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### **Distributed Real-Time Electric Power Grid Event Detection and Dynamic Characterization**

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#### **SUMMARY**

Synchrophasor data generated by Phasor Measurement Units (PMUs) allow time synchronized observations of disturbances and power oscillations on an electric grid caused by sudden generation loss, topology modifications and load changes. As PMUs expose (noisy) data streams with harmonic content in excess of 30Hz sampling, automatic detection and quantification of disturbance events is essential. Furthermore, disturbance events also contain valuable information on the dynamics of the electric power grid that can be used to quantify an event by its dynamic parameters. Signal processing techniques that are currently used for event detection on the basis of PMU data are based on either a moving Discrete Fourier Transform or specially designed (linear) band pass filters that extract features from the PMU data in user-specified frequency bands. These techniques are successful in many applications in which PMU data are used to monitor electric power quality. However, these techniques require the specification of accompanying threshold levels in the user-specified frequency bands for event detection and lack the ability to quantify an event by its dynamic parameters. In this paper we show how signal processing with recursive estimation can be used to facilitate real-time detection of disturbance events (in user-specified frequency bands) by automatically adjusting the threshold levels of each PMU distributed throughout the electric grid for event detection. Once a disturbance has been detected, it is shown how the event is quantified by its dynamic parameters by estimating the oscillation frequencies and damping parameters using a realization algorithm. Computations for adjustment of threshold levels and the real-time detection of disturbance events are implemented on each PMU independently, providing a scalable solution for a network with a limited bandwidth for PMU data transmission. The real-time event detection and dynamic characterization of disturbances is illustrated on PMU data measured at the University of California, San Diego.

#### **KEYWORDS**

Phasor Measurement Unit; Event Detection; Distributed Computing; Recursive Least Squares Estimation; Realization Algorithm

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## INTRODUCTION

The electric power industry is beginning to observe power grid dynamic behaviour not seen previously. This is partially due to the recent installation of over 1000 Phasor Measurement Units (PMUs) funded in part by the USA Department of Energy under the Smart Grid Investment Grant program. The observed disturbances are caused generally by generation loss, topology, load changes and increased penetration of renewable power sources. Additionally, measurements on distribution networks indicate harmonic and non-sinusoidal power flow and, especially in microgrids, they are showing that overall power quality may not meet standards.

In addition to external perturbations from the area electric power system (EPS), the University of California, San Diego (UCSD) campus (local EPS) experiences internal microgrid disturbances due not only to the high percentage of solar power generation located in the coastal fog zone and electric vehicle charging systems, but also to non-linear loads from laboratory experiments and hospitals on campus. Additional disturbances caused by the campus Combined Heating and Power Plant, local heating and additional electric chiller loads, fuel cell and large battery loads from multiple experimental battery systems continually perturb the power quality of the microgrid. At times, tens to hundreds of significant local disturbances occur each day on the UCSD campus and external disturbances within WECC can also be observed on the UCSD campus regularly.

Each disturbance event on a microgrid, either local or external, excites the dynamics of the power network. In case of the UCSD microgrid, a disturbance event provides valuable information on the dynamic parameters of the microgrid and can be used to study the stability of either the WECC grid or the UCSD microgrid, depending on whether the event is local or WECC wide. However, to study and monitor the stability of the grid, first the disturbance event must be detected. As PMUs distributed throughout a microgrid may produce multiple (noisy) data streams in excess of 30Hz sampling, automatic and real-time detection of disturbance events is a first prerequisite for the extraction of (dynamic) information from grid disturbance events.

Signal processing techniques that are currently used for event detection on the basis of PMU data are based on a moving Discrete Fourier Transform (DFT) [1] or specially designed (linear) band pass filters that extract features from the PMU data in user-specified frequency bands [2]. Although these techniques are successful in many applications in which PMU data are used to monitor electric power quality, it requires the specification of accompanying threshold levels in the user-specified frequency bands for event detection. The threshold values for event detection will depend highly on the quality and noise properties of the data produced by the PMU, requiring tuning for each PMU distributed on the electric grid. Furthermore, filtering or a DFT of the PMU signal does not extract the valuable information on the dynamic parameters of the microgrid.

In this paper we show how signal processing with recursive estimation can be used to facilitate real-time detection of disturbance events (in user-specified frequency bands) by automatically adjusting the threshold levels for each PMU distributed throughout the electric grid. Once a disturbance has been detected, it is shown how the event is quantified by its dynamic parameters by estimating the oscillation frequencies and damping parameters using a realization algorithm. Computations for adjustment of threshold levels and the real-time detection of disturbance events are implemented on each PMU independently, providing a distributed solution for a network with a limited bandwidth for PMU data streaming. The algorithm is robust to data outliers due to the monitoring of prediction error variance in the estimation of threshold levels. The real-time event detection and dynamic characterization of disturbances is illustrated on PMU data measured at UCSD.

