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Impact of Low Data Quality on Disturbance Triangulation Application using High-Density PMU Measurements

Xianda Deng[1], Student Member, Desong Bian[2], Member, IEEE, Di Shi[2], Senior Member, IEEE, Wenxuan Yao[1,3], Member, IEEE, Ling Wu[1], Yilu Liu [1,3], Fellow, IEEE.

Abstract— **High-density PMUs can be implemented to estimate the location of large power system disturbances based on the theory of Time Difference Of Arrival (TDOA). Unfortunately, real-world measurements suffer from low data quality issues frequently caused by various uncontrollable and unpredictable factors. In this paper, four types of practical low data quality issues from onsite PMUs are first identified from the industry perspective. Then the impacts of each low-quality data issue on disturbance triangulation are explored using real-time measurement cases from Jiangsu power grid with a high-density PMU network. This paper provides valuable guidance for utility operators and academic researchers to use actual PMU data for power grid applications.**

Index Terms— **Disturbance Triangulation, Low Data Quality, PMU Measurement, TDOA**

I. Introduction

The modern power grid is the most complicated artificial system, which has been evolving in recent decades with various technologies [1]-[5]. Meanwhile, renewable energy sources have been promoted and integrated into power grids [6]. Combined with communication system, the modern power grid structures and dynamic behaviors are becoming more complex, considering the flexibility of the new technologies and the fluctuating nature of renewable energy sources.

With the real-time GPS time-synchronized measurements at high data rates, Wide-Area Monitoring Systems (WAMS) reveals unprecedented insights into power grid dynamics and is envisioned to be one of the key foundations of the next-generation Energy Management System (EMS) [6]-[11].

However, massive amount of high-resolution PMU data brings two new challenges for real-time applications:

1. How to detect abnormal events in the power grid?
2. Where are the locations for abnormal events in the power grid?

To address the aforementioned challenges, a number of methods have been proposed for power system event detection and location identification based on PMU data. In 2001, the Frequency Monitoring Network (FNET/Grideye) system, a pilot WAMS system, was developed for power system event detection [12]. Decision tree and event detection techniques using the Rate Of Change Of Frequency (ROCOF) were proposed based on real-time measurements from the FNET/Grideye system [13], [14]. Meanwhile, event detection based on the generation-load mismatch and triangulation location identification technique were proposed and implemented [15]-[17]. Recently, Ref.[18] proposed a framework based on a sparse linear unmixing technique to detect multiple cascading events based on the power system in the FNET/Grideye system. Besides, algorithms used in other areas of power systems were also leveraged for event detection and location identification. Wavelet analysis was performed to extract the feature of FDRs data and support vector machine (SVM) was introduced to classify power system events in [19]. In [20], wavelet transform was employed on voltage and frequency measurements from PMU data to identify generation trip and load shedding events. Short time Fourier Transform and statistical techniques were applied to phase angle for online event detection in [21]. In [22], disturbance component can be solved with positive current phasor based on superposition theorem. The event types and location were identified by matching the calculated disturbance component with patterns extracted from historical fault events. Attempts to use principal component analysis (PCA) for power system event detection were conducted in [23]. Later, PCA was employed for real-time event detection at the distribution level [24]. A real-time event detection based on moving windows PCA was developed and demonstrated in the United Kingdom and Irish systems [25]. An investigation of using data mining technique to detect the event and identify event location was introduced in Ref.[26]. In [27], a change point method was proposed to detect sudden change in highly noisy data. It may be a potential solution for certain types of events detection in power system. One of the common scenario in the aforementioned papers is that the algorithms are tested based on PMUs with low density deployment for demonstration purpose. The accuracy and robustness of event detection applications are seldom tested and reported when it is applied in a power grid with industrial scale PMUs for operation purpose.

