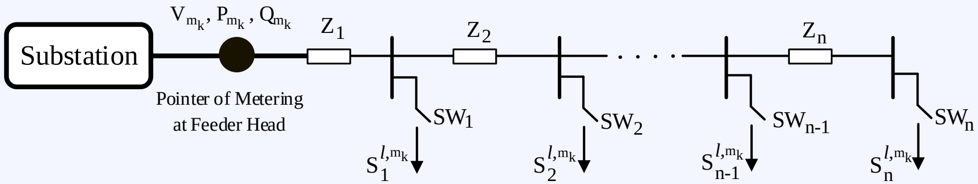
Innovations and Challenges

Feeder Aggregated Load Modeling:

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

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



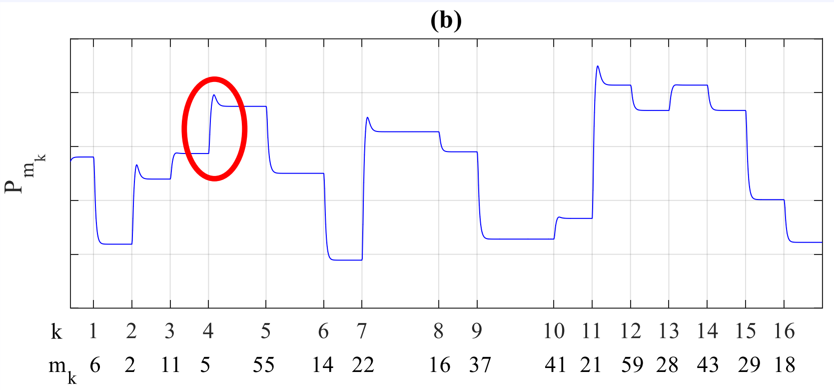


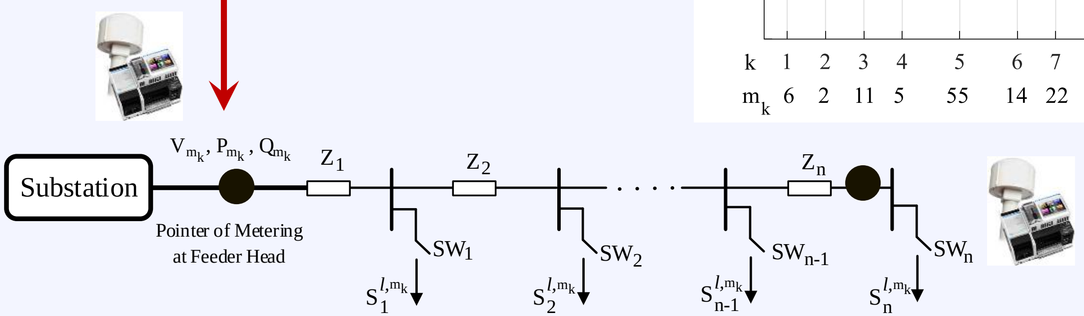
Innovations and Challenges

Individual Load Modeling:

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

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





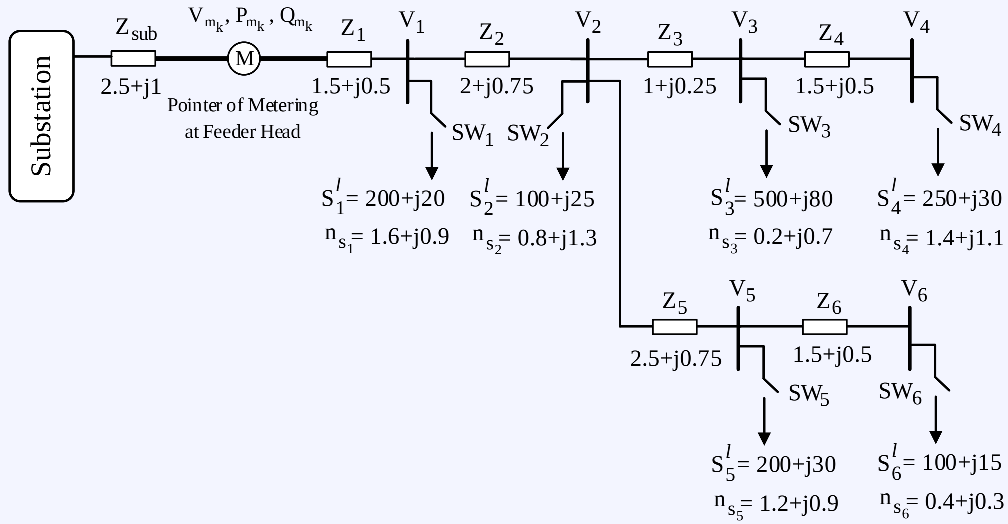
$$P_{m_k} = P_{m_h}\left(\frac{V_{m_k}}{V_{m_h}}\right)^{n_{p,i}}$$

