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EVENT-TRIGGERED STATE ESTIMATION FOR VARIABLE ENERGY RESOURCES MANAGEMENT

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ABSTRACT

In recent years, the power generation portfolio has expanded to include variable energy resources (VERs) such as wind and solar generation to meet increasing energy demand and environmental objectives. These sources inject uncertain amounts of power at time scales faster and generally dissimilar to that previously found in typical load profiles. As a result, in order to keep the balance of load and generation, the state of all power system buses becomes highly variable. Conventional measurement and state estimation (SE) techniques under these conditions may introduce errors which may impede the acquisition of an accurate picture of the system state. This paper considers an Event Triggered State Estimation (ETSE) for power networks incorporating VER. The proposed framework represents an improvement over Classical State Estimation (CSE) as it captures the variability associated with the VER while maintaining a high fidelity of the power network states. The effectiveness of the ETSE is demonstrated as compared to existing CSE on a standard IEEE 14 bus system.

1. INTRODUCTION

In recent years, the power generation portfolio has expanded to include variable energy resources (VERs) such as wind and solar generation to meet increasing energy demand and environmental objectives[1]. These sources inject uncertain amounts of power at time scales faster and generally dissimilar to that previously found in typical load profiles[1]. As a result, in order to keep the balance of load and generation, the state of all power system buses becomes highly variable. Conventional measurement and state estimation (SE) techniques[2] under these conditions may introduce errors which may impede the acquisition of an accurate picture of the system state; thus further impairing downstream situational awareness and decision making[1].

This paper seeks to enhance existing state estimation techniques by building upon the recent work on event triggered state estimation (ETSE)[3]. Conventionally, the computation of classical SE[2] occurs at fixed intervals whereas the recently published ETSE algorithm has a varying time interval. In the presence of VER, the regular interval based conventional SE algorithms may be unable to track the variability associated with such VER. At the same time, reducing the interval and computing the SE more times than required is a computationally intensive process. The concept of ETSE is to perform state estimation only when triggered by considerable “novelty” in the measurements from the field. The ETSE algorithm in [3] addressed novelty purely on the basis of the distance between the measured and previously estimated state. Such triggering ensures that the computational overheads are reduced and while the dynamics of the system states are closely followed.

The remainder of the paper develops in six sections. Section 2 provides the necessary background of classical state estimation (Section 2.1) and variable energy resources modeling (Section 2.2). Section 3 covers the formulation of the event-triggered state estimator while the simulation methodology is presented in Section 4. Section 5 presents the results using the IEEE 14 bus benchmark example but with VER integrated into two of the buses. Results from the ETSE are compared against two CSE implementations of relatively slow and fast computation intervals. The paper concludes in Section 6.

2. BACKGROUND

This section provides the necessary background for the development of the ETSE algorithm. Specifically, Section 2.1 provides an overview of CSE algorithm. Many aspects of the CSE algorithm are reincorporated into the development of the ETSE algorithm. Section 2.2 then models the integration of variable energy resources. In particular, attention is given to the characteristics of the VER and its effect on the variability of the state vector.

2.1 Classical State Estimation

Classical state estimation as applied to power systems was originally introduced in [4]. Since then, it has gained widespread adoption in the industry and has received much developmental attention in the academic literature [5, 6]. Here, the classical variant of the power system state estimation is presented as a weighted least square (WLS) problem solved by the common method of normal equations.

Given an N bus network, the state vector at time k is $x(k)=[\theta_1 \dots \theta_N, V_1 \dots V_N]^T$ where θ_i and V_i are the phase angle and voltage respectively at the i^{th} bus. The state vector $x(k)$ is derived from a measurement set $z(k)$ of length M which is obtained from the network through the supervisory control and data acquisition (SCADA) system [7]. The measurements obtained may be of many types. These include the active power injection P_i and reactive power injection Q_i at a bus i, the active power flow P_{ij} and the reactive power flow Q_{ij} between buses i and j, voltage measurements V_i or time stamped measurements from the phasor measurement units (PMUs) (V_i, θ_i) [8].

