Available online at www.sciencedirect.com
ScienceDirect
IFAC PapersOnline
CONFERENCE PAPER ARCHIVE
IFAC PapersOnLine 50-2 (2017) 98–103

Distributed Dynamic State Estimation for Smart Grid Transmission System

Md Ashfaqur Rahman *,**
Ganesh Kumar Venayagamoorthy *,***

* *Real-Time Power and Intelligent Systems Laboratory, Clemson, SC 29634 USA*
** *Dept. of Electrical and Computer Engineering, North South University, Dhaka, Bangladesh Email: marahma@clemson.edu*
*** *School of Engineering, University of Kwazulu-Natal, Durban 4041, South Africa Email: gkumar@ieee.org*

Abstract: The advancement of synchrophasor technologies validates the dynamic nature of the state variables of a power system. On the other hand, the need for privacy of data in the deregulated market and speed of computation for large power systems present the importance of a fast distributed state estimation method. To serve both purposes, a distributed dynamic state estimator is developed in this study. The advantages of a predictor, the constant Jacobian method and a combining unit are utilized. The system is distributed to the bus level that makes the distributed approach a parallel estimation. The accuracy and the smoothness of the proposed method are shown to be satisfactory through simulation on the IEEE 68-bus test power system. It is also shown that the proposed method can execute faster than the fastest data rate of the phasor measurement units currently deployed in the power system.

Keywords: Cellular computational network, distributed, dynamic, state estimation, state prediction.

1. INTRODUCTION

To monitor the power system properly, measurements are collected from different parts. The collected measurements contain noise that makes the process inefficient. State estimation is the process of removing errors from these measurements. It is an important tool for reliable and optimal operations of the power systems. The process of contingency analysis, load forecasting and security constrained optimal power flows directly depend on the output of the state estimator (Abur and Exposito (2004)). With the traditional data collection rate of SCADA, the centralized Weighted Least Square (WLS) estimator yields a very accurate result.

With the advancement of newer technologies like the Phasor Measurement Units (PMUs), the data collection rate is increasing significantly. The minimum reported data rate of a PMU is 30 Hz. The maximum can go upto 240 Hz. With the traditional SCADA rate of around one sample every two to six seconds, it may not be possible to track the dynamic nature of the states. But, with the PMU rate, it is possible to extract the dynamic nature and use that for power system operations like state estimation.

The dynamic nature creates the opportunity of predicting the states. Though state prediction is not used in the existing systems, it can be a helpful tool for various purposes. It can be effectively used to detect any sudden changes in the system and to increase the smoothness of the estimation results.

On the other hand, with the increase in size, the power system is getting decentralized and the energy market is getting deregulated (Pasqualetti et al. (2012)). The deregulated market requires the privacy of the participants that may get compromised with the centralized state estimation (Xie et al. (2010)). The privacy can be preserved with a distributed estimation.

Another important characteristic of the distributed estimation is parallelism. Though the WLS estimator is accurate, it is a slow process with some non-parallelizable parts. With the increase in size, the process gets slower. One major solution is to use the distributed estimation (Mutambara (1998)). If the distribution is made to the cell level, it clearly becomes parallelizable.

The main objective of this study is to develop a cellular dynamic estimator to keep the privacy of the energy market participants, to make the process fast, and to detect the sudden changes in the system. To achieve the objectives, a three-unit based estimator is developed using a Cellular Computational Network (CCN) as proposed by Luitel and Venayagamoorthy (2014). A computational cell is implemented on each bus of the system. Each cell includes a cellular predictor, a cellular estimator, and a

⋆ This work is supported in part by the US National Science Foundation (NSF) under grant #1312260, and the Duke Energy Distinguished Professor Endowment Fund. Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of NSF and Duke Energy Foundation.

10.1016/j.ifacol.2017.12.018

combining unit. To increase the estimation speed, the dishonest Gauss Newton method is used.

The main contributions of the paper are,

- The proposed estimator aggregates the quality of a dynamic and distributed estimator and provides the results faster than the highest rate of PMU.
- It keeps the privacy of the energy market and provides the opportunity to detect the sudden changes in the system with the help of the predictor.

The rest of the paper is organized as follows. The system model and the background of power system state estimation are discussed in Section 2. The structure of the proposed estimator is presented in Section 3. In Section 4, the test system is described and the performance of the estimator is demonstrated. The simulation results are analyzed in Section 5. The paper is concluded with future work plans in Section 6.

