Developing Scalable Smart Grid Infrastructure to Enable Secure Transmission System Control

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<tr><td>Abstract</td><td colspan="4">State estimation (SE) is now a fundamental and powerful tool for system operators to use in monitoring and controlling power systems. The goal of state estimation is to provide a reliable and accurate estimate of the state variables, which include bus voltages and phase angles. Dynamic state estimation or in other words real-time tracking of system dynamics (bus voltages and phase angles) is one of the great promises of synchronised phasor measurement technology. The present report investigates the recent techniques and advancements of dynamic state estimation for power networks.</td></tr>
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Abbreviations

CKF	Cubature Kalman Filter
DDoS	Distributed Denial-of-Service
DSE	Dynamic State Estimation
DSSE	Distribution System State Estimation
EKF	Extended Kalman Filter
EPF	Extended Particle Filter
LAV	Least Absolute Value
MASE	Multi-Area State Estimation
PMU	Phasor Measurement Unit
RTU	Remote Terminal Unit
SE	State Estimation
SMIB	Single-Machine Infinite-Bus
UKF	Unscented Kalman Filter
WLS	Weighted Least Squares

1. Introduction

State Estimation (SE) is now a fundamental and powerful tool for system operators to use in monitoring and controlling power systems. The goal of state estimation is to provide a reliable and accurate estimate of the state variables, which include bus voltages and phase angles. Dynamic state estimation or in other words real time tracking of system dynamics (bus voltages and phase angles) is one of the great promises of synchronized phasor measurement technology [1], [2]. The present report investigates the recent techniques and advancements of dynamic state estimation for power networks.

2. Estimator Methods

Conventional state estimators use the Weighted Least Squares (WLS) estimator, which is computationally efficient, but vulnerable to bad data. To increase the robustness of the estimators, a Least Absolute Value (LAV)-based state estimation method has been developed that is robust and computationally efficient if the measurement set consists of only Phasor Measurement Units (PMUs) [3]. However, this is computationally expensive for today's power grids since the measurement sets consist of both SCADA and PMU measurements. The WLAV estimator is the modified version of LAV estimator, which uses real and imaginary parts of the bus voltages as system states; it is shown to be robust against intentional (e.g. third parties or hackers tampering with selective PMUs) or unintentional (such as communication or transducer failures) errors in measurements [4]. Traditionally, detection, identification, and eliminating post-estimation bad data when using WLS estimators comes at a high computational cost and cannot be efficiently applied at fast scan rates such as those of PMU measurements.

There are also few efforts have been made to solve the estimation problem by using Kalman Filters. The Extended Kalman Filter (EKF) [5] uses first-order approximation of the Taylor series to solve the measurement function, causing its state estimation results to deviate from actual values, thereby rendering the EKF not quite suitable for dynamic state estimation of nonlinear systems such as the power system. Other researchers have used the Unscented Kalman Filter (UKF) [6], [7] to estimate the power system state, but because the UKF’s performance deteriorates with the increase in the number of state variables, it also is not suitable for estimating the state in large power systems.

Recently, the Cubature Kalman Filter (CKF) [1] has demonstrated potential benefits, such as accuracy and stability for the large state vector, over other Kalman filtering techniques. The CKF does not require Taylor series approximation of the nonlinear function and the Jacobian during its execution, and unlike with the UKF, its performance does not deteriorate with the increase in the size of the state variable vector.

3. A Hybrid State Estimator

SCADA updates vary from every 2 to 6 seconds, and the state estimator is executed every few minutes based on the received measurements and known system topology. On the other hand, PMU measurements are typically updated 50 times per second. As a consequence, the PMU incorporation into existing SCADA-based estimators presents a challenge due to the significant difference between the refresh rates of SCADA versus PMU measurements. (This has long been recognised, and different solutions have been proposed by researchers [8], [9]). The word hybrid refers to the fact that two different estimation methods are used in handling the PMU and SCADA measurements, which are received at different refresh rates.

In addition to the different refreshing rates, the next challenge of incorporating PMU and SCADA data is caused by the scarcity of PMUs in the power network. Most power systems will have only a limited number of PMUs, which is not sufficient to make the entire system observable. The system is unobservable at instants when only PMU measurements are received. At such instances, an updated version of the most recently scanned SCADA measurements will augment the PMU measurements in order to recover observability. Since the equipping of an existing power system with a sufficient number of PMUs requires investments and time, only incremental upgrades are realistic. Consequently, the technological solutions available in present-day power systems consider the scarcity of PMUs to enhance traditional state estimators.