The measurement vector $z(k)$ is related to the state vector $x(k)$ through [4]

$$z(k) = h(x(k)) + \varepsilon(k) \quad (1)$$

where $\varepsilon(k)$ is the measurement error at time k and it is assumed to be normally distributed such that a weighting matrix may be constructed for the individual measurement error variances σ^2 as

$$W = diag(\sigma_1^{-2}, \ \ \sigma_2^{-2}, \ \ \dots.., \ \ \sigma_M^{-2}) \ . \quad (2)$$

$h(x(k))$ is the function vector of length M that consists of the power flow equations that define power injections into buses and flows within branches. Explicitly, they are:

$$P_i = |V_i| \sum_{j=1}^{n} |V_j| \left(G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right) \quad (3)$$

$$Q_i = |V_i| \sum_{j=1}^{n} |V_j| \left(G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j) \right) \quad (4)$$

$$P_{ij} = |V_i||V_j| \left(G_{ij} \cos(\theta_i - \theta_j) + B_{ij} \sin(\theta_i - \theta_j) \right) - G_{ij} |V_i|^2 \quad (5)$$

$$Q_{ij} = |V_i||V_j| \left(G_{ij} \sin(\theta_i - \theta_j) - B_{ij} \cos(\theta_i - \theta_j) \right) + B_{ij} |V_i|^2 \quad (6)$$

from which an Mx2N jacobian matrix H can be defined

$$H(x) = \frac{\partial h(x)}{\partial x} \ . \quad (7)$$

Prior to presenting CSE as solved by the method of normal equations to the WLS problem, care must be taken to ensure that that measurement set yields full observability of the network [9, 10]. The measurement set must include a set of independent measurement of size greater than the length of the state vector i.e. $M \geq 2N$ [11] . This ensure that the matrix $(H^T W H)$ is nonsingular.

The WLS formulation of CSE is then presented as a minimization of the square error[11]:

$$Minimize: \quad f = [z(k) - h(\hat{x}(k))]^T W [z(k) - h(\hat{x}(k))] \quad (8)$$

$$s.t. \quad z_i(k) = h_i(x(k)) + \varepsilon_i(k) \quad i = 1 \dots M \quad (9)$$

CSE is executed and the state vector is updated at regular intervals. An iterative Newton-Raphson procedure is used to solve for $\hat{x}(k)$, the state estimate by normal equations is presented in Algorithm 1 [11].

Algorithm 1

1. Receive z from the SCADA system
2. Initialize the state vector $x = x^c$ and the iteration counter c.
3. Compute the measurement residual
   $r^c = z - h(x^c)$
4. Obtain $H(x^c)$ and $G(x^c)$
   $H(x^c) = \frac{\partial h(x^c)}{\partial x}$ and $G(x^c) = H^T(x^c) W H(x^c)$
5. Solve for the linear system
   $G(x^c)\Delta x^c = H^T(x^c) W \left[z - h(x^c) \right]$
6. Update the state vector and the iteration counter
   $x^{c+1} = x^c + \Delta x^c, \quad c = c + 1;$
7. Check stopping criterion at a maximum count c_max;
8. If stopping criterion is satisfied:
   $\hat{x} = x^c;$

2.2 Variable Energy Resources

The variability characteristic of solar and wind generation as they are integrated into the power grid necessitates the need for improved real-time monitoring which subsequently improves situational awareness, decision-making and automatic control[1]. These sources are called variable because of two complimentary characteristics: uncertainty and intermittency. They are uncertain in that their inputs of solar irradiance and wind speed are stochastic in nature and hence require prediction. Forecast model accuracy for wind or solar energy has improved in recent years and remains as a field of active research [12, 13]. VERs is intermittent in the sense that they are not dispatchable like conventional generators and hence introduce a new set of dynamics into the power grid.

In order to incorporate VERs into an ETSE, a stochastic input-to-output model of the VER is required. This paper presents a model for wind generation although a similar approach may be taken for solar generation. In-built controllers can reduce the variability in the wind power output, but wind speed ramps or sudden gusts may still cause significant fluctuations. The power output of a wind turbine is related to the wind velocity via[14]

$$P_w(v) = \frac{1}{2} \times \rho A v^3 \ . \quad (10)$$

Here, $P_w(v)$ is the wind power; ρ is the air density; A the area of cross section of the flow tube. The wind power is related to the mechanical power P_m from the turbine through [14]

$$P_m = C_p \times P_w(v) \quad . \tag{11}$$

The turbine coefficient C_p varies with the turbine design [14] and could be modeled as non-linear algebraic equation [15, 16]. The electrical power output is proportional to the mechanical power of the turbine through [14]

$$P_e = \eta \times P_m \tag{12}$$

where η is the generator efficiency and it varies with the choice of generator[17].

