R. C. Francy, A. M. Farid, and K. Youcef-Toumi, "An Event Triggered Tracking State Estimator for Power Systems with Integrated Wind Generation," in 2013 IEEE Power and Energy Society Powertech Grenoble, (Grenoble, France), pp. 1–6, 2013.

An Event Triggered Tracking State Estimator for Power Systems with Integrated Wind Generation

R Francy
Masdar Institute of Science & Technology, UAE
rfrancy@masdar.ac.ae

A M Farid
Masdar Institute of Science & Technology, UAE
afarid@masdar.ac.ae

K Youcef-Toumi
MIT, USA
youcef@mit.edu

***Abstract*— For many decades, state estimation has been a critical technology in the energy management systems utilized by transmission system operators. Over time, it has become a mature technology that provides an accurate representation of system state under fairly stable and well understood system operation. The integration of variable energy resources such as wind and solar generation, however, introduce new dynamics and uncertainties into the system. Along with increase in variability which needs real time monitoring, state estimation will be extended to the distribution networks which increase the size of the problem. Conventional solutions to this problem result in large problem sets being solved at a faster rate thereby becoming computationally intensive. This work builds upon the recent contribution of event-triggering where the state estimator is only called in the case of considerable "novelty" in the evolution of the system state. Specifically, the concept of tracking saves significant computational effort at minimal expense of error by allowing for the update of system state between two consecutive triggered instances. The new event-triggered tracking state estimator (ETTSE) is demonstrated on the standard IEEE 14-bus system, and the results are observed for a specific bus.**

***Index Terms*—State Estimation, Event triggered, and Tracking**

I. Introduction

In recent years, the growing demand for energy has resulted in the expansion of the power generation portfolio. The power generation now includes energy sources such as solar energy and wind energy which are known as Variable Energy Resources (VERs). The presence of VERs such as wind in the power grid introduces variability in the state variables as well. In [1], the correlation between the varying wind speed and the phase angles is established. The dynamic nature of the power grid requires improvements in monitoring techniques to enhance the downstream situational awareness and decision making[2].

State Estimation (SE) is the key tool of any Energy Management System (EMS). SE is an optimization algorithm which estimates the voltage (V) and phase angles (Θ) at every bus in a given power grid for a given set of measurements. The voltage and phase angles are defined as the state variables of the power grid and monitoring the variation of the states is important to ensure reliable operation of the power grid. The measurements used for SE includes active power injection, reactive power injection, active power flow, reactive power flow, phase angle and voltage measurements[3].

Text

Although SE has traditionally only been used in transmission EMS, the incorporation of Distribution Generation (DG) has now let to SE methods to be included in Distribution Management System (DMS) [4]. Distribution systems are characterized by more buses per unit area thereby dramatically increasing the problem size. The resulting computational expense, restricts the ability to sample at a higher speed to improve monitoring. The increase in network size, the increase in variability and the limitations on computational capability together are the motivation of this paper to look into different state estimation approaches to the enhance real time monitoring.

The Classical State Estimation (CSE) uses a Weighted Least Square (WLS) algorithm to estimate the state vector. The algorithm is performed at regular intervals to update the state vector x= [V, Θ]. The fixed interval CSE is unable to provide high fidelity in the value of the state variables because of the dynamics which exist today in the power grids. In [5] the concept of Event Triggered State Estimation (ETSE) using the variability in the wind was introduced. In the ETSE the WLS is performed only when triggered. The trigger is set when there is significant change in the power injection at the nodes with wind power generation. The triggering mechanism incorporates the variability of the wind into the SE. In this paper the concept of tracking state estimation [6]is combined with the triggering criteria in [5]to achieve real time monitoring of the state variables. The combination of tracking and triggering provides a SE which is suitable for the variability introduced by the VER such as wind generation.

The remainder of the paper develops into five sections. Section II includes the necessary background information on classical state estimation and WLS (Section II.A) as well as the overview of wind as a VER(Section II B) ,the event triggered criterion (Section II.C) and tracking[6] (Section II.D). The Section III covers the algorithm to perform Event Triggered Tracking State Estimation (ETTSE). The methodology and the results are outlined in Section IV and conclusion in Section V.