The authors in [1] have developed a multi-agent model to scan and process the PMU and the conventional RTU measurements separately. This model then combines the CKF results in every Kalman Filter cycle to estimate system states. To speed up the CKF processing, they used a factorisation approach that factorises the large measurement vector into sub-vectors. The CKF is processed in parallel using the sub-vectors to estimate the complete power system's various states. The role of the multi-agents in the proposed approach is to process these measurements separately in a collaborative manner for power system hybrid dynamic state estimation and then integrate its results to finally estimate the overall power system's states.

4. Robust State Estimation

The measurement data may contain random measurement errors due to the inaccuracy of the metering devices. Additionally, state estimation uses measurement data gathered from Remote Terminal Units (RTUs) or PMUs. These devices can be geographically far apart and the communication links are not 100% reliable and may be prone to malicious attacks. Any failures caused unintentionally or intentionally can deteriorate the Dynamic State Estimation (DSE) algorithm.

Unintentional communication failures include malfunctioning of equipment, human error, inadequate communication architecture, etc. Most of the power outages are reported to be related to communication errors. On the other hand, intentional communication failures can be caused by cyber-attacks such as Distributed Denial-of-Service (DDoS) attacks that will block the communication links.

Traditional WLS state estimation uses instantaneous measurement data to estimate the system state. This approach can provide a reasonably accurate state estimation when the current measurement data are not delayed or lost. When the system experiences some forms of communication failures, the performance of the WLS state estimation deteriorates to the extent that the system may even become unobservable.

Some literatures have discussed DSE with one time step random communication delay [10] without covering scenarios where communication failure lasts longer than one time step. To study the performance of dynamic state estimation under sustained communication failure a new DSE approach has been proposed in [11] which combines the time-forward kriging-based load forecasting technique with the extended Kalman filter. This combined DSE approach can predict and estimate system state even with partial communication failures.

5. Multi-area State Estimation

Real-time measurements are processed by the state estimators at the ISO control centers (CC). Each CC will have its own local SE which processes measurements received from its regional substations. A system-wide state estimation solution becomes necessary well beyond the extent covered by each CC. Hence, the idea of Multi-Area State Estimation (MASE) methods is currently gaining interest.

Two processing techniques are used to solve the MASE problem: parallel and distributed. A widely accepted distinction between them is that the parallel processing employs a number of closely coupled processors, while distributed processing employs a number of loosely coupled and geographically distributed computers.

For a large power system, distributed processing can bring more flexibility and reliability in monitoring and control and can save on large investments in communication networks. On the other hand, traditional DSE is not scalable enough to process the large amount of data generated over the grid, and is prone to computational bottlenecks. The majority of present DSE methods have focused on estimation accuracy by increasing either modelling or algorithmic complexity, which makes them computationally onerous, limiting their practical applicability to small-scale systems. Even with compromising the accuracy for speed, they might not be fast enough to predict the real-time behaviour of the system. Recently, researchers have started to employ modern parallel computing techniques to increase the estimation speed up to 15 times without a compromise in accuracy [12].

Although existing parallel computation-based SE algorithms are mostly designed for transmission systems, many of which take advantage of interconnected power systems that define each tie-line connected area as a zone, Nusrat et al. [13] have adopted a similar concept for Distribution System State Estimation (DSSE). They have proposed an SE algorithm that analyses a network that has been split into overlapping zones, enabling parallel application of the algorithm specifically for distribution networks. The novelty of the algorithm lies in its capability to generate feasible solutions for the voltage estimation with a much smaller number of real measurements.

6. Generator Dynamic State Estimation

In addition to PMU-based state estimation across the entire network, the dynamic states of the synchronous machines (rotor angle and speed) provide us a more sophisticated and detailed condition of the power system. The ability to estimate those using PMU measurement signals would therefore help us to implement new local and global control and protection strategies.

Numerous improper gapping of speed measurement probes or failure of physical or electrical connections has reduced the reliability of direct measurement of synchronous generator speed. Consequently, direct speed measurement is gradually being phased out in favour of dynamic state estimation using already available measurements provided by installed PTs and CTs.