Recently, UTK Power Information Laboratory cooperated with Global Energy Interconnection Research Institute North America (GEIRINA) to develop a real-time event detection and location identification application based on PMU mea-

[1] Department of Electrical Engineering and Computer Science, the University of Tennessee, Knoxville, TN, 37996, USA.
[2] Global Energy Interconnection Research Institute North America, San Jose, CA, 95134, USA
[3] Oak Ridge National Laboratory, Oak Ridge, TN, 37830, USA
Corresponding author: Wenxuan Yao (e-mail: wyao3@vols.utk.edu).
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surements from the Jiangsu power grid in China. It provides a good opportunity to further explore the capability of the event detection and triangulation in a power grid with high-density PMU measurements. Meanwhile, low data quality of PMU measurements brings new challenges to this application. In fact, bad data is introduced into PMU measurements due to measurement noise and instrumentation errors [28]. The impacts of the bad data in simulated PMU measurements have been discussed in other research areas of the power system and some solutions were also proposed in [29]-[34]. However, the impacts of low data quality in actual high-density PMU measurement on event detection and location estimation have not been reported yet.

In this paper, the authors use real-world PMU data from the Jiangsu power grid to evaluate the impacts of low data quality issues on the performance of disturbance triangulation. The event detection was implemented based on the pair-wise comparison from multiple location PMUs and triangulation technique was employed for event location identification. The main innovation of this paper is that the first attempt to employ real-time event detection application in a power grid with industrial scale PMU deployments for operation purpose. Four types of low data issues from actual PMU measurements are reported and their impacts on triangulation for generation and location events are first investigated.

The rest of the paper is organized as follows. In Section II, an overview of Jiangsu power grid with high-density PMU deployment and platform for triangulation application in GEIRINA are presented. Tests of TDOA using simulation and real-world PMU data are present in Section III. Four typical bad data issues from on-field PMUs are introduced in Section IV. In Section V, the impacts of low data quality PMU measurements on disturbance triangulation are explored using an actual generation trip case from Jiangsu power grid. The conclusions are drawn in Section VI.

II. Overview of Disturbance Triangulation in Jiangsu Power Grid

A. *Overview of High-Density Distributed PMU Deployment IN Jiangsu Power Grid Network*

Jiangsu power grid is located in the southeast of China and connects with multiple adjacent power grids. There are approximate 150 and 250 PMUs installed at northern and southern of Jiangsu power grid, respectively. As shown in Fig. 1, the density of distributed PMU is significantly high. PMUs are mainly installed at terminals of all 500kV transmission lines and parts of 220 kV transmission lines with the reporting rate 25 Hz. To utilize the PMU data for wide area monitoring, a PMU based situational awareness data analytic platform is developed by GEIRINA [35].

Once the PMU data are transmitted to the control center, the data is streamed into multiple power system applications. Event detection and location identification application has three components: event detection, event location identification, and event visualization. The event detection only focuses on detecting whether the system is experiencing a generation trip or load shedding events, while triangulation is designed to identify the event location in the power grid. To deploy the event detection and triangulation application on GEIRINA data analytic platform, an interface was implemented to achieve data exchanges. The flowchart of the event detection and triangulation application is shown in Fig. 2. The major modules in the application include: data pre-process module, event detection (EV) module, event triangulation (ET) module, and visualization module. The PMU measurements from GEIRINA are aligned based on the GPS timestamp and streamed into the event detection module frame by frame. A certain amount of frames are stored in the buffer temporarily. Once a disturbance is confirmed by EV module, the data in the buffer will be extracted and delivered to the ET module and visualization module.