The active power injection equation (3) shows the relation between the power injection and the state vector. Thus any change in the power injection at the bus will cause the state vector to change. In [18], the effect of wind generation on the phase angle is established using field data from an experimental work. Figure 1 shows the variation in phase angles in the Texas Independent Synchrophasor Network on April 4, 2009 a network due to wind generation as measured from the McDonald observatory in Ft. Davis.

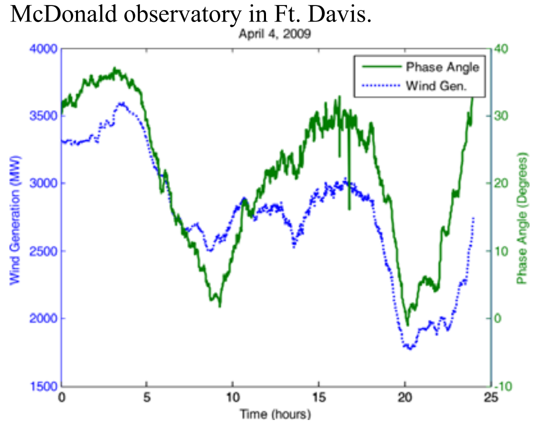

Figure 1: Phase Angle between Austin and Ft. Davis compared to Wind[18]

3. EVENT TRIGGERED STATE ESTIMATION

This section builds upon the background developments of the previous section so as to present how an event-triggered state estimator may be applied to address VERs. The concept of event triggered state estimation was first introduced as a technique to reduce communication overheads in distributed state estimators[3]. In contrast, this paper focuses on the inclusion of an event criterion to trigger when there is considerable novelty in the wind power output.

A number of triggering criteria can be used to capture the variability in the VER. In [3], the trigger is set by the square root error of the current measurement and the previous estimate. Here, the event is characterized as a considerable variation in the active power injection at the VER buses as considered by the 'Western Electric Rules' [19].

The 'Western Electric Rules' (WER) are used in the analysis of control charts to monitor statistical process control. They have been formulated to pick up non-random variations or trends in the process output so that necessary control action can be implemented. The rules are defined with respect to a central limit and the distance of recent measurements from the central limit. In stochastic process monitoring, the central limit μ is taken as the average of the measurement over a period of time or the expected value of the measurement. The WER are:

- If the measurement point lies outside $\mu \pm 3\sigma_i$.
- If two out of three measurement points are outside $\mu \pm 2\sigma_i$
- If four out of five consecutive points are outside $\mu \pm 1\sigma_i$.
- If eight consecutive points are on either side of μ

Where, σ_i is the standard deviation of the measurements in a given observation window. Here, the rules are applied to observe the active power injection at the buses with wind generation over a window that grows in size until the conditions of the triggering criterion are met; at which point it is reset back to a size of two.

Let the active wind power injection at time k at bus i be $P_{w,i}(k)$ and $\mu = \bar{P}_{w,i}(k)$ be the average of the measurements within a given observation window of size defined as $S_i(k)$;

$$S_i(k) = \begin{cases} 2; & \tau(k-1) = 1 \\ S_i(k-1)+1; & t(k-1) = 0 \end{cases} \tag{13}$$

$$\bar{P}_{w,i}(k) = \frac{\sum_{j=0}^{S_i(k)} P_{w,i}(k-j)}{S_i(k)} \tag{14}$$

where $\tau(k)$ is a boolean trigger which decides whether to perform state estimation upon receiving $P_{w,i}(k)$. The value of the previous trigger is used to update the window size.