II. BACKGROUND

A. *Classical State Estimation and Weighted Least Square (WLS)*

CSE was introduced to power grids in 1971 by Fred Schweppe [7] and since then has been an area of extensive research. There are several algorithms which have been developed to perform the estimation [8, 9]. The WLS algorithm is widely used and is adopted in this paper.

Given an N bus network, the state vector at time k is $x(k)=[\theta_1 \ldots \theta_N, V_1 \ldots V_N]^T$ 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 [10]. As mentioned in Section I, the measurements 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) [11].

The measurement set must include a set of independent measurements of size greater than the length of the state vector i.e. $M \geq 2N$ [3] . This ensures that the system is completely observable. Complete observability ensures that the measurements are sufficient to arrive at accurate estimates for all the state variables.

The measurement vector $z(k)$ is related to the state vector $x(k)$ through [7]

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

Where $h(x(k))$ 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:

$$P_i=|V_i|\sum_{j=1}^{n}|V_j|\left(G_{ij}\cos\left(\theta_i-\theta_j\right)+B_{ij}\sin\left(\theta_i-\theta_j\right)\right) \qquad (2)$$

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

$$P_{ij}=|V_i||V_j|\left(G_{ij}\cos(\theta_i-\theta_j)+B_{ij}\sin(\theta_i-\theta_j)\right)-G_{ij}|V_i|^2 \qquad (4)$$

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

from which an Mx2N Jacobian matrix H can be defined

$$H(x)=\frac{\partial h(x)}{\partial x} \ . \qquad (6)$$

$\varepsilon(k)$ 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

$$W=diag(\sigma_1^{-2},\ \ \sigma_2^{-2},\ \ \ldots..,\ \ \sigma_M^{-2}) \ . \qquad (7)$$

The WLS formulation of CSE is then presented as a minimization of the square error[3]:

$$Minimize: \quad f=[z(k)-h(\hat{x}(k))]^T W[z(k)-h(\hat{x}(k))] \ (2)$$

$$s.t. \quad z_i(k)=h_i(x(k))+\varepsilon_i(k) \quad i=1....M \qquad (3)$$

An iterative Newton-Raphson procedure is used to solve for $\hat{x}(k)$, the state estimate by normal equations is presented in Algorithm 1 [3]. In CSE, the Algorithm 1 is performed at regular intervals to update the state vector.

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 $G(x^c)=H^T(x^c)WH(x^c)$
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:
   $\hat{x}=x^c;$

B. *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[2]. 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 are 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]

$$P_w(v) = \frac{1}{2} \times \rho A v^3 \quad . \tag{4}$$

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]

$$P_m = C_p \times P_w(v) \quad . \tag{5}$$

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]

$$P_e = \eta \times P_m \tag{6}$$

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 [1], 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.

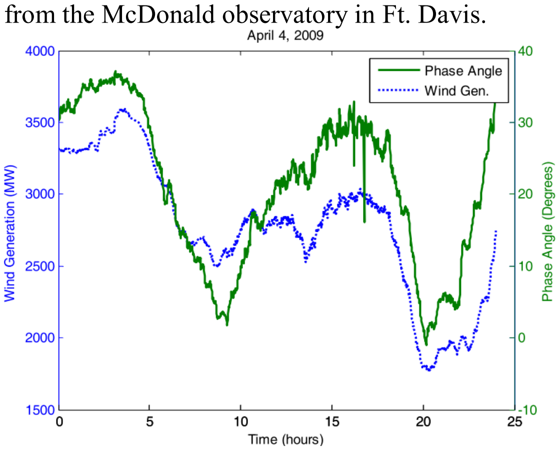

Figure 1: Phase Angle between Austin and Ft. Davis compared to Wind[1]

C. Event Triggered State Estimation – ETSE

The concept of event triggered state estimation is to update the state vector only when there is considerable novelty in the measurement set[18]. In[18] the trigger is set by the square root error of the current measurement and the previous estimate. In [5]the trigger is set based on the novelty in the power injections at the bus with VER wind generation. The event is identified using the Western Electric Rules (WER)[19] often used in stochastic process control.

