

UCR

Analysis of Cyber Attacks Against Distribution-Level PMUs: Event Source Location Case Study

(Tasks 1.2, 1.3, and 2.2)

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Application of Micro-PMUs:

- Capacitor Back Switching
- Fault Analysis
- Lightning Analysis
- Inverter Misoperation
- Event Classification
- Event Clustering
- Impedance Calculation
- Topology Identification
- Event Source Location Identification
- ...

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* (μ PMUs). μ 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 μ 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 μ PMUs are a prominent example of big data in power systems. Each μ PMU generates 124,416,000 readings per day. Therefore, μ PMUs installed on a handful of utility distribution feeders can generate terabytes of data on daily basis. Because μ PMUs

stream their measurements continuously, the data must be collected, cleaned, and processed, all in real time. The collected μ 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 μ PMU data.

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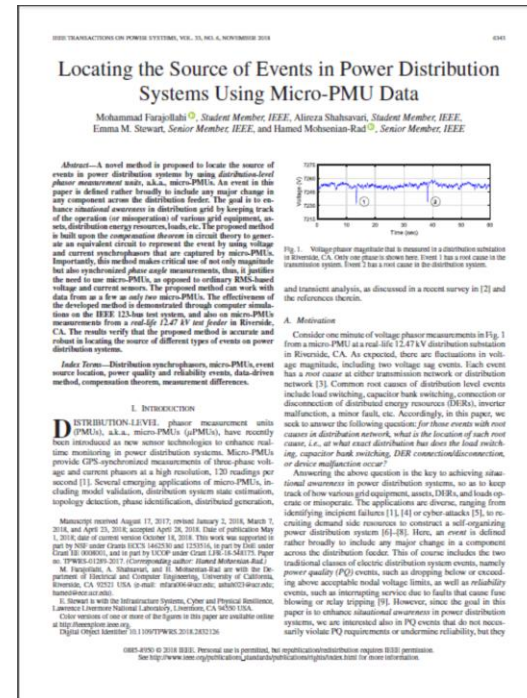
may/june 2018

IEEE Power and Energy
Magazine, May 2018

Application of Micro-PMUs:

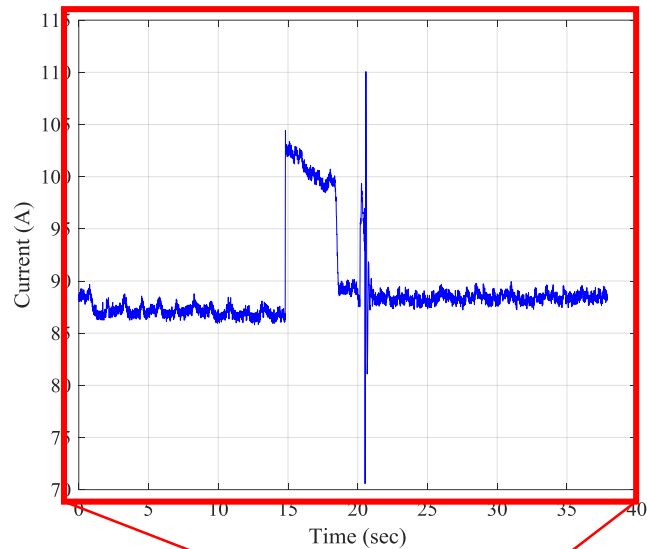
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- **Event Source Location Identification**
- ...

↪ Our Focus



IEEE Trans. on Power Systems, Nov 2018

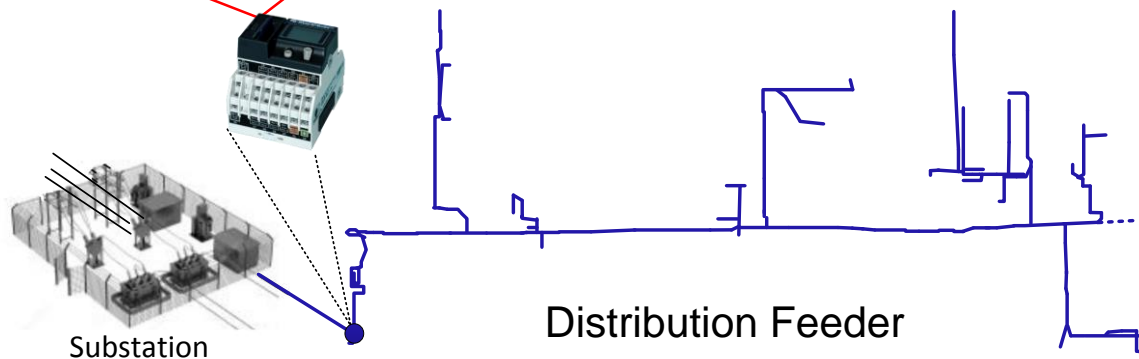
Locating Source of Events



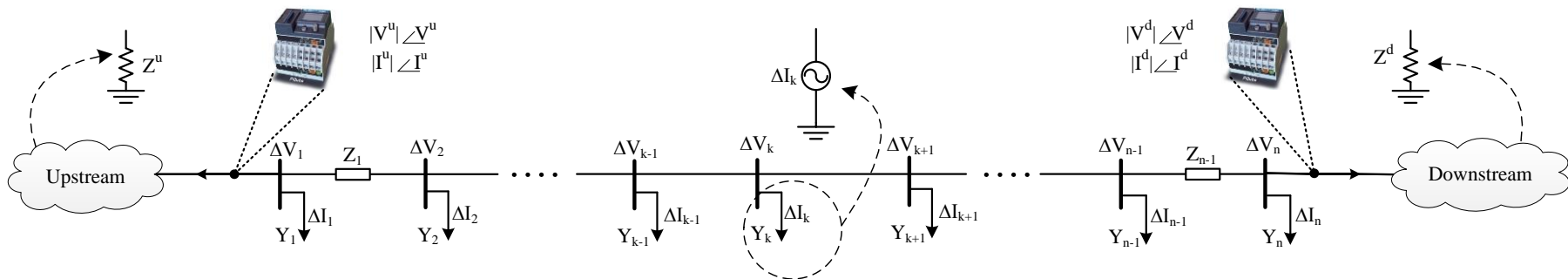
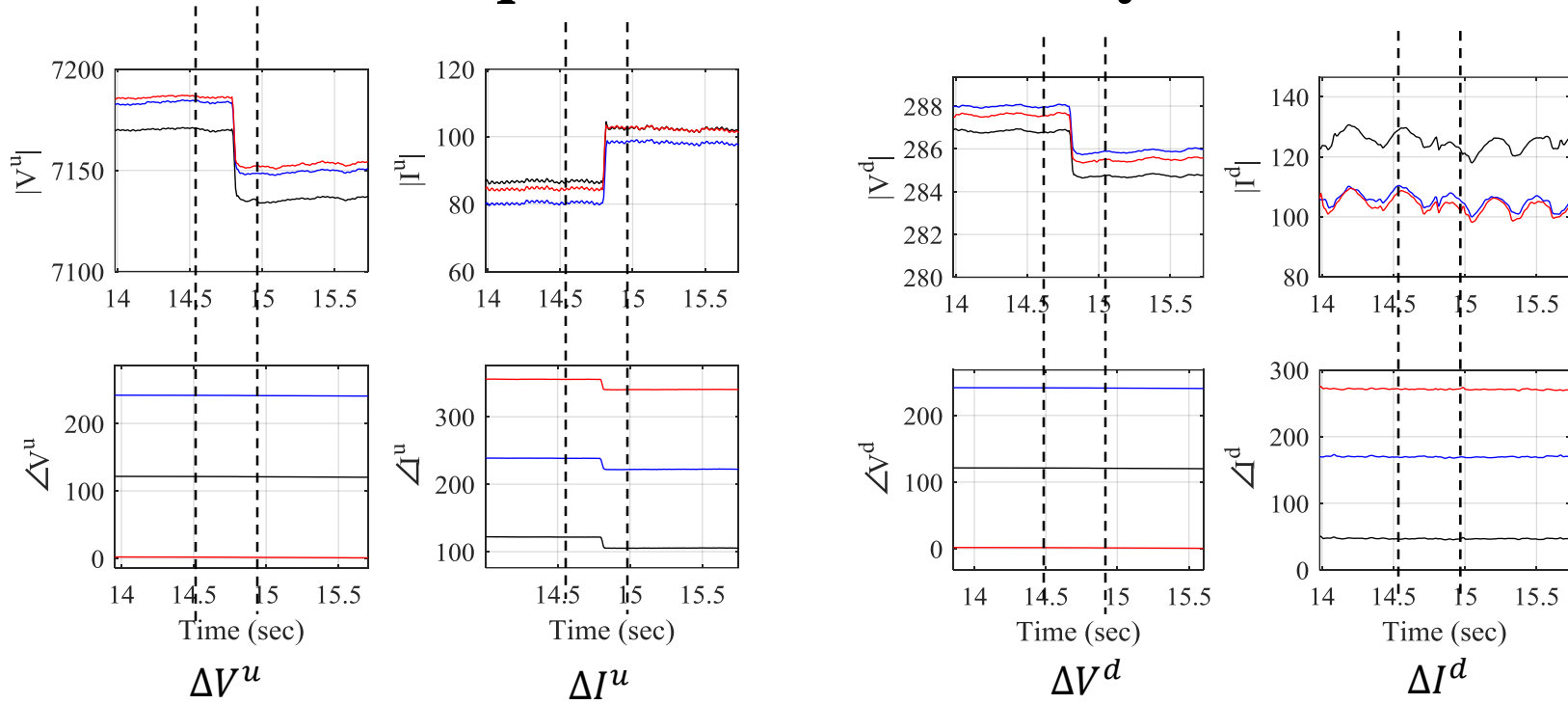
1) Is an event occurred on distribution feeder?