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

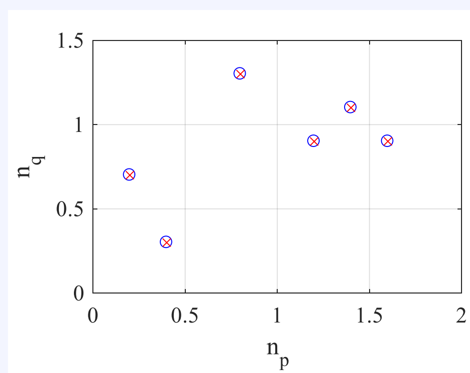
$$i = 1, 2, \ldots, n$$

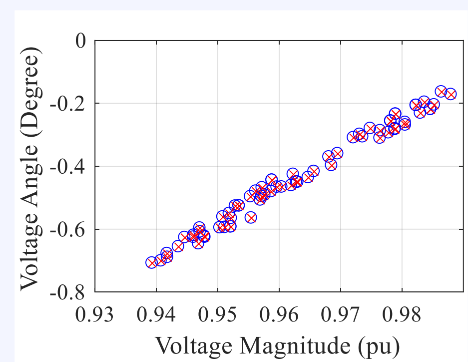
Individual Load Modeling:

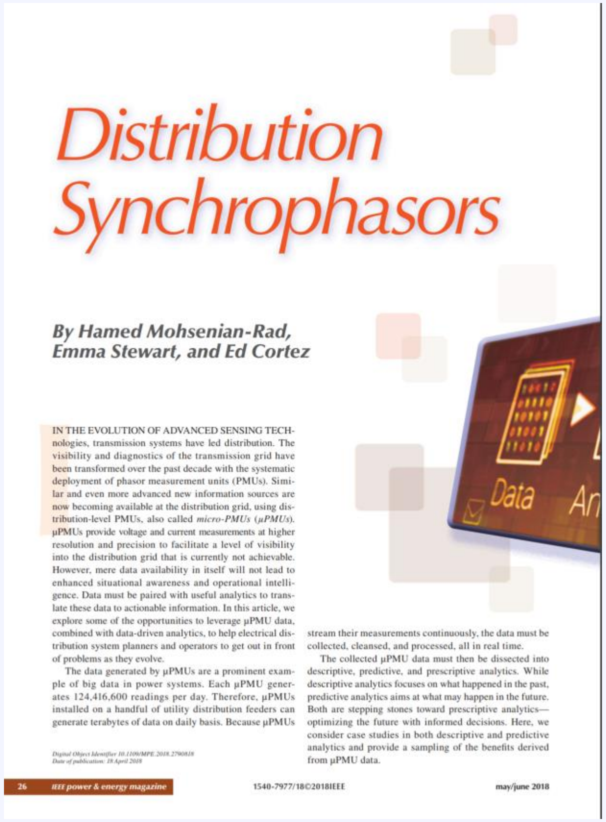
Configuration	SW_1	SW_2	SW_3	SW_4	SW_5	SW_6	Time
m_1	1	0	0	1	0	0	$[0\ ,\ t_1]$
m_2	1	0	0	1	0	1	$[t_1\ ,\ t_2]$
m_3	1	1	0	0	1	0	$[t_2\ ,\ t_3]$
m_4	0	0	1	1	0	1	$[t_3\ ,\ t_4]$
m_5	0	1	1	1	0	1	$[t_4\ ,\ t_5]$
m_6	1	1	0	0	1	1	$[t_5\ ,\ t_6]$
m_7	0	1	1	0	1	1	$[t_6\ ,\ t_7]$
m_8	1	0	1	1	1	0	$[t_7\ ,\ t_8]$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