Several studies have been reported in this area using different approaches to capture dynamic states of the power system. Most of them assumed exciter output voltage and rotor angle as two measurable signals or ignored the field voltage dynamics. As an example, a gain-scheduling scheme was used in [14] for state observer design in a Single-Machine Infinite-Bus (SMIB) system with constant external voltage, while the machine field voltage Efd and mechanical torque Tm were both assumed to bemeasurable.

Similarly, dynamic states of a SMIB test system were also estimated in [15] using Extended Particle Filter (EPF). The proposed estimation scheme was decentralised in that each estimation module is independent from others and only uses local measurements. What makes this method superior to the previous methods that are mainly based on the Kalman Filtering technique is that the estimation can still remain smooth and accurate in the presence of noise with unknown changes in covariance values. Moreover, this scheme can be applied to dynamic systems and noise with both Gaussian and non-Gaussian distributions [16].

In recent works, a proposed modified Extended Kalman Filter with Unknown Inputs (EKF-UI) algorithm [17]–[19] achieved a huge step forward by assuming that the mechanical input Tm and Efd are unknown and time-varying. Also, the previously required SMIB assumption has been removed while decoupling and decentralising the estimators at the PDC level, and keeping the required system data at a minimum level, since the new algorithm needs only the usual stability constants of the generator.

Finally, the statistical performance of four Bayesian-based filtering methods, i.e. Extended Kalman Filter, Unscented Kalman Filter, Ensemble Kalman Filter, and Particle Filter is compared using Monte Carlo methods and a two-area-four-machine test system by [20]. The results are shown in Table 1 in brief. Reader can refer to [20] for a detailed comparison study.

Table 1. Performance comparison of the four filtering methods

	EKF	**UKF**	**EnKF**	**PF**
Accuracy	0% diverged	33% diverged	0% diverged	20% diverged
Efficiency of interpolation	High	High	Low	High
Number of samples needed	N/A	Small	Medium	Large
Sensitivity to the missing data	Low	Low	Low	Low
Sensitivity to the outliers	Low	Low	Medium	High
Computation time	Shortest	Same order as EKF	Longer than EKF	Same order as EnKF

7. Grid Impedance Estimation

In addition to generator and line parameters estimation, further attempts have also been made to generalise this idea to grid impedance estimation. Reference [21] presents a recursive least-squares estimation algorithm with a forgetting factor to identify impedance parameters of a power grid, using the past and recent synchronised measurements for bus voltages and currents. The proposed method is an online estimation of impedance parameters of power systems with multi-source and multi-load. The result of such estimation methods can also be applied for tracking changing parameters, voltage stability monitoring, and fault detection.

8. Conclusion

The present report provides a classified review of the recent achievements in state estimation techniques. Key references are selected carefully from numerous publications in this area to both save time for the readers of this report as well as covering the main research categories in power system state estimation techniques. Out of the aforementioned sections, hybrid and robust state estimation have received more attention by the researchers, which is reflected in the higher number of relevant publications focusing on these two topics. On the other hand component modelling such as generators and transmission line parameters are gaining interest in recent estimation related publications using PMUs.

References

[1] A. Sharma, S. C. Srivastava, and S. Chakrabarti, “A multi-agent-based power system hybrid dynamic state estimator,” *Intell. Syst. IEEE*, vol. 30, no. 3, pp. 52–59, May 2015.

[2] M. Khan, P. Ashton, M. Li, G. Taylor, I. Pisica, and J. Liu, “Parallel detrended fluctuation analysis for fast event detection on massive PMU data,” in *Power Energy Society General Meeting, 2015 IEEE*, 2015, p. 1.

[3] M. Göl and A. Abur, “LAV Based Robust State Estimation for Systems Measured by PMUs,” *Smart Grid, IEEE Trans.*, vol. 5, no. 4, pp. 1808–1814, Jul. 2014.

[4] M. Gol and A. Abur, “A Hybrid State Estimator For Systems With Limited Number of PMUs,” *Power Syst. IEEE Trans.*, vol. 30, no. 3, pp. 1511–1517, May 2015.

[5] J. K. Mandal, A. K. Sinha, and L. Roy, “Incorporating nonlinearities of measurement function in power system dynamic state estimation,” *Gener. Transm. Distrib. IEE Proceedings-*, vol. 142, no. 3, pp. 289–296, May 1995.