## OVERVIEW OF PMU MEASUREMENTS AT UCSD

For the past three years, five or more relay based PMUs and dedicated PMU devices have been operational on the microgrid of UCSD. An overview of the location of the current operating PMUs are shown on the UCSD campus map in Fig. 1. Typically, 40 or more measurements from each PMU are



electric power grid and adaptation must be used for event detection. In our approach we chose to develop an automatic method of event detection that does not entirely depend on a threshold crossing. Instead, it includes three distinguishable components: (1) one step ahead prediction error minimization, (2) a filtered rate of change, and (3) an adaptive threshold crossing explained below.

For the one step ahead prediction error minimization, consider the frequency signal  $F(k)$  generated by a PMU as function of the time index  $k$ . The time index  $k$  is related to the time stamp  $t_k = k\Delta_t$  where  $\Delta_t$  is the sampling time (typically 1/30 sec.) of the time synchronized PMU. In the absence of a disturbance event, we assume that the noise in the frequency signal  $F(k)$  can be modelled by a filtered white noise operation  $F(k) = H(q, \theta)e(k)$  where  $e(k)$  is a (unknown) white noise sequence and  $H(q, \theta)$  is a monic stable and stably invertible discrete-time filter. Such filter formulations are standard in estimation techniques used to capture the spectral contents of a noisy (frequency) signal [3]. Using the notation  $E\{\cdot\}$  to indicate the mean value, the standard properties of a white noise  $e(k)$  given by  $E\{e(k)\} = 0$  and  $E\{e(k)e(k - \tau)\} = 0$  for any  $\tau \neq 0$  allows the parameters  $\theta$  of the noise filter  $H(q, \theta)$  to be optimized by minimizing the variance of the one step ahead prediction error  $\varepsilon(k, \theta) = H(q, \theta)^{-1}F(k)$ . A linear parameterization of the filter  $H(q, \theta)$  given by

$$F(q, \theta) = \frac{q^n}{q^n + a_1q^{n-1} + \dots + a_{n-1}q^1 + a_0}, \quad \theta = [a_1 \quad \dots \quad a_n]^T$$

And also known as an Auto Regressive (AR) filter of order  $n$ , allows the prediction error  $\varepsilon(k, \theta) = H(q, \theta)^{-1}F(k)$  to be written into a linear regression format

$$\varepsilon(k, \theta) = F(k) + \varphi(k)\theta, \quad \varphi(k) = [F(k-1) \quad \dots \quad F(k-n)], \quad \theta = [a_1 \quad \dots \quad a_n]^T$$

With the linear regression format, minimization of the variance of the one step ahead prediction error  $\varepsilon(k, \theta) = H(q, \theta)^{-1}F(k)$  can be solved via a standard (Recursive) Least Squares solution [3]. The end result is that the monic discrete-time filter  $H(q, \theta)$  can be used in a filtering  $\varepsilon(k, \theta) = H(q, \theta)^{-1}F(k)$  of the noisy frequency signal  $F(k)$ .

Any changes in the white noise properties of  $\varepsilon(k, \theta)$  can now be used for real-time detection of events. To facilitate the detection of changes in the properties of  $\varepsilon(k, \theta)$ , an additional filter operation  $d(k) = L(q)\varepsilon(k, \theta)$  can be used where the discrete-time filter  $L(q)$  consists of specially designed (linear) band pass filter. For the definition of a filtered rate of change signal  $d(k)$  in our event detection algorithm, the band pass filter  $L(q)$  is given by the product of two first order filters:

$$L(q) = \frac{1.9}{2} \cdot \frac{q-1}{q-0.9} \cdot \frac{0.1367q + 0.1367}{q-0.7265}$$

For the interpretation of this filter, consider a PMU that provides sampled data at 60Hz. In that case, the first filter is a standard discrete-time derivative (1<sup>st</sup> order high-pass filter) with a cut-off frequency of approximately 1Hz, whereas the second filter is a standard 1<sup>st</sup> order low-pass Butterworth filter with a cut-off frequency of 3Hz. The results of this filtering  $d(k) = L(q)\varepsilon(k, \theta)$  leads to a filtered rate of change (FRoC) signal  $d(k)$  that is used for event detection.