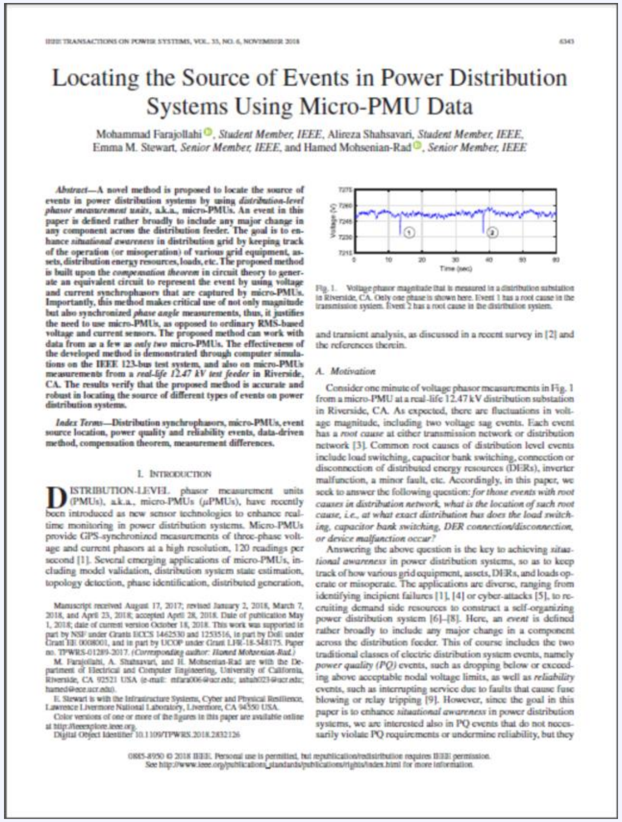
	# of Equations	# of Unknowns
Circuit Model	84	120
Load Model	42	6
Combined	126	126







IEEE PES Magazine 2018



IEEE T. on Power Systems 2018

Innovations and Challenges

IEEE T. on Smart Grid 2018

IEEE T. on Power Systems 2019

SunShot U.S. Department of Energy

(DE-EE0008001) UC RIVERSIDE UNIVERSITY OF CALIFORNIA

Innovations and Challenges

With Line Current Sensors:

- Topology Identification
  1. Reliable Solution
  2. Fast Calculation
  3. Light Computation
  4. Switch Malfunction

Topology Identification in Distribution Systems using Line Current Sensors: Deterministic and Stochastic MILP Methods

Mohammad Farajollahi, *Student Member, IEEE*, Alireza Shahsavari, *Student Member, IEEE*, and Hamed Mohsenian-Rad, *Senior Member, IEEE*

***Abstract*—This study is motivated by the recent advancements in developing non-contact line sensor technologies that come at a low cost, but have limited measurement capabilities. While they are intended to measure current, they cannot measure voltage and power. This poses a challenge to certain distribution system applications, such as topology identification (TI), because they commonly use voltage and power measurements. To address this open problem, in this paper, we propose a new TI algorithm that works solely based on the measurements that come from line current sensors. We first develop a generic TI problem formulation in this context in form of a mixed integer nonlinear program (MINLP). Several reformulation steps are then adopted to tackle the nonlinearities to express the TI problem in form of a mixed integer linear program (MILP). The proposed method is able to identify all possible topologies, including radial, loop, and island configurations, which extends the application of TI to identify switch malfunctions and to detect outages. In addition, recommendations are made with respect to the number and location of the line current sensors to ensure performance accuracy of the TI method. Importantly, a novel stochastic TI algorithm is also proposed to use multiple measurement snapshots to improve the TI accuracy and robustness against errors in pseudo-measurements. The effectiveness of the proposed TI algorithms is examined on the IEEE 33-bus test case as well as a test case based on a real-world feeder in Riverside, CA. The results demonstrate the efficiency and robustness of both the deterministic and stochastic TI algorithms.**

***Keywords*: Topology identification, line sensors, distribution network, mixed integer linear program, stochastic optimization.**

I. Introduction

Correct knowledge of the network topology is vital for various aspects of the distribution network's operation, including state estimation, fault location, Volt-VAR control, demand side management, etc. If the network topology is known incorrectly, then the above applications also produce incorrect results. Therefore, a continuous procedure to identify the topology of the network is necessary. However, in practice, topology identification (TI) is a challenging task for distribution systems due to the limited measurements as well as unavailable or unreliable information about the status of switches and circuit breakers across distribution feeders.

The most common TI approach in practice for utilities is to dispatch their field crew members to examine the switches status at the field. Of course, it is a costly option and cannot be done frequently in order to continuously track changes in topology. An alternative approach is to use measurement-based TI algorithms that estimate the status of switches based on available sensor measurements.

Several different measurement-based methods have been proposed in the literature. One class of TI algorithms uses various field measurements to conduct distribution system state estimation for every possible topology configuration, and then chooses the topology that results in the minimum residue errors in state estimation [1], [2]. However, such exhaustive approach is often computationally complex. A remedy is to integrate the TI problem into the state estimation problem formulation so as to simultaneously estimate not only the system states but also the status of the switches [3], [4]. This can help improve computational efficiency. However, the issue with any TI algorithm that somehow involves state estimation is that one may not have sufficient field measurements to do full state estimation; even though the available measurements could be sufficient for the sole purpose of TI.