The WER have been formulated to pick up non-random variations or trends in the process output so that necessary control action can be implemented. In [5], 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 resets back to a size of two.

The rules are defined with respect to a central limit and the distance of recent measurements from the central limit. The distance is defined as σ_i which is the standard deviation of the measurements in a given observation window. 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

Formally, the application of event triggering is as follows: 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 $S_i(k)$;

$$S_i(k) = \begin{cases} 2; & \tau(k-1) = 1 \\ S_i(k-1)+1; & t(k-1) = 0 \end{cases} \tag{10}$$

$$\bar{P}_{w,i}(k) = \frac{\sum_{j=0}^{S_i(k)} P_{w,i}(k-j)}{S_i(k)} \tag{11}$$

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) is able to pick up events such as ramps but cannot recognize 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:

$$\left| P_{w,i}(k) - P_{w,i}(k-1) \right| > \alpha \times P_{w,i}(k-1) \tag{12}$$

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

$$\tau(k)=\begin{cases} 1, & P_{w,i}(k)\geq\left(\bar{P}_{w,i}(k)+3\sigma_i\right)\vee P_{w,i}(k)\leq\left(\bar{P}_{w,i}(k)+3\sigma_i\right) \\ 1, & \bigvee_{j=0}^{2}\left(P_{w,i}(k-j)\geq\left(\bar{P}_{w,i}(k)+2\sigma_i\right)\right)\geq 2 \\ 1, & \bigvee_{j=0}^{2}\left(P_{w,i}(k-j)\leq\left(\bar{P}_{w,i}(k)-2\sigma_i\right)\right)\geq 2 \\ 1, & \bigvee_{j=0}^{4}\left(P_{w,i}(k-j)\geq\left(\bar{P}_{w,i}(k)+1\sigma_i\right)\right)\geq 4 \\ 1, & \bigvee_{j=0}^{4}\left(P_{w,i}(k-j)\leq\left(\bar{P}_{w,i}(k)-21\right)\right)\geq 4 \\ 1, & \bigvee_{j=0}^{8}\left(P_{w,i}(k-j)\geq\bar{P}_{w,i}(k)\right)\geq 8 \\ 1, & \bigvee_{j=0}^{8}\left(P_{w,i}(k-j)\leq\bar{P}_{w,i}(k)\right)\geq 8 \\ 1, & \left|P_{w,i}(k)-P_{w,i}(k-1)\right|>\alpha\times P_{w,i}(k-1) \\ 0, & Otherwise \end{cases} \quad (13)$$

D. Tracking State Estimator

The state variables are updated using the method of tracking between two consecutive triggers [6]. The tracking method utilizes the available state estimate $\hat{x}(k-1)$ and current measurement set $z(k)$ to evaluate the update $\Delta x(k)$ which should be added to the state estimate $\hat{x}(k-1)$ to obtain $\hat{x}(k)$.

$$\hat{x}(k)=\hat{x}(k-1)+\Delta x(k) \quad (14)$$

The $\Delta x(k)$ is obtained by solving the following:

$$\Delta x(k)=G^{-1}(\hat{x}_t)H(\hat{x}_t)(W[z_k-h(\hat{x}(k-1))] \quad (15)$$

Where $\hat{x}_t$ is the state vector which is obtained from executing the WLS at time ***t*** when the trigger is set. The inverse matrix $G^{-1}(\hat{x}_t)$ also known as the gain matrix and $H(\hat{x}_t)$ the Jacobian is calculated only when the trigger is set and $\hat{x}_t$ is estimated using the Algorithm 1. The Gain matrix and the Jacobian matrix once calculated retain their value till the next event is identified. During the period between consecutive events the state variable is updated by Equation (13). The method of tracking is computationally less intensive than the optimization program outlined in Algorithm 1 because the Gain matrix is not computed for each update.