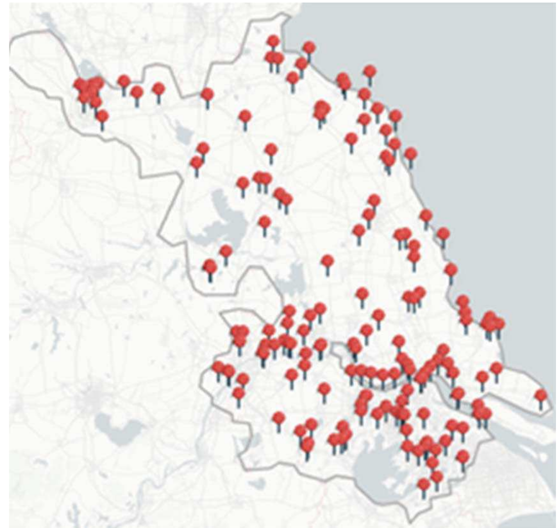

Fig. 1. Map of PMU deployment in Jiangsu power grid

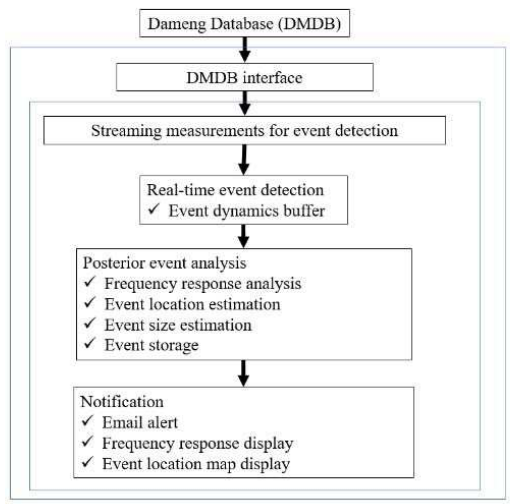

Fig. 2. Scheme of event detection and triangulation for GEIRINA

B. *Mechanism of Disturbance Detection and Triangulation*

1) Event Detection: Generation trip or load shedding events in a power grid always cause a large amount of active power exchange due to imbalances of generation and load. Consequently, frequency in the system also has abrupt change during the events. To detect generation trip and load shedding event, frequency changes $\frac{df}{dt}$ of PMUs at time t_1 can be calculated by

$$\frac{df}{dt_{n\_t1}} = \frac{f_{n\_t1} - f_{n\_t0}}{t_1 - t_0} \tag{1}$$

where n is the index number of PMU deployed in the system. Additional, to distinguish frequency patterns of generation trips and load shedding from other relatively smaller disturbance, i.e. line trip event, the consecutive frequency changes of PMU must over an empirically determined threshold τ, which can be expressed as :

$$\sum_{h=0}^{H-1} \frac{df}{dt_{n\_th}} > n\tau \tag{2}$$

where H is the numbers of the consecutive frequency changes. Once the changes in the system continuously exceed the threshold, an event is detected, and then the buffered PMU data is sent to the ET module for event location estimation.

2) Event Triangulation: As frequency perturbations travel throughout grid as electromechanical waves dispersing at finite (measurable) speeds, the PMUs located throughout the grid detects said waves with unique time delays proportional to the electrical distance between each respective unit and the disturbance location. Thus disturbance triangulation mainly involves two steps: (1) the determination of the wave-front detected by each unit and its corresponding arrival time and (2) estimating the disturbance location.

Once the PMUs close to the disturbance are selected via wave-front detection, the disturbance location can be triangulated by using least squares optimization to minimize the estimated distance error as

$$\begin{aligned}
\min \quad & \sum_{i=1}^{I} \left[(\alpha_i - \alpha_d)^2 + (\beta_i - \beta_d)^2 - v^2 (t_i - t_d)^2 \right]^2 \\
\text{s.t.} \quad & \alpha_{min} < \alpha_d < \alpha_{max} \\
& \beta_{min} < \beta_d < \beta_{max} \\
& 0 < t_d < t_i, \quad \forall i \in \{1, 2, \dots, I\}
\end{aligned} \tag{3}$$

where I denotes the number of PMUs used to estimate disturbance location, (α_i, β_i) and (α_d, β_d) represent the coordinates of Lambert projection from i-th PMU and real disturbance location, v denotes the propagation speed of the electromechanical wave, t_d denotes the start time of the disturbance and t_i denotes the wave-front arrival time of i-th PMU.

3) PMU Measurement Preprocessing Module: Data quality of raw real-world PMU measurements from power grids may degrade due to various impacts, such as temporal communications failure, synchronization inaccuracy, etc. To eliminate the noise and extract the signal of interest events from raw PMU measurements, a PMU data preprocessing filter was designed and implemented [36]. The block diagram of the PMU data preprocessing filter is shown in Fig. 3. Raw PMU measurements are fed into a threshold filter to remove random noises. Then a low-pass filter combining with a moving median filter is used to remove high-frequency noise. Another low-pass moving average filter is employed to extract the trend of filtered frequency measurements, which can be expressed as

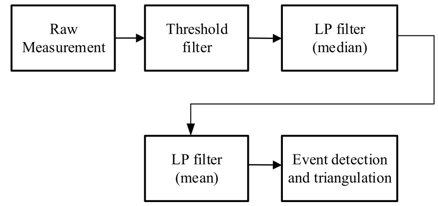

Fig. 3. PMU measurement preprocessing block diagram

$$\overline{f_{t0}} = \frac{1}{K} \sum_{k=0}^{K-1} f_{t0-k} \tag{4}$$

where K is time windows of the moving median filter, f_{tk} is PMU frequency measurement at k time point. When a new frequency measurement is streamed into the filter, a successive value of moving median is calculated by:

$$\overline{f_{t1}} = \overline{f_{t0}} + \frac{f_{t1}}{K} + \frac{f_{t1-K}}{K} \tag{5}$$

The data after preprocessing filter is delivered to the event detection and triangulation application for further analysis.