The Western Electric Rules (WER) recognizes events such as ramps but cannot pick up random events such as gusts which may result in sudden spikes. In order to capture such an event, an additional criterion is introduced as follows:

$$\left|P_{w,i}(k) - P_{w,i}(k-1)\right| > \alpha \times P_{w,i}(k-1) \tag{14}$$

where α is a tuning parameter. Together, this criterion and WER are combined to explicitly state the full triggering function $\tau(k)$,

$$\tau(k)=\begin{cases} 1, & P_{w,i}(k)\geq\left(\bar{P}_{w,i}(k)+3\sigma_i\right)\vee P_{w,i}(k)\leq\left(\bar{P}_{w,i}(k)+3\sigma_i\right) \\ 1, & \bigvee_{j=0}^{2}\left(P_{w,i}(k-j)\geq\left(\bar{P}_{w,i}(k)+2\sigma_i\right)\right)\geq 2 \\ 1, & \bigvee_{j=0}^{2}\left(P_{w,i}(k-j)\leq\left(\bar{P}_{w,i}(k)-2\sigma_i\right)\right)\geq 2 \\ 1, & \bigvee_{j=0}^{4}\left(P_{w,i}(k-j)\geq\left(\bar{P}_{w,i}(k)+1\sigma_i\right)\right)\geq 4 \\ 1, & \bigvee_{j=0}^{4}\left(P_{w,i}(k-j)\leq\left(\bar{P}_{w,i}(k)-21\right)\right)\geq 4 \\ 1, & \bigvee_{j=0}^{8}\left(P_{w,i}(k-j)\geq\bar{P}_{w,i}(k)\right)\geq 8 \\ 1, & \bigvee_{j=0}^{8}\left(P_{w,i}(k-j)\leq\bar{P}_{w,i}(k)\right)\geq 8 \\ 1, & \left|P_{w,i}(k)-P_{w,i}(k-1)\right|>\alpha\times P_{w,i}(k-1) \\ 0, & Otherwise \end{cases} \tag{15}$$

The algorithm for the ETSE is as follows:

Algorithm 2

1. Receive active power measurement $P_{w,i}(k)$ from all the buses with wind generation
2. Update $S_i(k)$ and compute $\bar{P}_{w,i}(k)$
3. Update $\tau(k)$ using equation (15)
4. If $\tau(k)=1$ receive measurement set of the entire network and perform SE using Algorithm 1
5. Else if $\tau(k)=0$, then $\hat{x}(k)=\hat{x}(k-1)$
6. Wait for $P_{w,i}(k+1)$

4. SIMULATION METHODOLOGY

As mentioned in Section 1, the performance of the ETSE is studied relative to CSE by evaluating three different SE approaches:

- The fast SE (FSE) which runs Algorithm-1 for every instant the measurement set is available (2s).
- The new ETSE which executes Algorithm-2.
- The CSE which executes Algorithm-1 every 10s.

The FSE is to mimic the real time SE and is used as a benchmark to compare the new ETSE and CSE. The CSE is implemented to reflect the current practice in SE in energy management systems.

In each case, the wind speed follows the composite wind speed model presented in [15]. This is taken as a stochastic input to the DFIG wind turbine model provided in SimPower[20]. These results are integrated into the IEEE 14-bus system[21] in Figure 2. The three SE approaches are tested for two levels of VER penetration:

- when Bus 2 has VER connected,
- when Bus 2 and Bus 6 are replaced with VER.

The measurement set is obtained from the power flow analysis performed in PSAT. The measurement set is defined such that the system is observable. A normally distributed measurement error of standard deviation 0.2 and mean 0.5 is

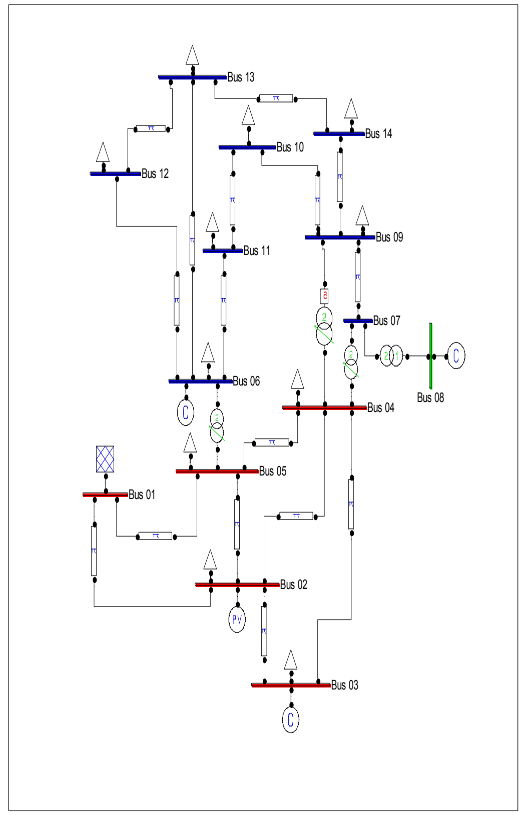

Figure 2: IEEE 14 bus system

introduced to the measurement set before executing the SE. The tuning parameter α is set to 0.25.