The combination of event triggered and tracking allow real time monitoring of the state variables without high computational overheads.

III. EVENT TRIGGERED TRACKING STATE ESTIMATOR

Traditionally, CSE executes the WLS algorithm at regular but relatively slow intervals (10-30s) under the assumption that the power system under observation evolves quasi statically between consecutive executions of the WLS. The increasing penetration of VER in recent years has introduced greater dynamics thus potentially violating this assumption. To keep up with the variation in the states, reductions in the CSE execution interval has been proposed as a solution. Here, the concept of tracking in Section II C and triggering in Section II D are now combined to give a more computationally efficient ETTSE algorithm with improved real time monitoring capability as an alternative solution.

In this paper the entire WLS is performed using Algorithm 1, only when an event occurs. The event is identified using the criterion explained in Section II.B.

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 $\mu=\bar{P}_{w,i}(k)$ using equation (10) ,(11) respectively.
3. Update $\tau(k)$ using Equation (13)
4. If $\tau(k)=1$, receive measurement set z of the entire network and perform SE using Algorithm 1 to update $\hat{x}(k)$.
5. If $\tau(k)=0$ receive measurement set z of the entire network update $\Delta x(k)$ using Equation (15) and $\hat{x}(k)$ using Equation (14).
6. Wait for active power measurement $P_{w,i}(k)$.

The Algorithm 1 which executes the gain matrix is only performed when the trigger is set. The remaining step to update the state vector is performed using Equation (14) and (15). The results of this new approach are studied in a case study in the following section.

IV. CASE STUDY: METHODOLOGY AND RESULTS

A. Methodology

The standard IEEE 14 bus system[20] is used to illustrate the scheme proposed in this paper. The measurement set is predefined to be : Voltage measurement at Bus 1, Power injection (active and reactive) at Bus 2, 3 7, 8, 10, 11, 12 and 14 and Power flow (active and reactive) on branches between the following buses 1-2; 2-3; 2-4; 2-5; 4-5; 4-7; 4-9; 5-6; 6-11; 6-13; 7-9 and 12-13.

Standard methods of observability[3] are applied to assure that the measurement set results in a full column rank of H given by Equation (6). The tuning parameter in Equation (12) is set to 0.25.

The following 3 scenarios are observed and compared against each other:

- Execute Algorithm 1 every 2s interval which is Fast SE (FSE)
- Perform Event Triggered State Estimation(ETSE)[5]
- Perform Event triggered Tracking State Estimator (ETTSE) using Algorithm 2

The FSE is the ideal scenario which is used as the benchmark to assess the ETTSE. 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[21] to obtain the variability in power injection at Bus 2. These results are integrated into the IEEE 14-bus system. MATPOWER is used to obtain the power flow measurements for variation in the power injection. Two different wind profiles are used to test the three scenarios.

A normally distributed measurement error of standard deviation 0.07 per unit (p.u) and mean 0.06 p.u is introduced.

The results of the simulations are assessed on the basis of the relative error. Relative error is assessed on the basis of the norm

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

B. Results

The results in the variation of the phase angle at Bus 5 for two different wind profiles are studied. Case 1 represents a spike in the wind power injection and in Case 2 there are ramp events and higher variability. Also, the Δx is observed and compared to the difference between the real update obtained from the FSE.

Case	ETSE	ETTSE
Case 1	1.04×10^{-2}	3.94×10^{-4}
Case 2	2.9×10^{-2}	1.2×10^{-3}

Table 1: Relative error of the two SE approaches compared to FSE

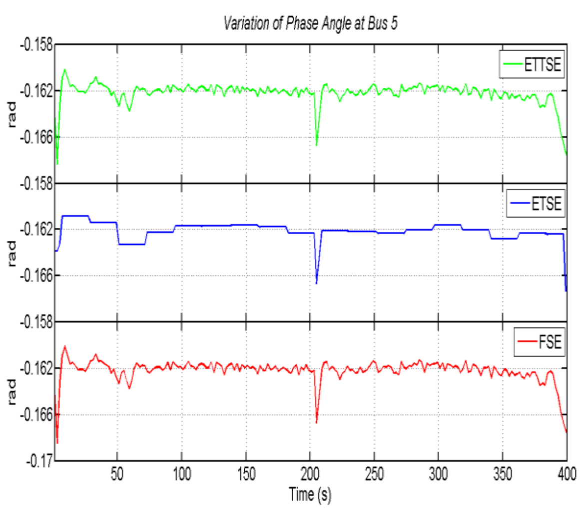

Figure 2: Variation in the phase angle at Bus 5 presented by the different SE approaches for Case 1