III. Simulation and Real-World Case Test of TDOA

To investigate the performance and robustness of TDOA for event detection and triangulation, tests including both simulation and real-world events are conducted.

A. Case Study With Simulated Data

To verify the effectiveness of the event detection and triangulation application in a power grid with high-density PMU, 8 generation trip and 2 load shedding events in Jiangsu power grid are simulated. The Jiangsu power grid covers 39,614 mi^2 and consists of two major regions: Su Nan and Su Bei. The power grids in two regions are connected via four 500 kV transmission lines. Jiangsu power grid is modeled as a system with approximate 2500 buses and 5000 branches within PSD-BPA. PSD-BPA is a power system analysis software developed by China Electric Power Research Institute (CEPRI) [37]. To comprehensive evaluate the performance TDOA for event localization, the events are selected at different locations in the two regions and the amount of generation and load impacted by the events are from 200 MW to 1167 MW. The details of the simulation cases and actual event locations are summarized in Table 0. Each case contains 1 minute of PMU measurements, which are collected with a 25 Hz sampling rate. All the event occur at the 5th second of the simulation time series.

The event detection and triangulation application successfully detected all the simulation events at the correct time and the event location is pinpointed accurately. The reported locations of the applications are marked in a red circle in Fig. 4 and Fig. 5. It demonstrates that the performance of the event detection and triangulation applications in Jiangsu power grid is remarkable in the simulation cases.

TABLE I

DESCRIPTION OF SIMULATED CASES

Case Name	Event type	Size (MW)	Truth	
			Latitude	Longitude
Bixi	Generation trip	1167	31.xxxx	120.xxxx
Nantong	Generation trip	412	32.xxxx	120.xxxx
Yang er	Generation trip	728	32.xxxx	119.xxxx
Xinhai	Generation trip	1145	34. xxxx	119.xxxx
Chuzhong	Load shedding	218	Chongming	
Yang er	Load shedding	1000	32.xxxx	119.xxxx
Jianbi	Generation trip	1000	32.xxxx	119.xxxx
Gaogang	Generation trip	1000	32.xxxx	119.xxxx
Chenjia	Generation trip	660	34.xxxx	119.xxxx

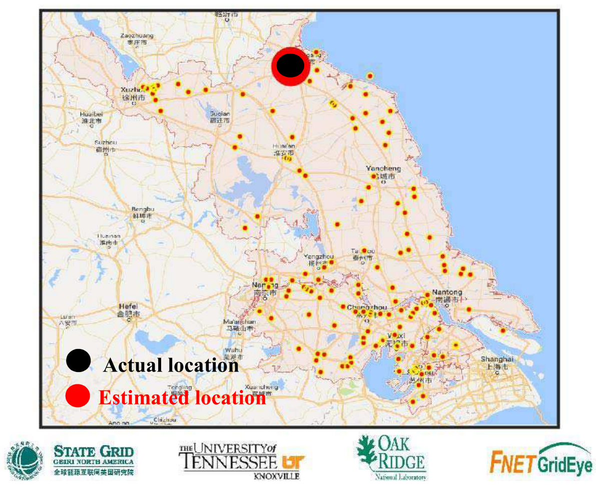

Fig. 4. Event detection and triangulation results of Chenjia Gang case

B. Real-World Generation Trip Case

To further evaluate the capability of TDOA for the event detection and triangulation, a real-world generation trip case, which occurred in Jiangsu power grid in 2015, is tested. The generation case includes 7 minutes of measurements collected from Jiangsu power grid. The measurements started at 21:57:00 and the event happened at 21: 57:59. The frequency measured by PMUs during the event is plotted in Fig. 6. As shown in Fig. 7, the event was successfully detected and located. The estimated location is approximately 12 miles away from the actual location which is acceptable for the Jiangsu power grid.