2) If yes, where is the exact location?

3) What we need for location identification?



Equivalent Circuit Analysis



K: Event Bus (Unknown)

Voltage Comparison

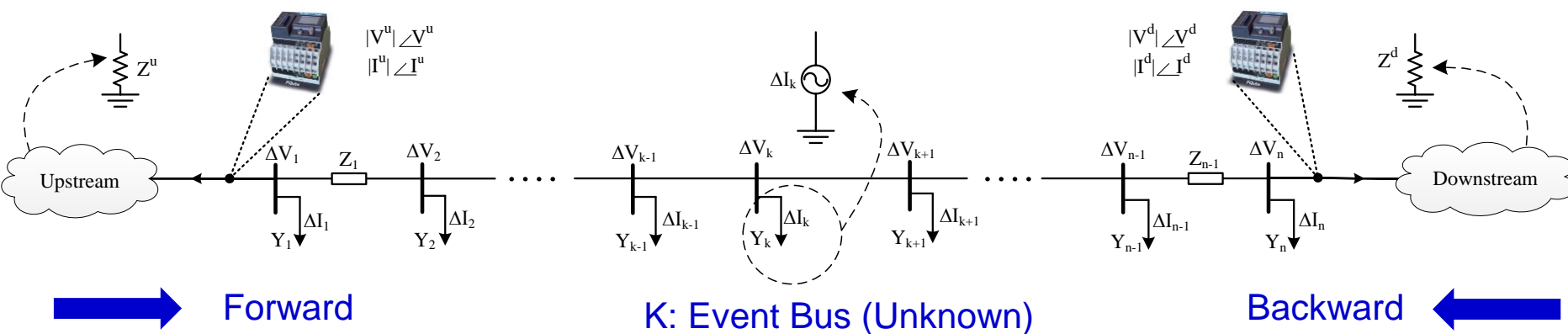
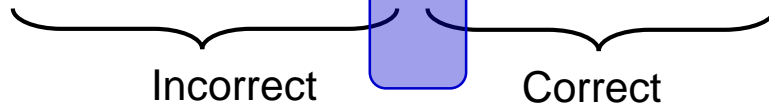
Forward: $\{\Delta V_1^f, \Delta V_2^f, \dots, \Delta V_{k-1}^f, \Delta V_k^f, \Delta V_{k+1}^f, \dots, \Delta V_n^f\}$



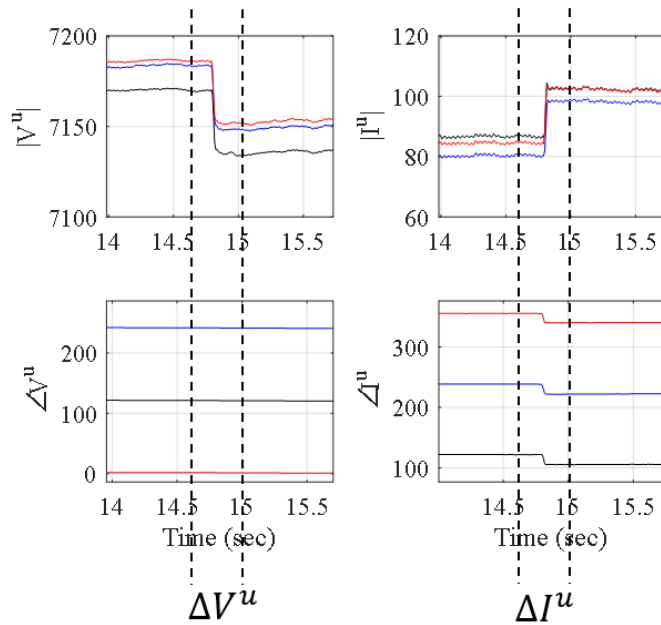
$\xrightarrow{\quad} k = \arg \min_i |\Delta V_i^f - \Delta V_i^b|^2$

ϕ_i

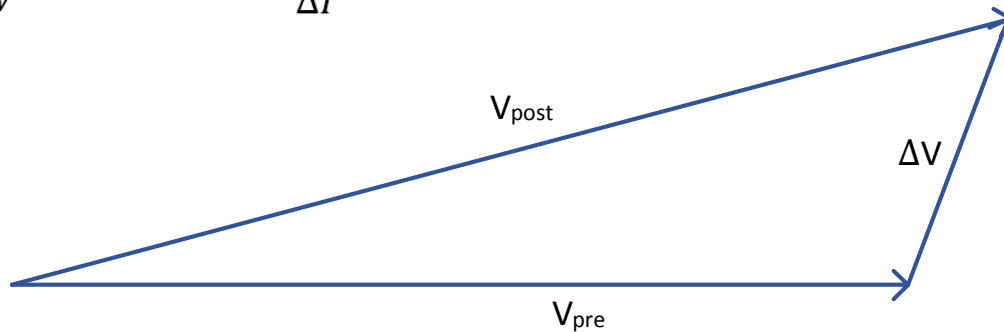
Backward: $\{\Delta V_1^b, \Delta V_2^b, \dots, \Delta V_{k-1}^b, \Delta V_k^b, \Delta V_{k+1}^b, \dots, \Delta V_n^b\}$