As can be seen in Fig.2 and Fig.3 the modulation in the phase angle for the different wind profiles have been faithfully captured by the ETTSE.

The Table 1 shows the relative error for the phase angle at Bus 5 for the new ETSE and the ETTSE. In both cases of wind power injection profile the ETTSE has less error than the ETSE. The relative error is used to compare the fidelity of the ETSE and ETTSE approaches

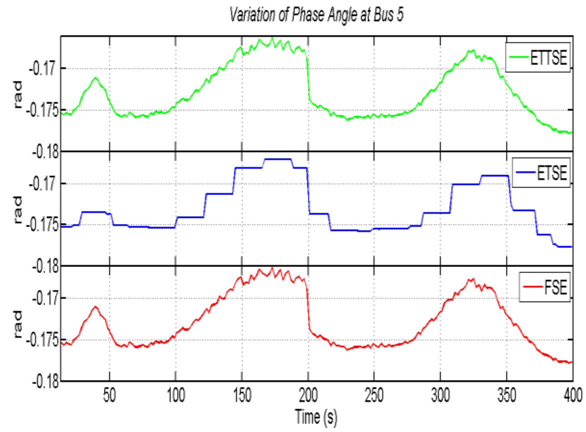

Figure 3: Variation in the phase angle at Bus 5 presented by the different SE approaches for Case 2

.

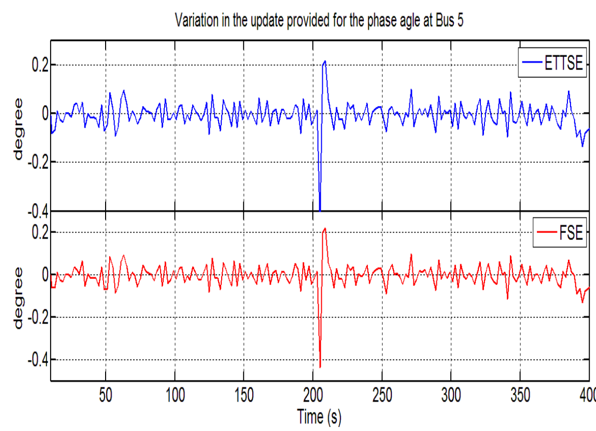

Figure 4: Variation in the update provided by ETTSE compared to the update provided by FSE for wind profile in Case 1

The difference $\hat{x}(k) - \hat{x}(k-1)$ for the phase angle estimate at Bus 5 is recorded for the FSE and compared to the Δx calculated at every update using the equation (15), for the corresponding state variable. Fig 4. observes that the ETTSE method is able to provide accurate update of the state variables at the same time the update mechanism in ETTSE represented by Equation (15) is not complex compared to the computation of the WLS in Algorithm 1.

V. Conclusion

The presence of VERs in the grid, with high variability such as wind, stresses the need for improved state estimators which can keep up with the variability without exponential increase in the computational requirement. This paper presented a combination of event triggered tracking state estimator which is able to incorporate the variability of the VER introduced and meet the real time monitoring demands of a dynamic power grid with reduced computational overheads.

VI. REFERENCES

[1] A. J. Allen, S. Santoso, and W. M. Grady, "Voltage phase angle variation in relation to wind power," in *Power and Energy Society General Meeting, 2010 IEEE*, 2010, pp. 1-7.