[6] S. Wang, W. Gao, and A. P. S. Meliopoulos, “An Alternative Method for Power System Dynamic State Estimation Based on Unscented Transform,” *Power Syst. IEEE Trans.*, vol. 27, no. 2, pp. 942–950, May 2012.

[7] G. Valverde and V. Terzija, “Unscented kalman filter for power system dynamic state estimation,” *Gener. Transm. Distrib. IET*, vol. 5, no. 1, pp. 29–37, Jan. 2011.

[8] A. Simões Costa, A. Albuquerque, and D. Bez, “An estimation fusion method for including phasor measurements into power system real-time modeling,” *Power Syst. IEEE Trans.*, vol. 28, no. 2, pp. 1910–1920, May 2013.

[9] G. N. Korres and N. M. Manousakis, “State estimation and bad data processing for systems including {PMU} and {SCADA} measurements,” *Electr. Power Syst. Res.*, vol. 81, no. 7, pp. 1514–1524, 2011.

[10] C.-L. Su and C.-N. Lu, “Interconnected network state estimation using randomly delayed measurements,” *Power Syst. IEEE Trans.*, vol. 16, no. 4, pp. 870–878, Nov. 2001.

[11] C. Gu and P. Jirutitijaroen, “Dynamic State Estimation Under Communication Failure Using Kriging Based Bus Load Forecasting,” *Power Syst. IEEE Trans.*, vol. 30, no. 6, pp. 2831–2840, Nov. 2015.

[12] H. Karimipour and V. Dinavahi, “Extended Kalman Filter-Based Parallel Dynamic State Estimation,” *Smart Grid, IEEE Trans.*, vol. 6, no. 3, pp. 1539–1549, May 2015.

[13] N. Nusrat, P. Lopatka, M. R. Irving, G. A. Taylor, S. Salvini, and D. C. H. Wallom, "An Overlapping Zone-Based State Estimation Method for Distribution Systems," *Smart Grid, IEEE Trans.*, vol. 6, no. 4, pp. 2126–2133, Jul. 2015.

[14] J. Chang, G. N. Taranto, and J. H. Chow, "Dynamic state estimation in power system using a gain-scheduled nonlinear observer," in *Control Applications, 1995., Proceedings of the 4th IEEE Conference on*, 1995, pp. 221–226.

[15] N. Zhou, D. Meng, and S. Lu, "Estimation of the Dynamic States of Synchronous Machines Using an Extended Particle Filter," *Power Syst. IEEE Trans.*, vol. 28, no. 4, pp. 4152–4161, Nov. 2013.

[16] K. Emami, T. Fernando, H. H.-C. Iu, H. Trinh, and K. P. Wong, "Particle Filter Approach to Dynamic State Estimation of Generators in Power Systems," *Power Syst. IEEE Trans.*, vol. 30, no. 5, pp. 2665–2675, Sep. 2015.

[17] E. Ghahremani and I. Kamwa, "Local and Wide-Area PMU-Based Decentralized Dynamic State Estimation in Multi-Machine Power Systems," *Power Syst. IEEE Trans.*, vol. PP, no. 99, p. 1, 2015.

[18] E. Ghahremani and I. Kamwa, "Dynamic State Estimation in Power System by Applying the Extended Kalman Filter With Unknown Inputs to Phasor Measurements," *Power Syst. IEEE Trans.*, vol. 26, no. 4, pp. 2556–2566, Nov. 2011.

[19] A. K. Singh and B. C. Pal, "Decentralized Dynamic State Estimation in Power Systems Using Unscented Transformation," *Power Syst. IEEE Trans.*, vol. 29, no. 2, pp. 794–804, Mar. 2014.

[20] N. Zhou, D. Meng, Z. Huang, and G. Welch, "Dynamic State Estimation of a Synchronous Machine Using PMU Data: A Comparative Study," *Smart Grid, IEEE Trans.*, vol. 6, no. 1, pp. 450–460, Jan. 2015.

[21] J. Yang, W. Li, T. Chen, W. Xu, and M. Wu, "Online estimation and application of power grid impedance matrices based on synchronised phasor measurements," *Gener. Transm. Distrib. IET*, vol. 4, no. 9, pp. 1052–1059, Sep. 2010.