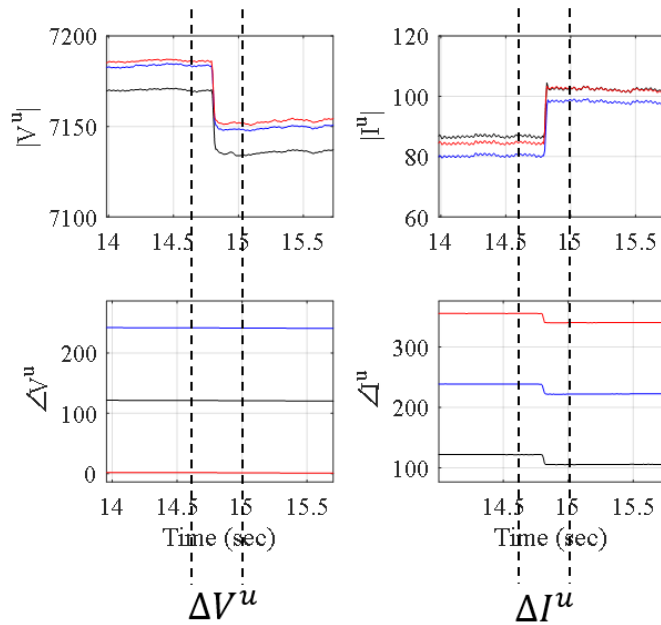
Micro-PMU Measurements



$$\Delta V = V_{post} - V_{pre}$$

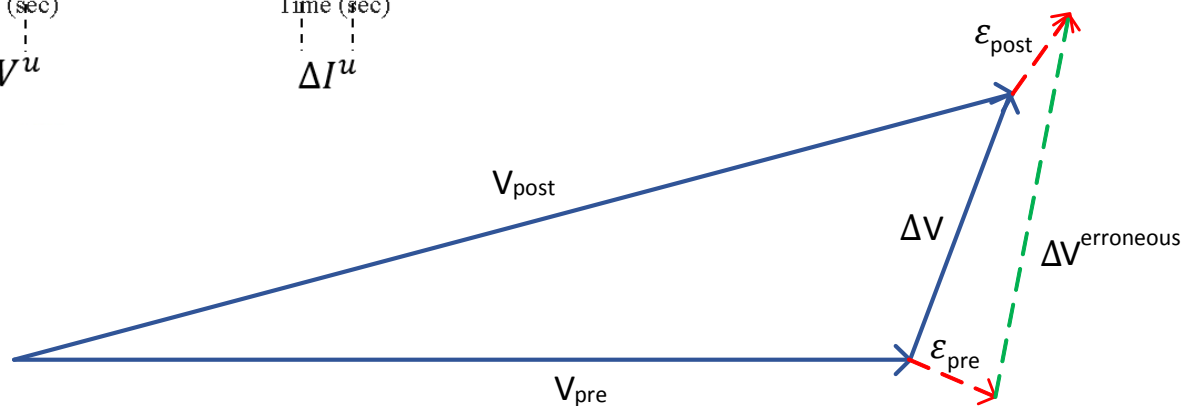


Micro-PMU Measurements

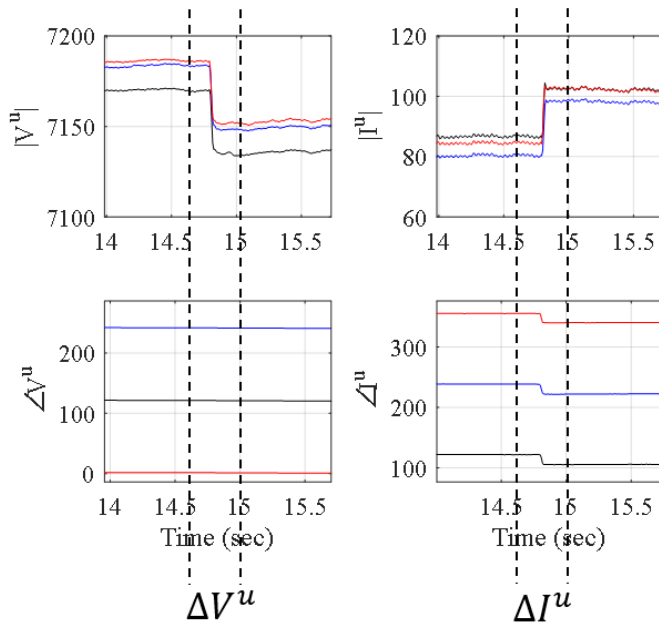


$$\Delta V = V_{post} - V_{pre}$$

$$\begin{aligned} \Delta V_{erroneous} &= V_{post} + \epsilon_{post} - (V_{pre} + \epsilon_{pre}) \\ &= \Delta V + (\epsilon_{post} - \epsilon_{pre}) \end{aligned}$$

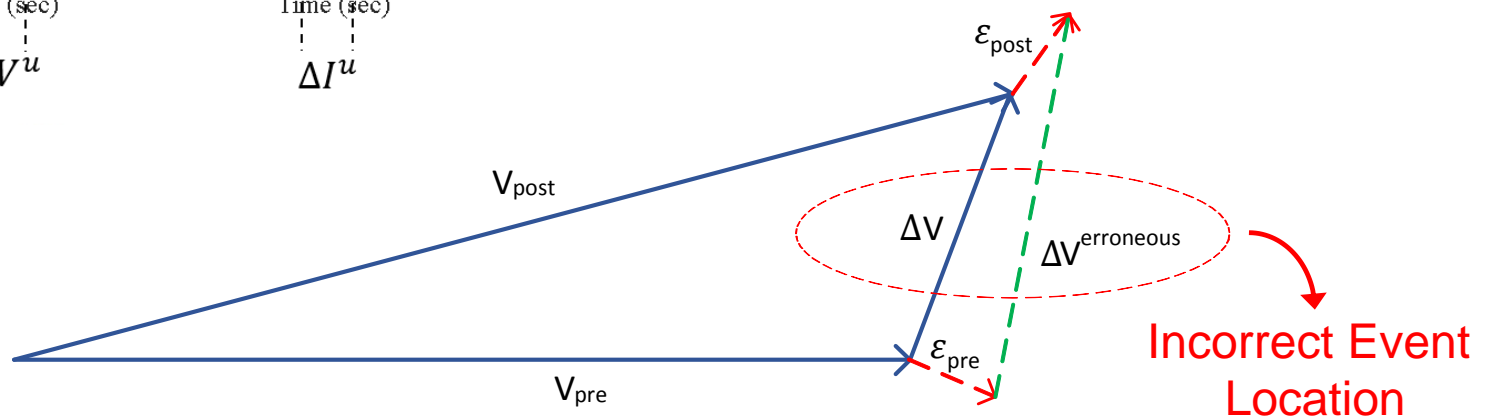


Micro-PMU Measurements

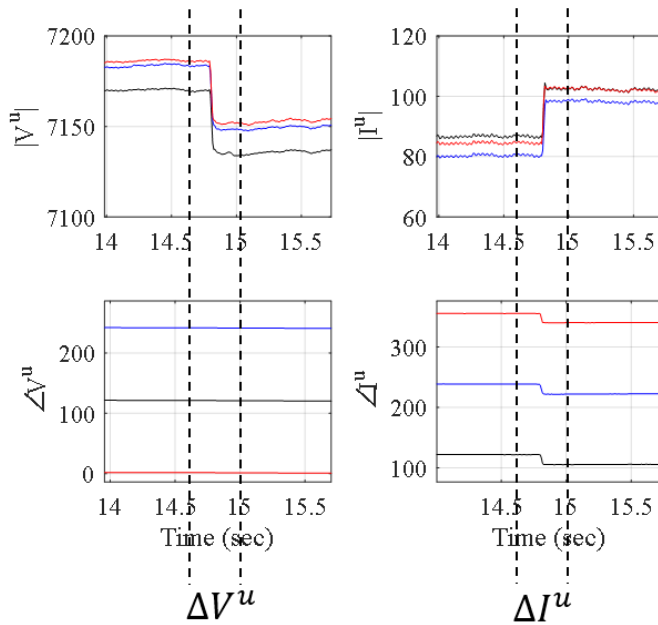


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Micro-PMU Measurements

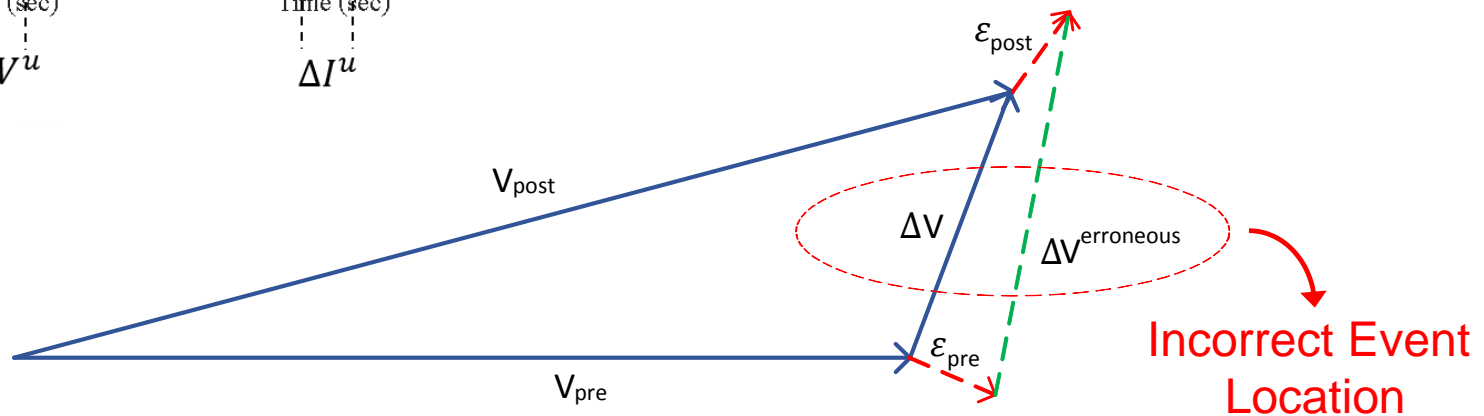


Intentional?