IV. Practical Data Quality Issues of High-Density Deployed PMU

In practical industrial applications, measurements from onsite PMU are likely to contain different types of low data

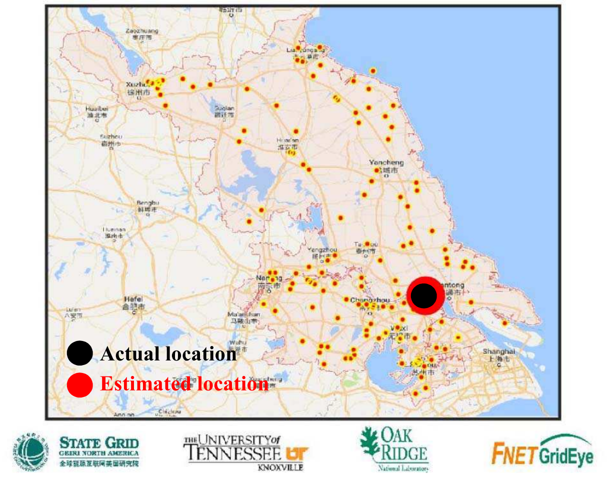

Fig. 5. Event detection and triangulation results of Nantong power plant case

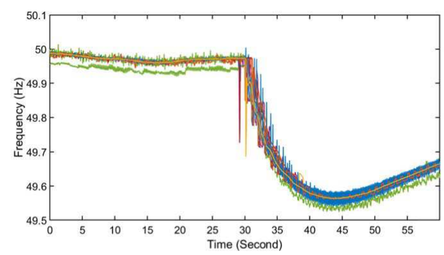

Fig. 6. PMU frequency measurements during a generation trip in Jiangsu power grid

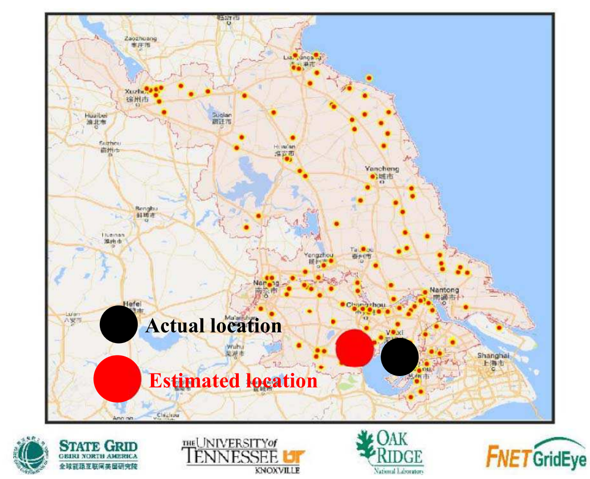

Fig. 7. Generation trip event location and estimated location in Jiangsu power grid

quality issues caused by communication or PMU hardware malfunction. This section presents four major data issues discovered in PMUs deployed in Jiangsu power grid.

A. Constant Measurements

Constant PMU measurements are mainly caused by PMU hardware issues. The value of measurements periodically repeats with different intervals under both ambient or event