The estimated filter  $H(q, \theta)$  leads to a white noise one-step ahead predictor  $\varepsilon(k, \theta)$  with the smallest possible variance and therefore the FRoC signal  $d(k) = L(q)\varepsilon(k, \theta)$  with the fixed filter  $L(q)$  will have the smallest possible variance. Since the variance of  $\varepsilon(k, \theta)$  is known and adapted via the Recursive Least Squares (RLS) estimation, the resulting variance  $\sigma^2 = E\{d(t)^2\}$  of the FRoC signal  $d(k) = L(q)\varepsilon(k, \theta)$  is known due to the fixed filter  $L(q)$ . As a result, the threshold value for event detection on the FRoC signal  $d(k)$  can be set to a standard  $3\sigma$  level, where the value of  $\sigma$  is known and adapted via the RLS estimation of the filter  $H(q, \theta)$ . Even when the filter  $H(q, \theta)$  is estimated only once and not adapted via a RLS, the value of  $\sigma$  is automatically calibrated based on the variance  $\sigma^2 = E\{d(t)^2\}$  of the FRoC signal  $d(k) = L(q)\varepsilon(k, \theta)$ . Finally, real-time event detection is performed using a standard  $3\sigma$  level and the requirement that the FRoC signal must satisfy  $|d(k)| > 3\sigma$  for at least  $m$  subsequent data points to avoid detection of single data point anomalies in the data. The value of  $m$  is user specified and is typically determined by the effective duration of the impulse response of the filters used in creating the FRoC signal  $d(k)$ .

## APPLICATION OF EVENT DETECTION

To illustrate the proposed event detection based on the one step ahead prediction error minimization, followed by adaptive threshold crossing of a filtered rate of change (FRoC) signal, we use frequency measurements  $F(k)$  from PMUs located at UCSD and distributed in the WECC during May 30, 2013 from noon till 9pm. An overview of the PMU data used for this illustration is depicted in Fig. 2, indicating a major power disturbance event around 4pm but small initial and subsequent events are also present in the data. The proposed event detection algorithm should be able to detect these events automatically.

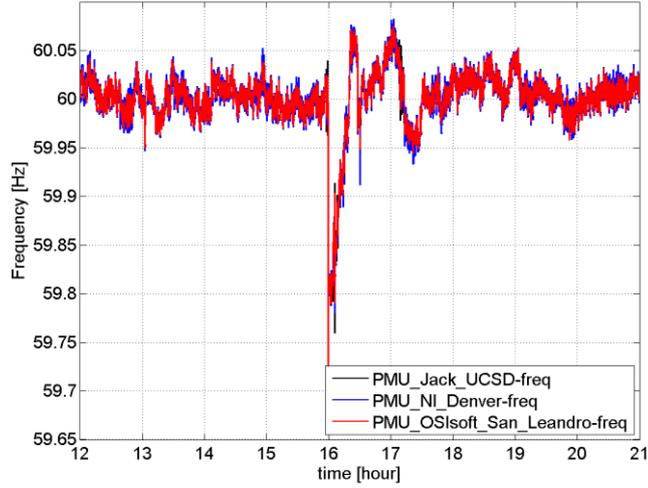


Figure 2: Frequency measurements of 3 different PMUs during May 30, 2013 from noon till 9pm, sampled at 60Hz

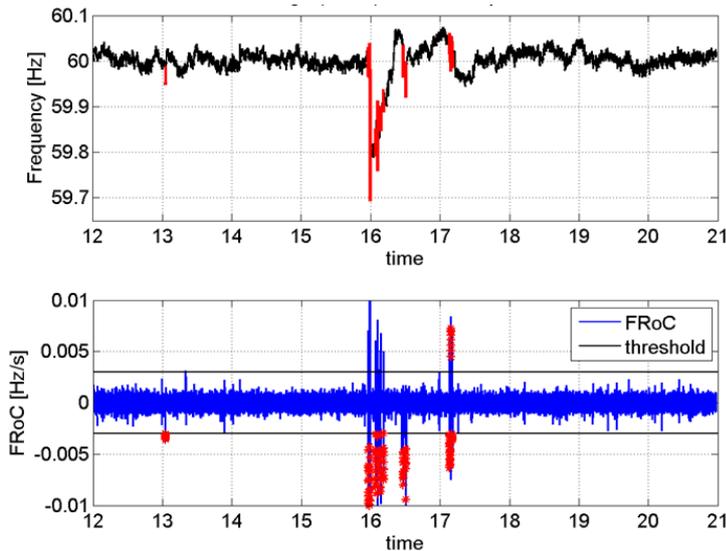


Figure 3: measured PMU frequency data at UCSD (top) and FRoC signal with estimated threshold (bottom).

Based on initial measurements of the PMU frequency signal  $F(k)$ , before any power disturbances were present, the parameters  $\theta$  of the prediction error filter  $\varepsilon(k, \theta) = H(q, \theta)^{-1}F(k)$  are calibrated and the resulting variance  $\sigma^2$  of the FRoC signal  $d(k) = L(q)\varepsilon(k, \theta)$  is estimated. Real-time event detection is performed using a standard  $3\sigma$  level and the requirement that the FRoC signal must satisfy  $|d(k)| > 3\sigma$  for 5 subsequent data points to avoid detection of single data point anomalies in the data. The results are depicted in Fig. 3, indicating that the proposed event detection algorithm marks several events. In addition, the event detection marks the frequency

measurements  $F(k)$  right after the detected event for further processing to quantify the event.