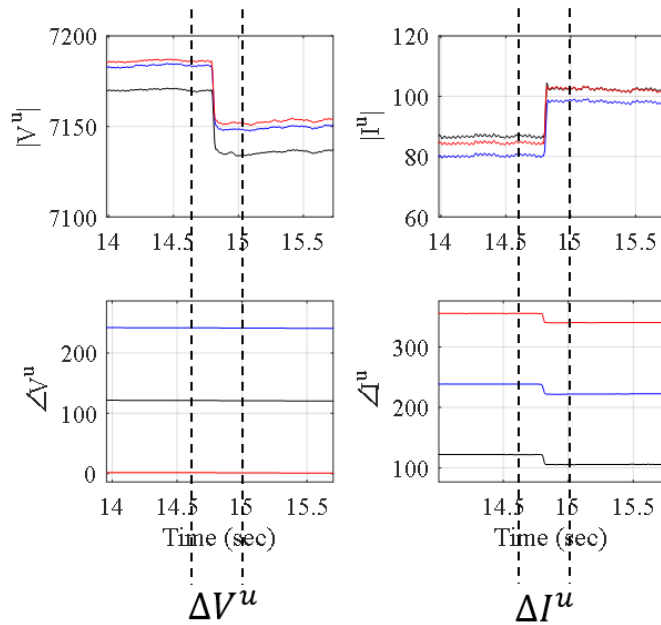
$$\Delta V = V_{post} - V_{pre}$$

$$\Delta V_{erroneous} = \underbrace{V_{post} + \epsilon_{post}} - \underbrace{(V_{pre} + \epsilon_{pre})}$$

$$= \Delta V + (\epsilon_{post} - \epsilon_{pre})$$



Micro-PMU Measurements

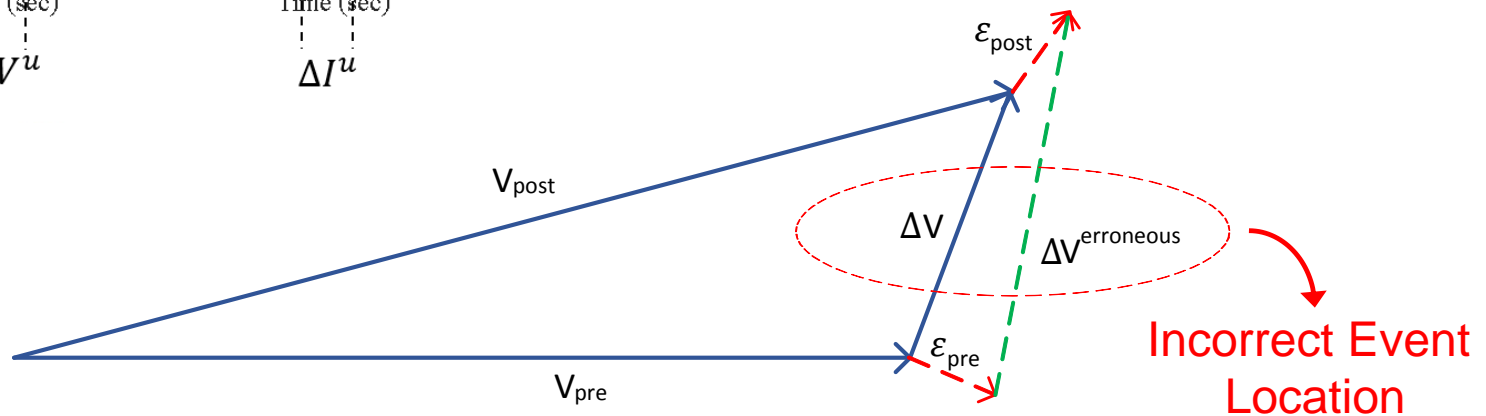


False Data Injection Attack

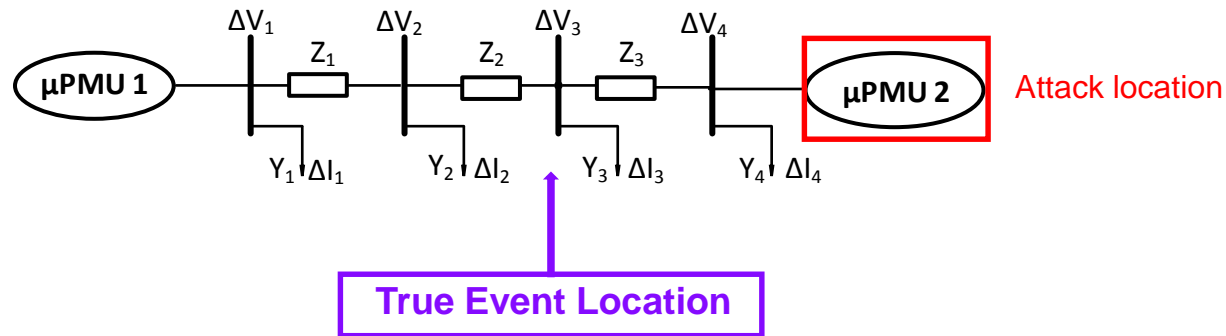
$$\Delta V = V_{post} - V_{pre}$$

$$\Delta V_{erroneous} = V_{post} + \epsilon_{post} - (V_{pre} + \epsilon_{pre})$$

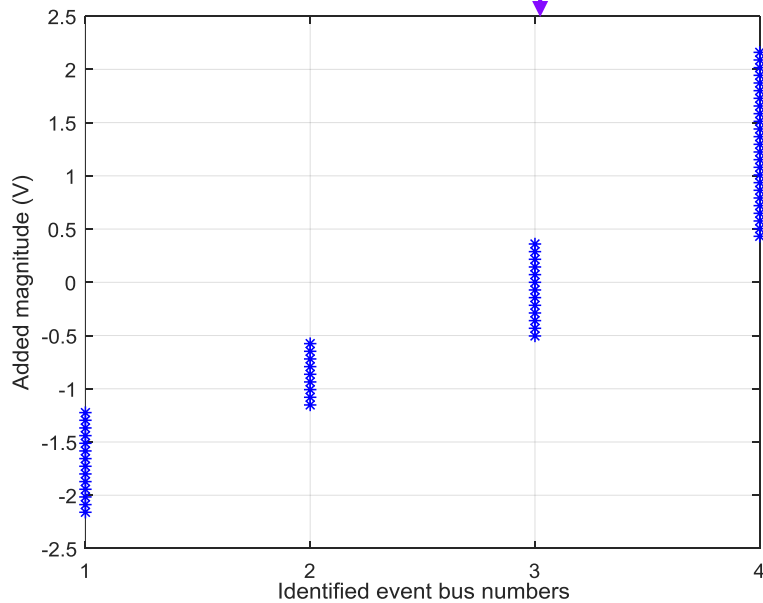
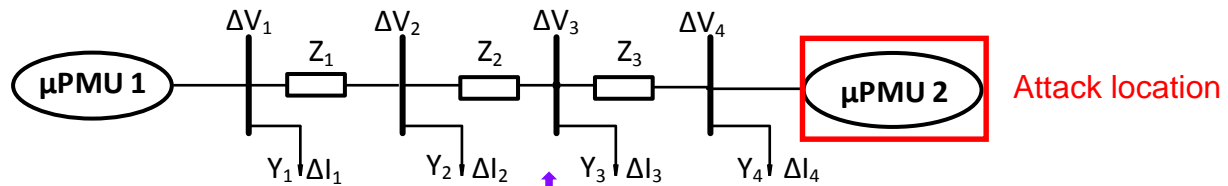
$$= \Delta V + (\epsilon_{post} - \epsilon_{pre})$$