The entire simulation is conducted within a Matlab environment on a Windows 7 HP laptop with an Intel Core i5 CPU running at 2.27Ghz.

The results of the simulations are assessed on the basis of both computation time and relative error. The computation time for the three SE approaches and two VER penetration levels is recorded for a simulation interval of [2s, 400s]. Relative error is assessed on the basis of the norm

$$norm(err)=\sqrt{\sum_{j=1}^{n} err_j^2} \tag{16}$$

of the deviation of the CSE and ETSE approaches relative to the FSE which records the state vector. Specifically, the phase angle at Bus 4 is arbitrarily chosen for inspection.

5. RESULT

This section presents the results of the simulation methodology explained in the previous section. The simulation results include the graph of the variation in phase angle at Bus 4 which is observed by the various SE approaches. The computation time as well as the relative error is also recorded for the different SE approaches.

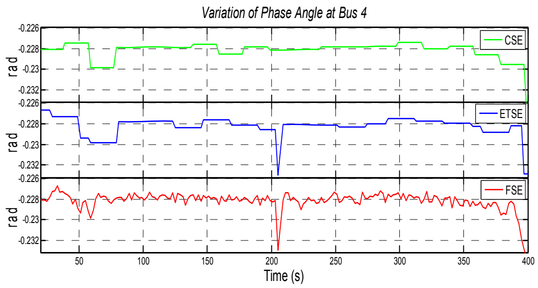

Figure 3: Variation in phase angle at Bus 4 when Bus 2 has VER connected

The Figure 3 shows the variations of the phase angle at Bus 4 for the three different SE approaches. The ETSE algorithm has a variable time interval between consecutive updates while the CSE on the other hand, has a fixed time interval of 10s. The variable time interval in the ETSE is able to detect the drop in phase angle at t=204s, but this is missed by the CSE.

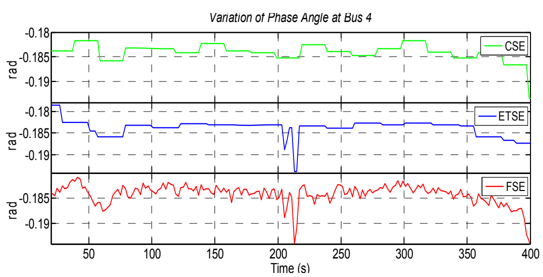

Figure 4:Variation in phase angle at Bus 4 when Bus 2 and Bus 6 have VER connected

The Figure 4 shows the variability in phase angle at Bus 4 with VER connected at Bus 2 and Bus 6. The ETSE captures the drop in the phase angle at t=204s and t=208s which is missed by the CSE.

Approaches	FSE	ETSE	CSE
Processing Time-bus2	109.618s	53.69s	20.148s
Processing Time- bus2 &bus4	211.25s	64.273	20.19s

TABLE 1: Computation time of the three SE approaches

As seen in Table 1, the computation time taken for FSE is the highest since it invokes the optimization Algorithm 1 for every instant the new measurement is obtained. There is a significant reduction in the computation time in the CSE followed by the ETSE

Approaches	ETSE	CSE
Measure of error at bus 4-1 WIND GEN	1.01e-2	5.04e-2
Measure of error at bus 4-2WIND GEN	2.4e-2	1.748e-1

TABLE 2: Relative error of the two SE approaches compared to FSE

The Table 2 shows the relative error for the phase angle at Bus 4 for the new ETSE and the CSE. In both the scenarios of wind integration the ETSE has less error than the CSE. The relative error is used to compare the fidelity of the ETSE and CSE approaches.

5. CONCLUSIONS

The new ETSE algorithm proposed in this paper created a trigger criterion based on the power output of the VER in the network. The trigger criterion included the historical data of the power output and the used concepts of WER to identify the events such as ramps and surge in the power output. The results of the ETSE compared to the CSE relative to the FSE show higher fidelity of the state. The computation time of the new ETSE is higher than the CSE but is significantly lower than the FSE.

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