## ANALYSIS OF EVENTS VIA STEP-BASED REALIZATION ALGORITHM

Disturbance events contain valuable information on the dynamics of the electric power grid in terms of oscillation frequencies and their damping coefficients. Once the event has been detected and data has been marked as in Fig. 3, ring down analysis can be done by various methods available in the literature [4]. In our approach we use a step-based realization algorithm (SBRA) based on the step response algorithm given in [5] to quantifying an event by its dynamic parameters. Assuming a disturbance is caused by a step change in power generation or loss, the advantage of the SBRA method is the direct computation of a discrete-time state space model

$$x(k+1) = Ax(k) + Bu(k)$$

where the number of states (size of vector  $x(k)$ ) can be chosen automatically by the SBRA method.

We summarize the SBRA method here and one is referred to [5] for more details on the step-based realization algorithm. The computation of the  $A$ -matrix in the state space realization requires frequency measurements  $F(k)$  that were marked right after the detected event to be stored in a matrix  $R$  on which a Singular Value Decomposition (SVD) is computed. Using  $k = m$  to indicate the first value of  $k$  for which the frequency measurements  $F(k)$  was marked, the matrix  $R$  is given by

$$R = H - Y, \quad H = \begin{bmatrix} F(m+1) & \cdots & F(m+N) \\ \vdots & \ddots & \vdots \\ F(m+N) & \cdots & F(m+2N-1) \end{bmatrix}, \quad R = \begin{bmatrix} F(m) & \cdots & F(m) \\ \vdots & \ddots & \vdots \\ F(m+N-1) & \cdots & F(m+N-1) \end{bmatrix}$$

where  $H$  is a (block) Hankel matrix and  $R$  is a (block) constant row matrix, where  $F(k)$  may be time synchronized frequency measurements from multiple PMUs to allow for a Multi-Output Ring Down analysis model. The computation of the  $A$ -matrix in the state space realization is based on the fact that the matrix  $R$  has a finite rank  $n$  for noise free PMU data  $F(k)$ , where  $n$  is the size of the square  $A$ -matrix (and state vector  $x(k)$ ). The effective rank for noisy PMU data  $F(k)$  can be automatically computed by a SVD with a threshold value on the singular values, whereas projection matrices computed from the SVD are used to compute the actual  $A$ -matrix. Once the  $A$ -matrix of the discrete-time state space model is computed, the eigenvalues of  $A$  give direct insight in the resonance frequencies and damping coefficients via a zero-order-hold conversion of the discrete-time model.

## APPLICATION OF SBRA METHOD

To illustrate the use of the step-based realization algorithm (SBRA), the time synchronized frequency measurements from the three different PMUs given in Fig. 2 are used to quantify the detected event at approximately 4pm. When zooming in on the detected event, the difference in dynamics between the different PMU data can be observed, while the SBRA algorithm requires 10 states (5 resonance modes) to accurately capture the oscillation frequencies and their damping coefficients. With the estimated discrete-time state space model we can also re-simulate the event and provide a direct comparison with the measured time synchronized frequency measurements from the three different PMUs. The results are depicted in Fig. 4, indicating that an excellent fit of the measured data is obtained with a single Multi-Output Ring Down analysis model.

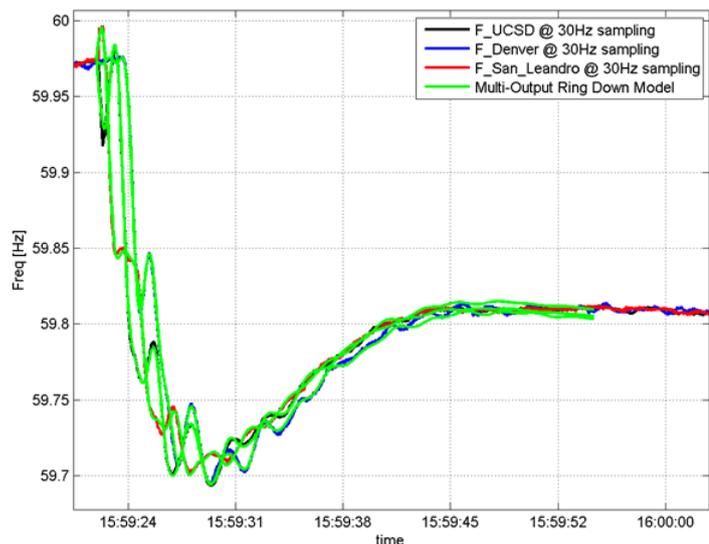


Figure 4: Comparison between PMU data and simulated data based on estimated discrete-time state space model via the SBRA algorithm for the analysis of the event at 4pm.

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