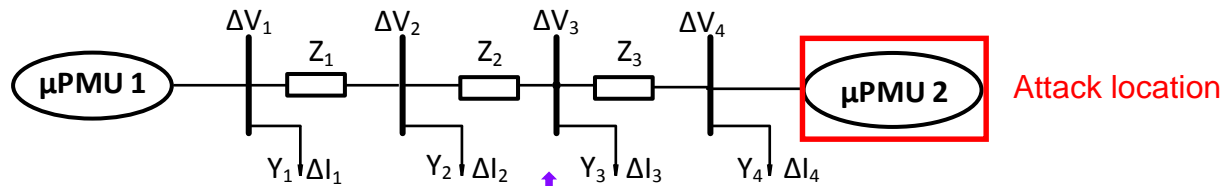
FDIA Against Micro-PMU data



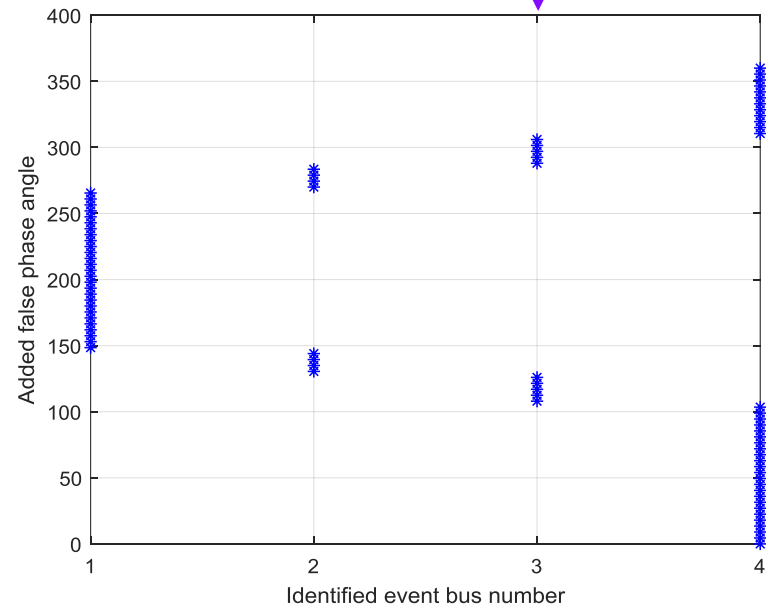
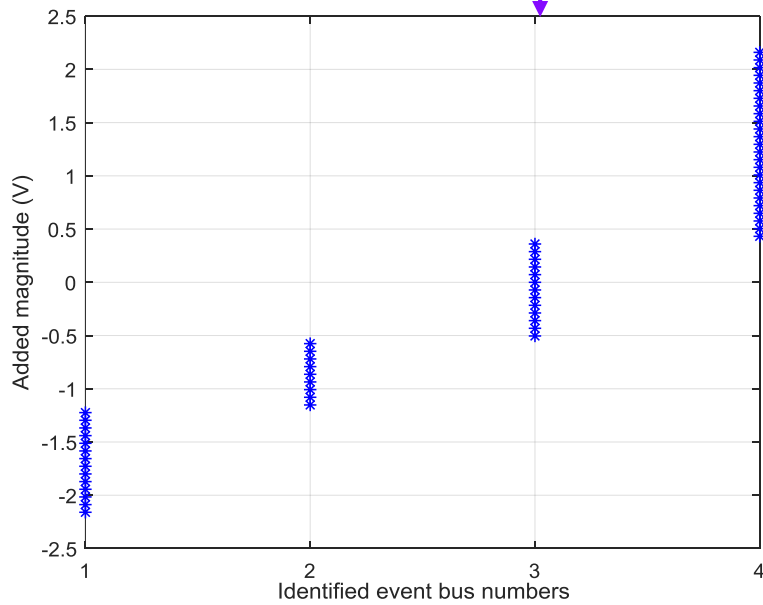
FDIA Against Micro-PMU data



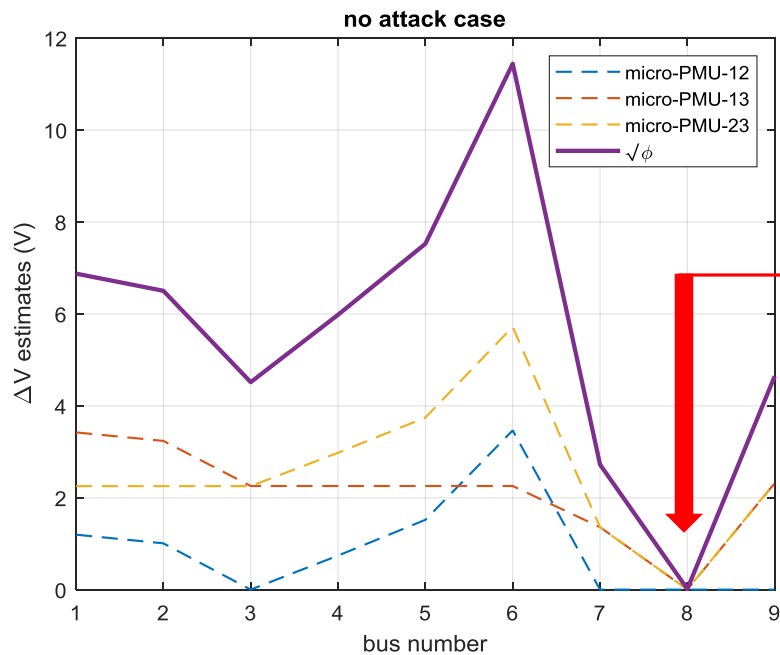
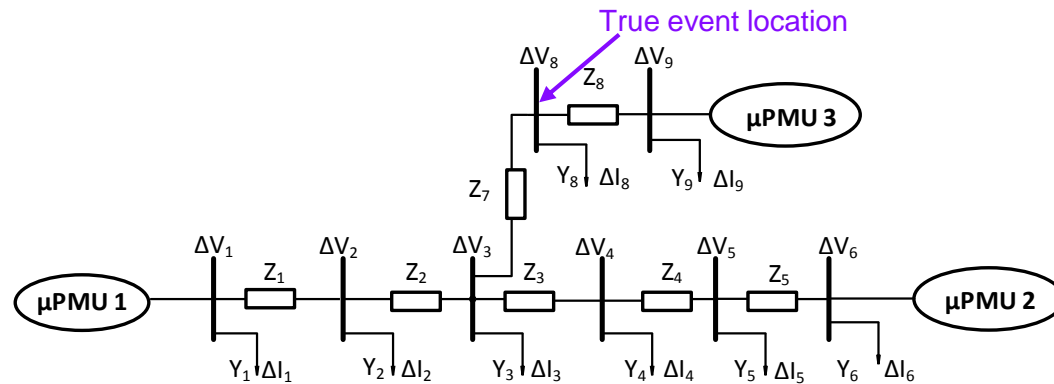
FDIA Against Micro-PMU data



True Event Location

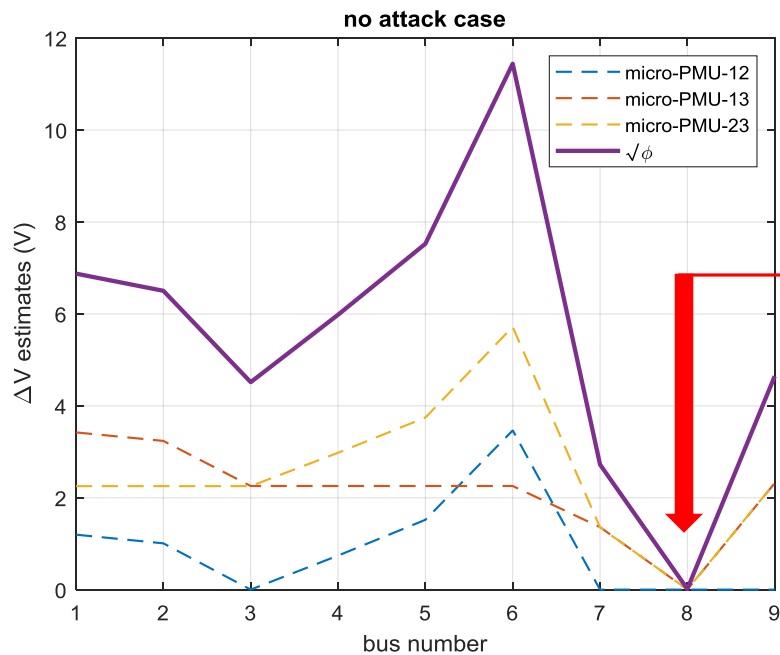
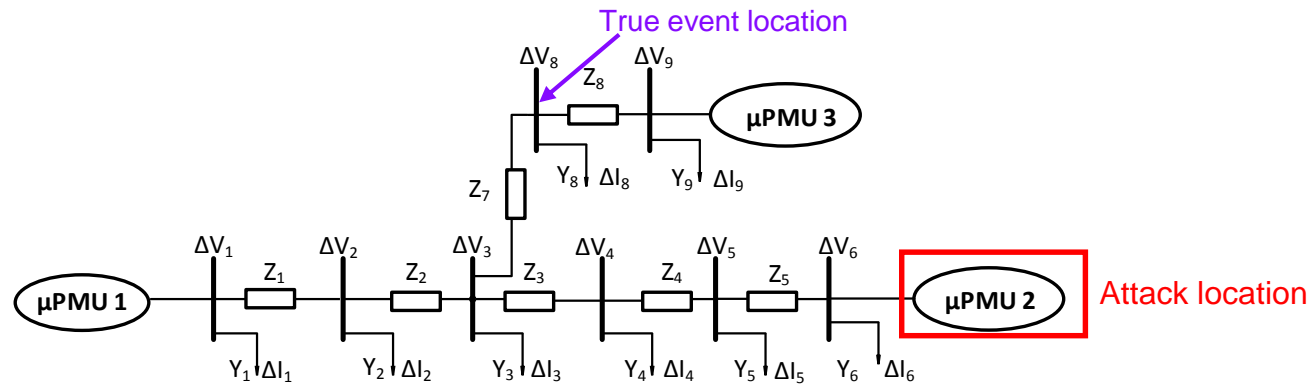