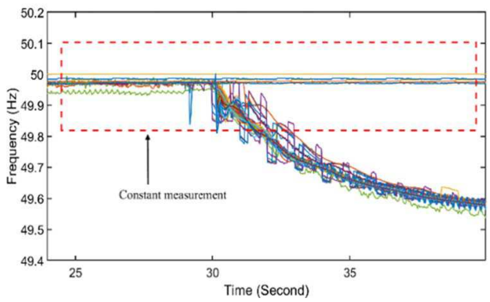

Fig. 8. Illustration of constant measurement during a generation trip

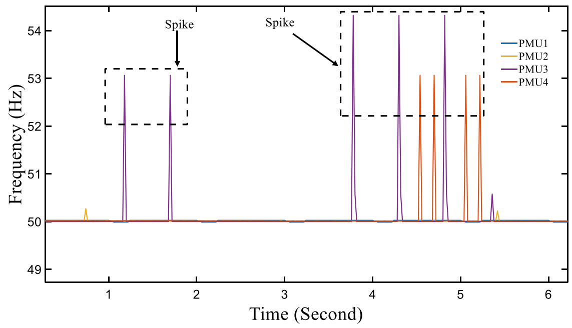

Fig. 9. Illustration of spike issue

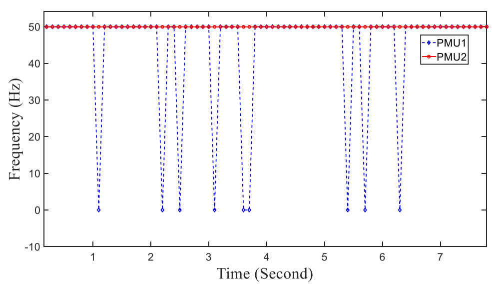

Fig. 10. Illustration of data missing issue

conditions. A typical constant measurement is presented in Fig, 8. When the most PMU frequency measurements drop during a generation trip event, some of the PMU measurements keep the constant periodical patterns before and after the event thus missing the information of the power system dynamic.

B. Spikes in Measurements

The random spike in measurements is another typical data quality issue caused by PMU hardware issues. The frequency and magnitude of the spikes vary case by case. Thus it is difficult to extract the feathure of the spike and apply a uniform filter to remove them. It can be observed in Fig. 9 that some measurements have random spikes in the aspect of amplitude and time interval. Additionally, some spikes keep swinging around system frequency as shown in Fig. 9. The tendency of the swing indicates that the mean value of the measurement keeps changing over time.

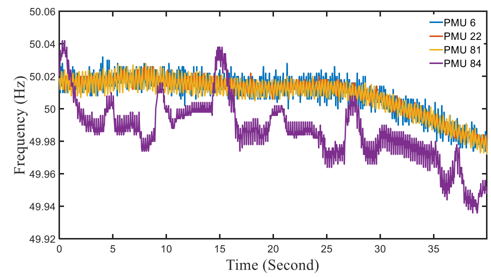

Fig. 11. Illustration of the high-frequency noise issue

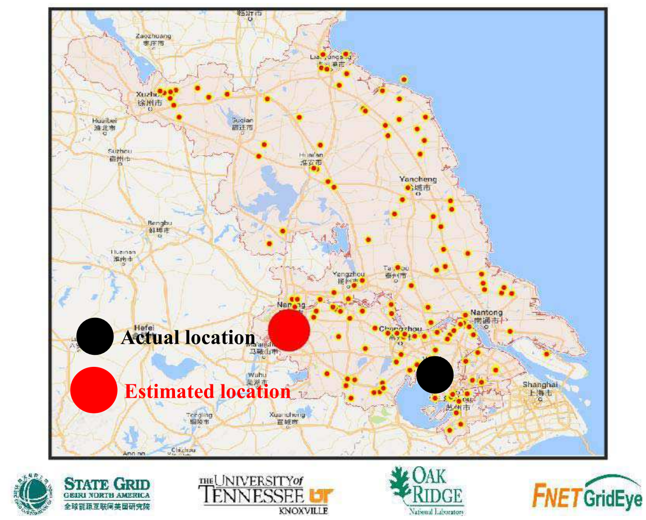

Fig. 12. Case 1: PMU1 with constant measurement

C. Missing Data in Measurements

Missing data happens in PMU measurements due to several uncontrollable factors (e.g. GPS signal lost, network failure, power failure, etc.[38]). Detecting the missing data is straightforward since each PMU measurement is assigned a unique time index thus a discontinuous timestamp implies the existence of missing data. The entire raw data are broken down into several non-overlapping frames. The miss data results in discontinuity and outlines of PMU measurements. As shown in Fig. 10, missing data at the GEIRINA PMUs platform can occur frequently and result in a sudden drop to “0” Hz in frequency measurement from PMU2.

D. High-Frequency Noise in Measurements

The measurement with high-frequency noise can be caused by an inaccurate sampling interval control related to PMU calibration and wrong PMU hardware configuration [30]. It makes the measurements having high-frequency noise and keeping swinging around the actual system frequency. Based on the measurement data from the Jiangsu Power grid, the amplitude of the noise varies in a relatively wide range, from 0.01 to 0.2 Hz. As shown in Fig. 11, high-frequency noise for each PMU has slight differences in amplitude. Thus, the randomness and variety of the high-frequency noise make it difficult to be removed with a uniform threshold filter.