[2] J. G. Kassakian, R. Schmalensee, G. Desgroseilliers, T. D. Heidel, K. Afridi, A. M. Farid, J. M. Grochow, W. W. Hogan, H. D. Jacoby, J. L. Kirtley, H. G. Michaels, I. Pérez-Arriaga, D. J. Perreault, N. L. Rose, G. L. Wilson, N. Abudaldah, M. Chen, P. E. Donohoo, S. J. Gunter, P. J. Kwok, V. A. Sakhrani, J. Wang, A. Whitaker, X. L. Yap, and R. Y. Zhang, "The Future of the Electricity Grid: An Interdisciplinary MIT Study," MIT, Cambridge, MA2011.

[3] G. m.-E. s. Antonio and A. Ali, "State Estimation," in *Electric Energy Systems*, ed: CRC Press, 2008, pp. 127-164.

[4] N. Nusrat, M. Irving, and G. Taylor, "Development of Novel State Estimation Algorithms for Active Distribution Networks," *Universities' Power Engineering Conference (UPEC), Proceedings of 2011 46th International,* pp. 1-6, 2011.

[5] R. Francy, A. Farid, A.Adegbege, and K. Y. Toumi, "EVENT-TRIGGERED STATE ESTIMATION FOR VARIABLE ENERGY RESOURCES MANAGEMENT," presented at the 9th IET International Conference APSCOM Hong Kong, 2012. in press.

[6] F. C. Schweppe and R. D. Masiello, "A Tracking Static State Estimator," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-90, pp. 1025-1033, 1971.

[7] F. C. Schweppe and J. Wildes, "Power System Static-State Estimation, Part I: Exact Model," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-89, pp. 120-125, 1970.

[8] A. Monticelli, "Electric power system state estimation," *Proceedings of the IEEE,* vol. 88, pp. 262-282, 2000.

[9] M. S. Kurzyn, "Real-Time State Estimation for Large-Scale Power Systems," *Power Apparatus and Systems, IEEE Transactions on,* vol. PAS-102, pp. 2055-2063, 1983.

[10] S. A.Boyer, *SCADA- Supervisory Control And Data Acquisition*, 3rd ed. U.S.A: ISA, 2004.

[11] D. Tholomier, H. Kang, and B. Cvorovic, "Phasor measurement units: Functionality and applications," in *Power Systems Conference, 2009. PSC '09.*, Clemson, SC, 2009, pp. 1-12.

[12] J. G. C.Ferreira, L.Matia, A.Botterund, J.Wang, "A Survey on Wind Power Ramp Forecasting," Argonne, IL: Argonne National Laboratory, U.S. Department of Energy,2010.

[13] A. Moreno-Munoz, J. de la Rosa, R. Posadillo, and V. Pallares, "Short term forecasting of solar radiation," in *Industrial Electronics, 2008. ISIE 2008. IEEE International Symposium on*, 2008, pp. 1537-1541.

[14] G. L. Johnson, *Wind Energy Systems*: Kansas State University, 2006.

[15] F. Milano, *Power System*: Springer-Verlag Berlin Heidelberg, 2010.

[16] F. Lingling, R. Kavasseri, M. Zhixin Lee, and Z. Chanxia, "Modeling of DFIG-Based Wind Farms for SSR Analysis," *Power Delivery, IEEE Transactions on,* vol. 25, pp. 2073-2082, 2010.

[17] S. L. Andreas Petersson, "Energy Efficiency Comparison of Electrical Systems for Wind Turbines," in *Nordic Workshop on Power and Industrial Electronics*, Stockholm, Sweden, 2002.

[18] N. Kashyap, S. Werner, and H. Yih-Fang, "Event-triggered multi-area state estimation in power systems," in *Computational Advances in Multi-Sensor Adaptive Processing (CAMSAP), 2011 4th IEEE International Workshop on*, San Juan, 2011, pp. 133-136.

[19] C. Western Electric, *Statistical quality control handbook*. New York: The Company, 1958.

[20] F. Milano, "Power System Analysis Toolbox Documentation for PSAT version 2.1.6," ed, 2010.

[21] MathWorks. (2012). *SimPowerSystems User's Guide*.