Effects of bad measurements in Micro-PMU data



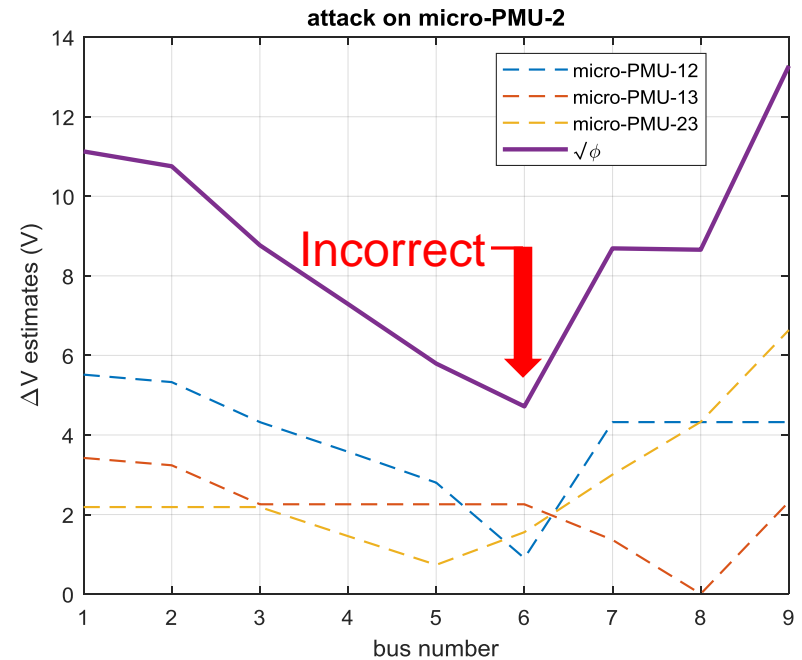
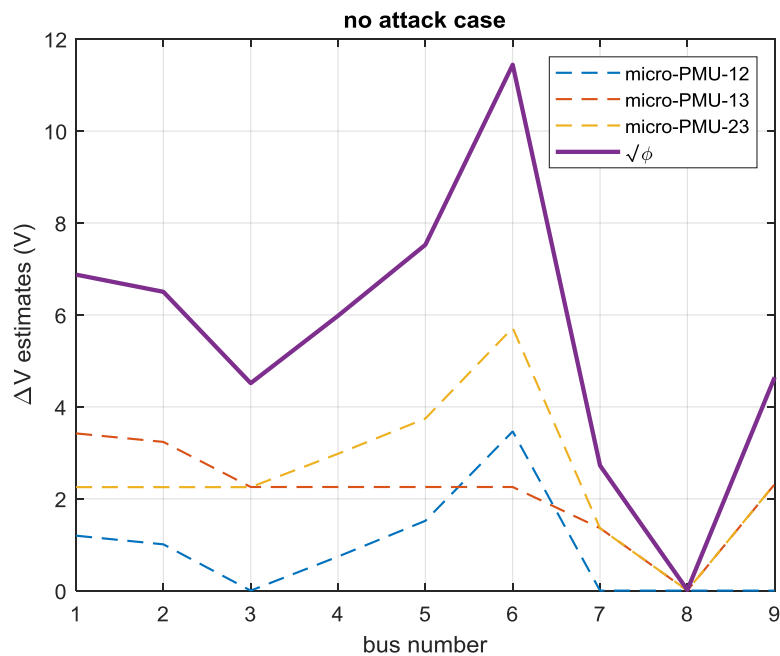
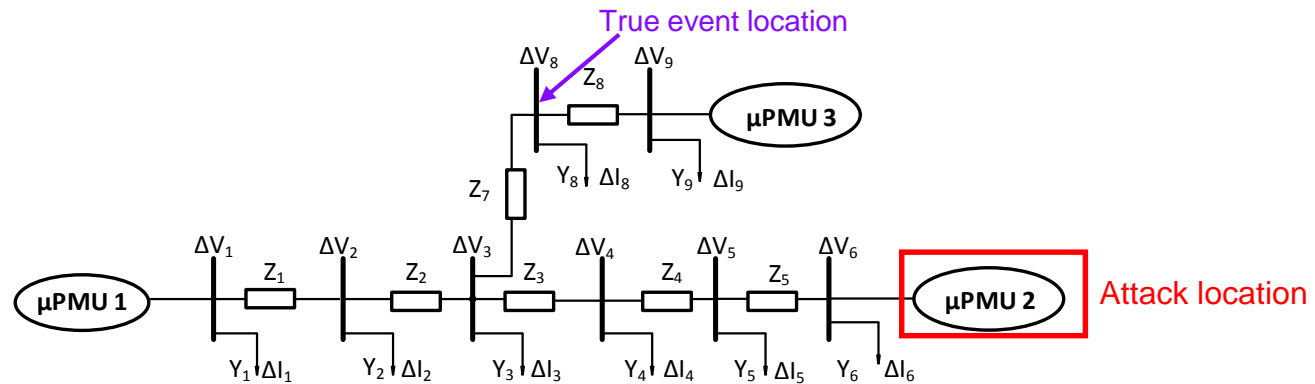
Correct Location
(Farajollahi, et. al. 2018)

Effects of bad measurements in Micro-PMU data

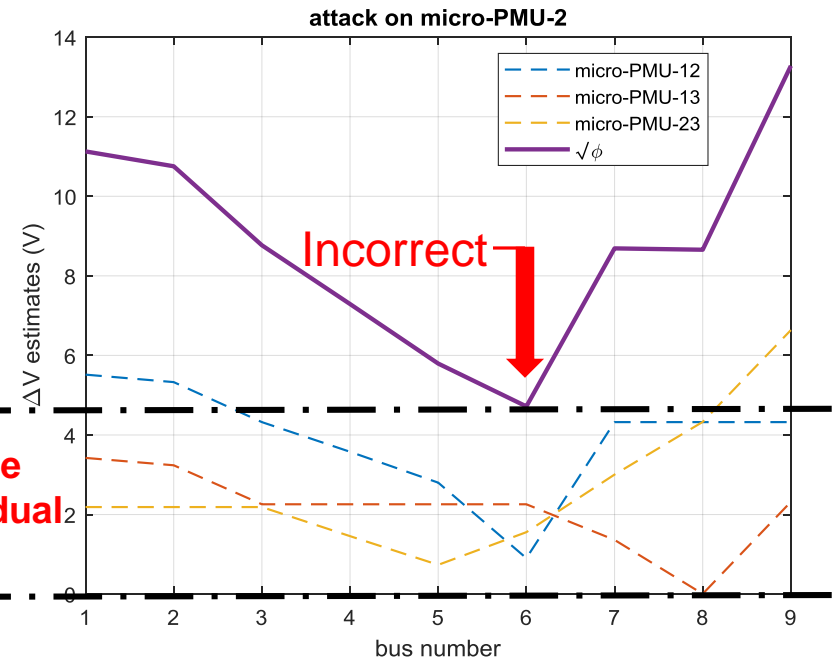
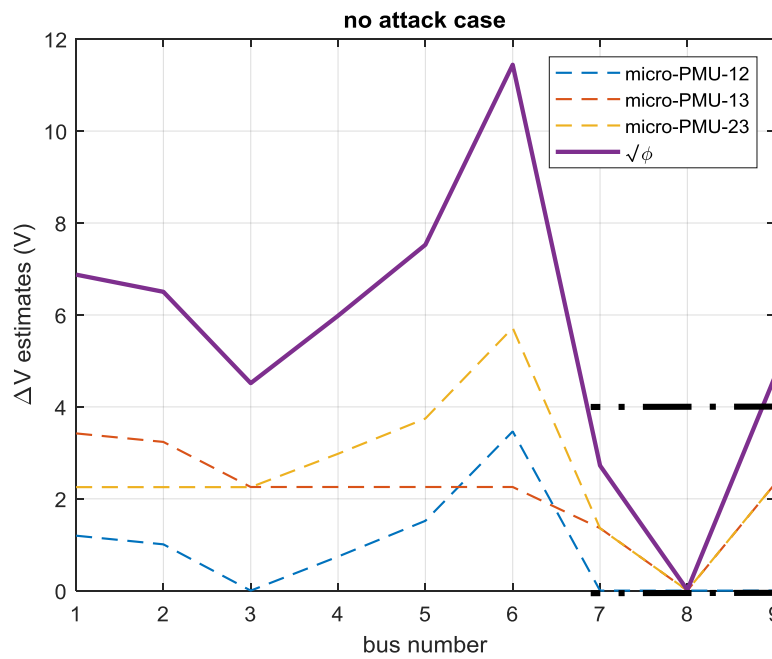
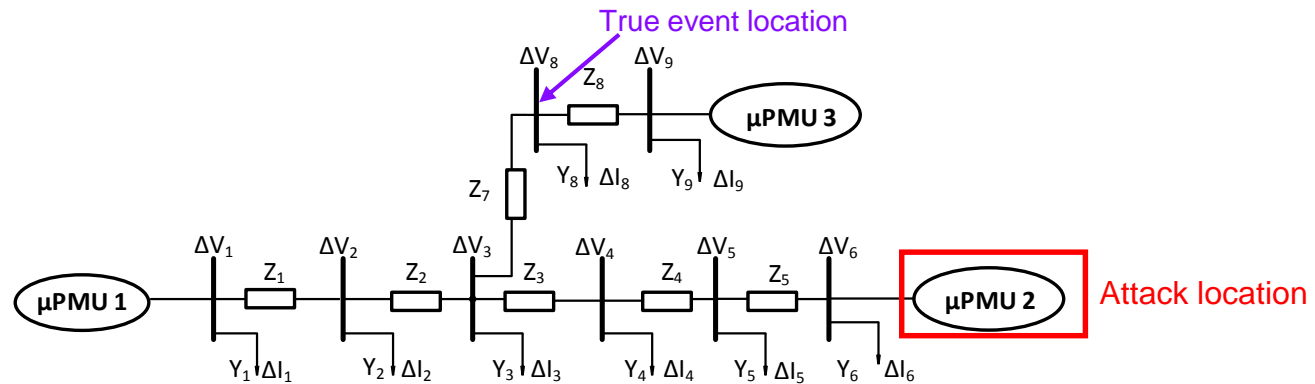