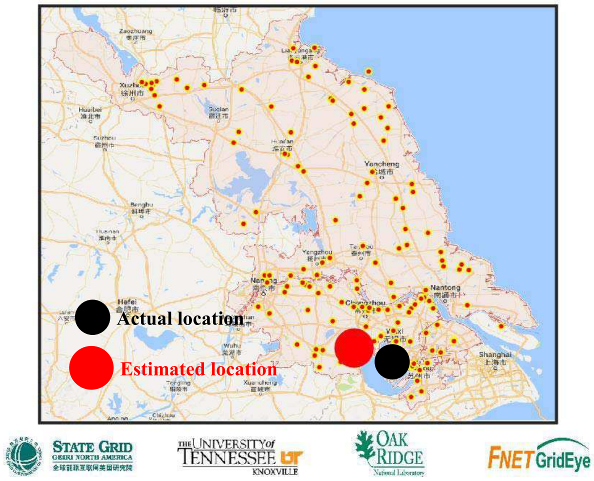

Fig. 13. Case 2: PMU1 with random spikes

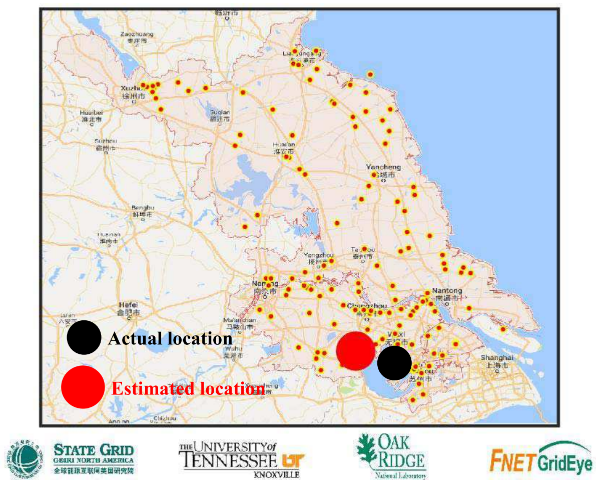

Fig. 14. Case 3: PMU1 with high-frequency spikes

Fig. 14. Case 3: PMU1 with high-frequency spikes

V. Impact of Data Quality on Event Triangulation

The purpose of this section is to investigate the impacts of low data quality on the accuracy of event triangulation when using high-density PMU measurements. To this end, an actual generation trip in the Jiangsu power grid is selected for this study. All low data quality issues mentioned in Section IV are considered. It is assumed that the measurements of a PMU that is the first one responding to the actual event disturbance, referred as PMU1, encounters with low data quality issues. The scenarios of each testing case are given below:

1) Case 1: PMU1 with constant measurement issue
2) Case 2: PMU1 with spike and missing data issue
3) Case 3: PMU1 with the high-frequency noise issue

Employing the triangulation method, the estimated locations for each case are illustrated from Fig. 12 to Fig. 14. The summary result is listed in Table 2. It can be seen from Fig. 12 that the constant measurement issue leads to a large estimation error. The estimated location is more than 100 miles far away from the actual location. The impact of other types of data

TABLE II

Summary of the impact of low data quality on event triangulation

Cases	Latitude	Longitude	Error to the actual location (miles)	Impacts
Case 1	31. xx	118.xx	100	High
Case 2	31. xx	119. xx	12	Negligible
Case 3	31. xx	119. xx	12	Negligible

issues including spike, missing data, and the high-frequency spike is negligible, which indicates that the preprocessing filter has successfully eliminated the impact of these bad data issues before the measurements been fed into TDOA algorithm.

VI. Conclusion

Real-world PMU measurements have low data quality issues due to various uncontrollable and unpredictable factors, which degrades the performance of measurement based applications. To investigate this problem from an industry perspective, this paper first discovers four typical low data quality issues from real high-density PMU measurements. Since the event triangulation is one of the commonest applications using high-density PMUs, the impacts of the low data quality issues on event triangulation are explored using measurements from the Jiangsu power grid as an example. It is discovered that the constant measurement will cause the inaccuracy of event triangulation significantly while the impacts of other low data quality issues are negligible due to the utilization of the preprocessing filter. This paper provides a practical reference for utilizing PMU data in the application of event triangulation.

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