There are other TI methods proposed in the literature that use a rather limited set of measurements solely for the purpose of TI. A common approach in this line of work is to make use of *voltage measurements*. For example, in [5], the authors reconstruct the power distribution grid topology by conducting a correlation analysis of voltage measurements. In [6], the authors utilize a time-series signature verification method to identify network topology using synchronized voltage phasor data. The usage of voltage measurements coming from smart meters in TI application is also reported in [7] and [8].

In this paper, we seek to develop a TI algorithm that makes use of *line current measurements*. Our study is motivated by the recent advancements in developing non-contact line current sensor technologies that come at a low-cost and they can be installed very easily using hot sticks, when compared with the traditional utility sensors that measure voltage and power. The features of these new sensor technologies will be explained in details in Section II-A. There already exists a verity of commercial choices for non-contact line current sensors, e.g., see [9], [10], and a growing number of utilities, such as in Riverside, CA, are looking into installing such low-cost sensors on their medium and low voltage distribution lines.

While the aforementioned line current sensor technologies are capable of measuring electric field, they are not capable of measuring voltage. More precisely, they cannot measure voltage while keeping their cost down at a level that justifies their application in power distribution systems. As a result, they

The authors are with the Department of Electrical and Computer Engineering, University of California, Riverside, CA, USA. This work was supported by NSF grants 1462530 and 1253516 and DoE grant EE 0008001. The corresponding author is H. Mohsenian-Rad, e-mail: hamed@ece.ucr.edu.

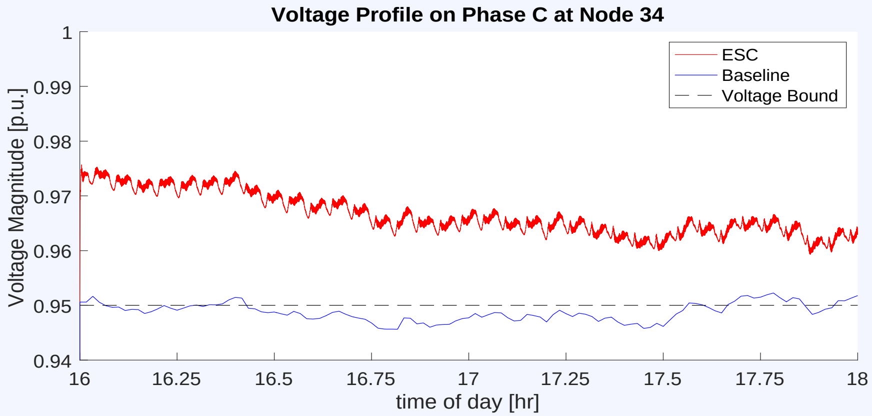
IEEE T. on Smart Grid 2019

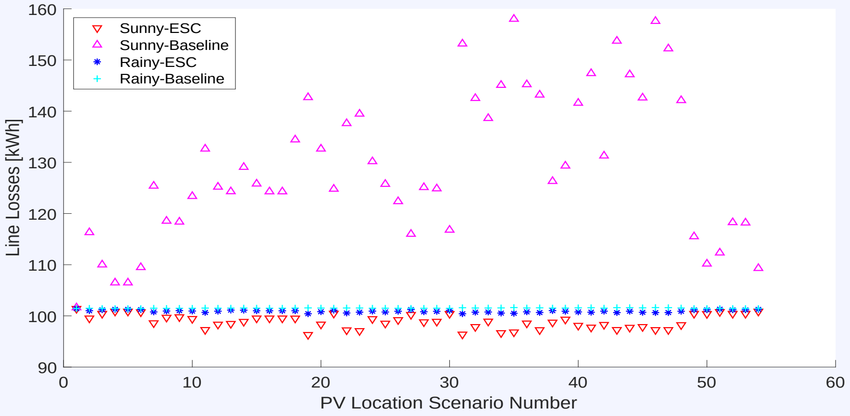
Innovations and Challenges

DER Control Based on Extremum-Seeking Iterations:

- Model Free
- Probe Signal
- Gradient Descent

(LBNL)





Innovations and Challenges

Realities in Field Implementation

- Limited Utility Resources
- Limited Project Resources

Innovative Solutions

New Technologies

Publications

Thank You!

https://www.ece.ucr.edu/~hamed