Correct Location
(Farajollahi, et. al. 2018)

Effects of bad measurements in Micro-PMU data

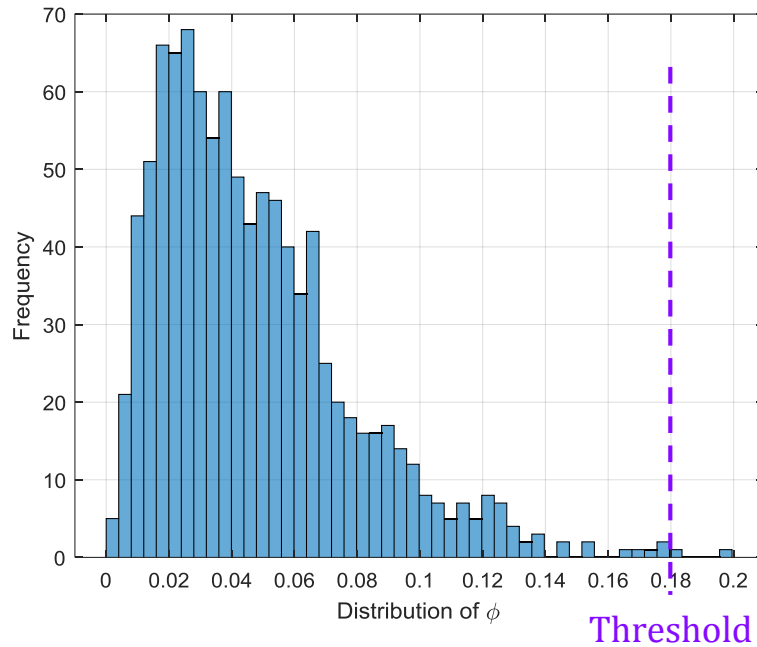


Effects of bad measurements in Micro-PMU data

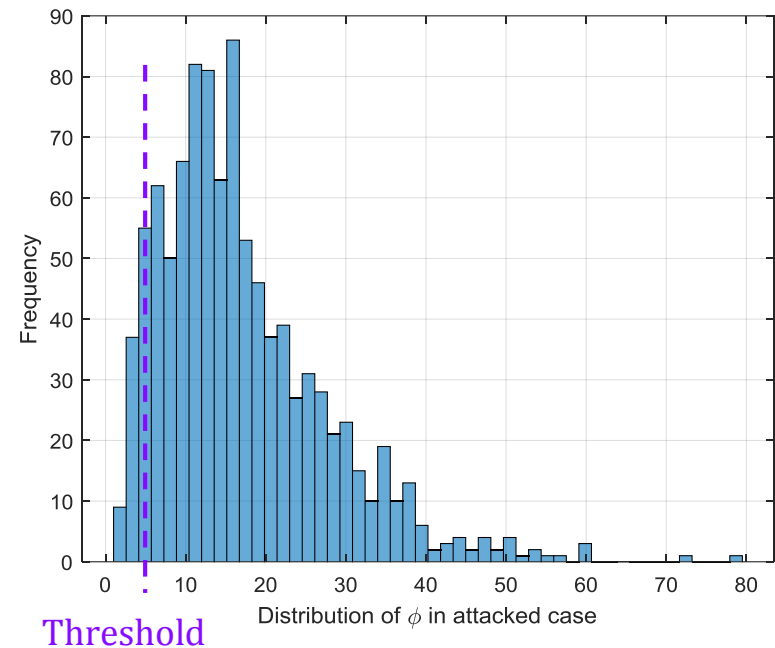


Proposed Attack Detection Method

Non-attacked case



Attacked case



$$\mathbb{I}(\varphi > \tau) = 1$$

$$\text{prob}(\varphi_i > \tau \mid \varphi_i \text{ is chi-squared}) = \alpha$$

$$\varphi_i = |\Delta V_i^f - \Delta V_i^b|^2$$

Proposed Attack Identification Method

$$\arg \min_j \frac{1}{N-1} \sum_{j=1}^N (\Delta V I_j)^2 - \left(\frac{1}{N-1} \sum_{j=1}^N \Delta V I_j \right)^2$$

$$\text{subject to } \sum_{j=1}^N I_j = N - 1$$

$$I_j \in \{1,0\}$$

Where

$$I_j = \begin{cases} 1, & \text{if } \mu\text{PMU } j \text{ is kept} \\ 0, & \text{if } \mu\text{PMU } j \text{ is dropped} \end{cases}$$

Proposed Attack Identification Method

$$\arg \min_j \frac{1}{N-1} \sum_{j=1}^N (\Delta V I_j)^2 - \left(\frac{1}{N-1} \sum_{j=1}^N \Delta V I_j \right)^2$$

$$\text{subject to } \sum_{j=1}^N I_j = N - 1$$

$$I_j \in \{1,0\}$$

Variance across measurements in absence of dropped micro-PMU

Where

$$I_j = \begin{cases} 1, & \text{if } \mu\text{PMU } j \text{ is kept} \\ 0, & \text{if } \mu\text{PMU } j \text{ is dropped} \end{cases}$$

Proposed Attack Identification Method

$$\arg \min_j \frac{1}{N-1} \sum_{j=1}^N (\Delta V I_j)^2 - \left(\frac{1}{N-1} \sum_{j=1}^N \Delta V I_j \right)^2$$

$$\text{subject to } \sum_{j=1}^N I_j = N - 1$$

$$I_j \in \{1,0\}$$

Variance across measurements in absence of dropped micro-PMU

The number of micro-PMUs kept

Where

$$I_j = \begin{cases} 1, & \text{if } \mu\text{PMU } j \text{ is kept} \\ 0, & \text{if } \mu\text{PMU } j \text{ is dropped} \end{cases}$$

Proposed Attack Identification Method

$$\arg \min_j \frac{1}{N-1} \sum_{j=1}^N (\Delta V I_j)^2 - \left(\frac{1}{N-1} \sum_{j=1}^N \Delta V I_j \right)^2$$

$$\text{subject to } \sum_{j=1}^N I_j = N - 1$$

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Variance across measurements in absence of dropped micro-PMU

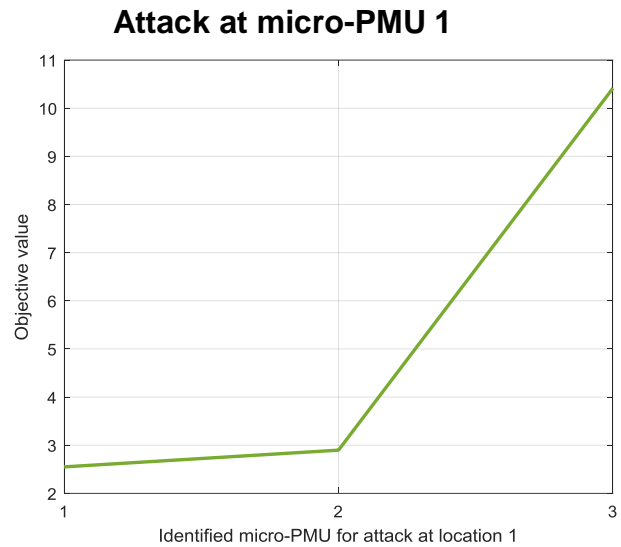
The number of micro-PMUs kept

Where

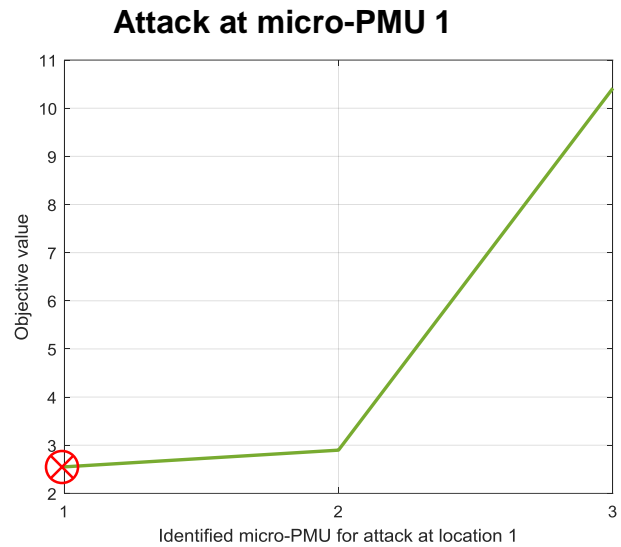
$$I_j = \begin{cases} 1, & \text{if } \mu\text{PMU } j \text{ is kept} \\ 0, & \text{if } \mu\text{PMU } j \text{ is dropped} \end{cases}$$