2. BACKGROUND

Measurements can be taken in different forms like power flows in the transmission lines, power injections and voltage magnitudes of the buses, phase differences of connected buses, current flows etc. In power systems state estimation, the states are derived from the measurements of different types.

The state vector forms the set of variables with minimum cardinality which can describe the whole system. The voltage magnitudes and phase angles are taken as the state vector in nonlinear estimation. All other variables can be derived from these state variables directly.

2.1 System Model

Let, $\mathbf{z}$ denote an $m_s \times 1$ measurement vector with errors. So, the relation between $\mathbf{z}$, the nonlinear function of the measurements $h(.)$, the state vector $\mathbf{x}$, and the measurement error $\mathbf{e}$ is written as,

$$\mathbf{z} = h(\mathbf{x}) + \mathbf{e} \tag{1}$$

The angle of the reference bus is considered as the reference angle and all other angles are calculated with respect to that. If there are N buses, the state vector $\mathbf{x}$ can be represented as,

$$\mathbf{x} = [\theta_2 \ \theta_3..\theta_N \ V_1 \ V_2..V_N]^T \tag{2}$$

Here, θ and V, with proper subscripts, represent voltage angles and magnitudes respectively. If the number of buses in the system is N, there will be $2N-1$ state variables. In the process of estimation, the number of measurements exceeds the number of states to form an overdetermined system.

2.2 Weighted Least Squares Estimation

Like other nonlinear problems, WLS estimator linearizes the system over a small range. Then it applies linear operations to get an updated value. The system is linearized again based on this updated value and uses the linear estimation. This process is repeated unless the estimated value converges. In these methods, $\mathbf{x}$ is started with a close value to the solution. In the beginning, when there is no previous value, all voltage magnitudes start as 1 and all voltage angles as 0 which is known as flat start (Monticelli (1999)),

$$\mathbf{x} = [0 \ 0...0 \ 1 \ 1...1]^T \tag{3}$$

After collecting m_s measurements and constructing the Jacobian matrix $\mathbf{H}(\mathbf{x})$ at flat start, in WLS estimation, the following steps are repeated until the state vector converges to a solution,

- step 1: $\mathbf{\Delta x} = (\mathbf{H}^T\mathbf{W}\mathbf{H})^{-1}\mathbf{H}^T\mathbf{W}(\mathbf{z} - \mathbf{h}(\mathbf{x}))$
- step 2: $\mathbf{x}_{n+1} = \mathbf{x}_n + \mathbf{\Delta x}$
- step 3: update $\mathbf{h}(\mathbf{x})$ with $\mathbf{x} = \mathbf{x_{n+1}}$
- step 4: update $\mathbf{H}(\mathbf{x})$ with $\mathbf{x} = \mathbf{x_{n+1}}$

Here, the matrix, $\mathbf{W}$ denotes the relative weights of the measurements that are usually taken as the inverse of the corresponding error variances.

The most time consuming part of the process is the calculation of $\mathbf{H}$. To avoid that, a faster method is used named the dishonest method (Monticelli (1999)). In this method, $\mathbf{H}$ is kept constant over iterations.

2.3 Dynamic Nature of States

In the traditional SCADA system, measurements are taken at a very slow rate of around 1 sample per 2-6 seconds. With this rate, the collected samples miss some important changes and they may look random. So, the use of the static WLS estimator is rational for this rate.

However, the estimator is getting faster day by day, and it requires a faster rate of collection of measurements. In recent time, PMUs are serving this purpose. With the slowest PMU rate, i.e., 30 samples per second, the measurements show a complete dynamic nature (Rahman and Venayagamoorthy (2016)). The actual values of the voltage magnitude is shown in Figure 1.

Using a static estimator can be inefficient in dynamic system. Though the WLS estimator is the most efficient static estimator, it tries to optimize the states for one sample only and does not take the advantage of the dynamic nature. As a result, it cannot yield a smoother results than the dynamic estimators (Huang and Nieplocha (2008)).

3. DISTRIBUTED DYNAMIC ESTIMATOR

In order to develop a distributed dynamic estimator, the dishonest Gauss Newton method is distributed to the cell level. A prediction unit is also added to the process. A third unit functions as a combiner of the two. All of them are implemented at the cell level using CCN. This makes the distributed method suitable for parallel implementation. The block diagram of a cell is shown in Fig. 2. In the figure, t denotes the time-step, z denotes the measurements, x denotes the state variables and the subscripts n_1, n_2 etc. denote the neighbors.