Decision Variable

Identified affected μ PMU

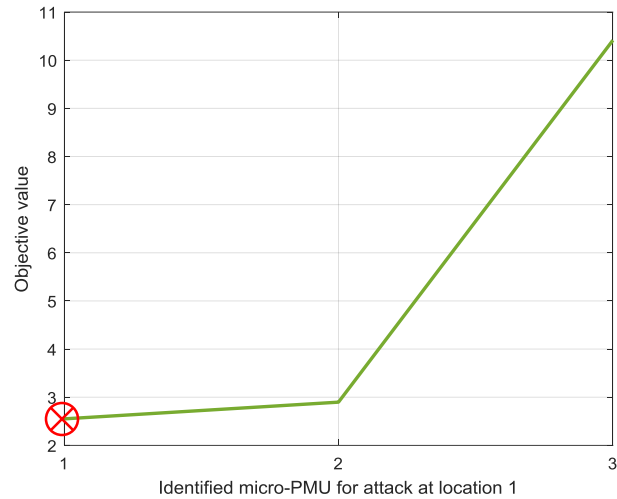


Identified affected μ PMU

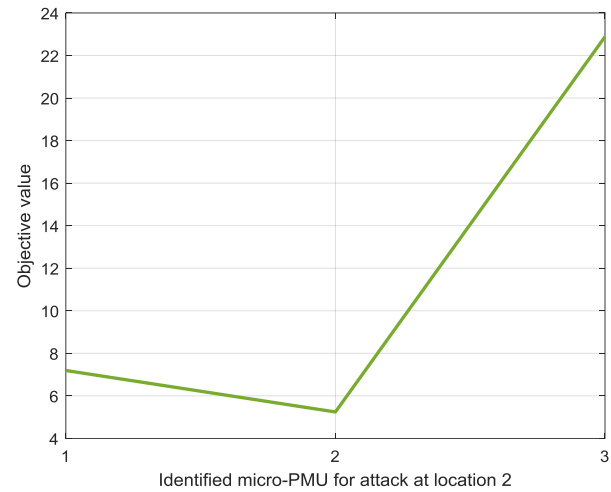


Identified affected μ PMU

Attack at micro-PMU 1

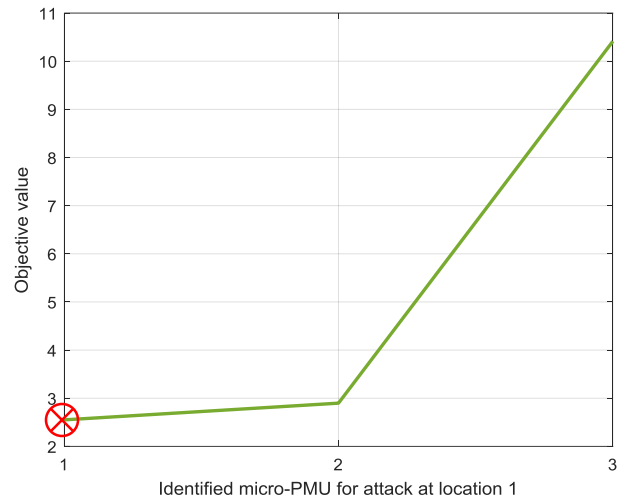


Attack at micro-PMU 2



Identified affected μ PMU

Attack at micro-PMU 1

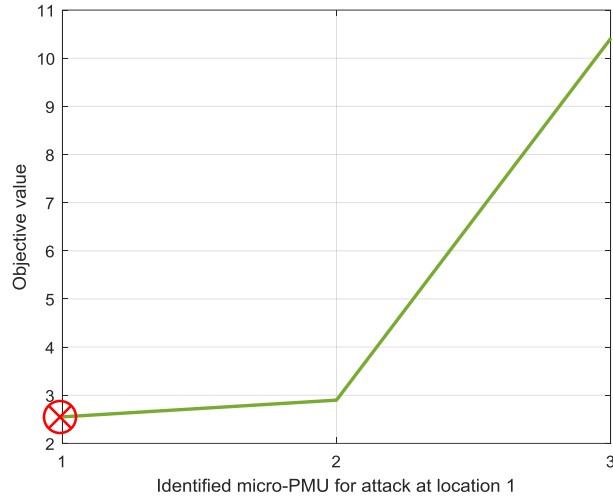


Attack at micro-PMU 2



Identified affected μ PMU

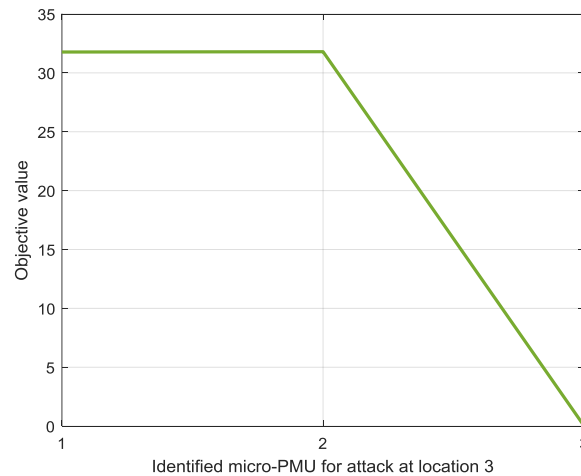
Attack at micro-PMU 1



Attack at micro-PMU 2

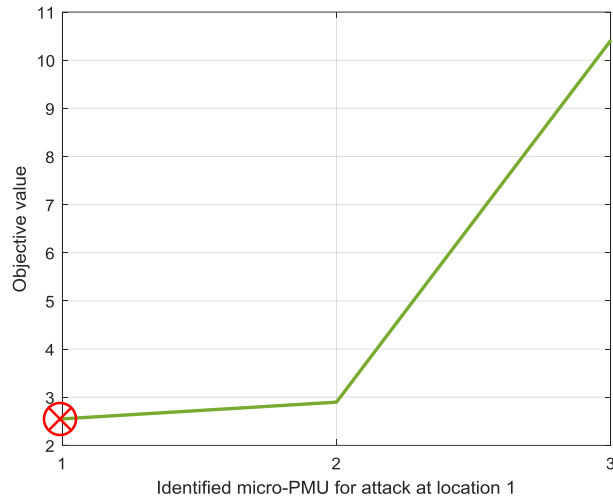


Attack at micro-PMU 3



Identified affected μ PMU

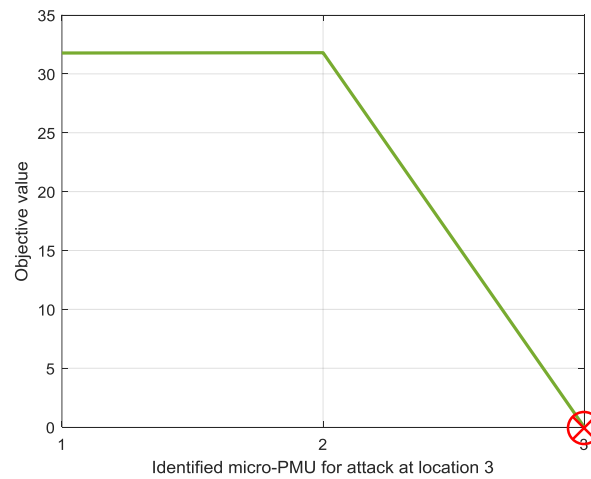
Attack at micro-PMU 1



Attack at micro-PMU 2



Attack at micro-PMU 3



References

- [1] Mohsenian-Rad, Hamed, Emma Stewart, and Ed Cortez. "Distribution synchrophasors: Pairing big data with analytics to create actionable information." IEEE Power and Energy Magazine 16.3 (2018): 26-34.
- [2] Farajollahi, Mohammad, et al. "Locating the source of events in power distribution systems using micro-pmu data." IEEE Transactions on Power Systems 33.6 (2018): 6343-6354.
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- [5] R. Deng, P. Zhuang and H. Liang, "False Data Injection Attacks Against State Estimation in Power Distribution Systems," in IEEE Transactions on Smart Grid.
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- [7] M. Farajollahi, A. Shamsavari, H. Mohsenian-Rad, "Tracking State Estimation in Distribution Networks Using Distribution-level Synchrophasor Data," accepted for publication in IEEE Power & Energy Society General Meeting, Portland, OR, August 2018.
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