DISTRIBUTED STATE ESTIMATION FOR MEGA GRIDS

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Abstract – This paper presents a distributed state estimator for the monitoring of mega grids. Mega grids are formed as a result of merging the operation of several power system areas in order to manage power system transactions between remote parts of deregulated power systems. The paper proposes a distributed solution that will address two problems associated with mega grid state estimation, namely the increase in problem dimension and the lack of information and measurement exchange between areas within the grid.

Keywords: Network analysis, decomposition, state estimation, topology errors, large scale systems, bad data processing, network observability.

1 INTRODUCTION

There is growing evidence that power systems will further expand in size as the regional systems are operated as a single grid in order to facilitate remote power transactions. As computer memory becomes cheaper to acquire and processors become ever more powerful and faster, increased dimensions of the problems to be solved, may not appear as a significant challenge. Unfortunately, this is not the case due to technical as well as non-technical constraints. These constraints are natural consequences of the way mega-grids are configured. A mega-grid is an interconnected set of several area systems, each having some degree of autonomy, i.e. each operates as a stand-alone system while respecting the constraints associated with the scheduled transactions with which it is directly or indirectly involved. Individual areas typically are reluctant to share network or operational data and information among themselves, but they may be willing to communicate this data to an independent central entity such as an independent system operator (ISO). In that case, the ISO will face the daunting task of collecting real-time information and data from all parts of the mega-grid and execute application functions on this very large-scale system model. While conceptually simple, this sort of single hub execution of integrated system applications leads to ever increasing demands on memory and computation power as the mega-grid expands to include additional areas or models of the sub-transmission or low voltage networks.

In the specific case of state estimation, either a fully centralized or a distributed solution approach can be employed. The former approach requires system wide measurements to be tele-metered to a central location and their processing will require the use of very large-scale system models and solution methods. The latter will rely on local processing of measurements; however these locally obtained solutions need to be coordinated at a central location in order to eliminate boundary errors and also to obtain the system wide solution. Previous work in this area produced several viable alternative solutions [1-5]. These studies propose different decomposition strategies for the network, by nodes [1], tie-lines [2],[3] or simply based on the structure of the gain matrix [4]. Depending upon the adopted decomposition strategy for the network, these boundary measurements may be ignored [2] or may be included but require iterations between the local and central estimators [3]. If not identified and eliminated, any errors in these measurements will bias the estimated system state [2], [4].

In this paper, the distributed approach will be described in some detail and simulation examples will be used to highlight its advantages. The use of phasor measurement units for improving measurement redundancy and facilitating coordination of individual area state estimation solutions will also be discussed.

2 DISTRIBUTED STATE ESTIMATION OF MEGA GRIDS

Consider a mega grid with *n* areas. These areas are separated by tie-lines, whose terminal buses belong to different areas. Definition of areas is arbitrary and may simply follow geographical or company boundaries. It is assumed that each area has its own established power system operation tools and database. Hence, each area's state estimator may be based on a different algorithm, may use different methods to test observability and to check for bad data. Furthermore, individual areas may employ different kinds of measurements. While some may employ conventional power injection and flow measurements, others may have current magnitude, voltage and current phasor measurements.

When solving the state estimation problem for individual areas, each area estimator will use measurements from its own area. However, there will be boundary measurements, which will be a function of state variables of both neighboring areas. There are two possible ways to circumvent this problem. One is to ignore all boundary measurements and the other is to augment the state variable vector of a given area by the few state variables of the neighboring areas, which are required to express boundary measurements. In this paper, the latter approach is taken. As an example, consider the 14-bus system shown in Figure 1 where the system is made up of two areas. Area 1 state vector will be augmented by the states associated with buses B6, B7 and B9, so that the boundary measurements such as the power injection at bus B4 can be expressed as a function of this augmented state vector.

The method used for state estimation by each area is irrelevant in this set-up, however due to its popular usage, it will be assumed that all area estimators are of weighted least squares (WLS) type. Hence, individual area state estimators will solve the following problem:

$$\begin{aligned} &\text{Minimize } J_i = r_i^T R_i^{-1} r_i \\ &\text{Subject to } z_i = h_i(x_i) + r_i \end{aligned} \tag{1}$$

where:

z_i : is the vector of available measurements in area *i*,

r_i : is the measurement residual vector in area i,

x_i : is the state vector for area i. This vector contains voltages at buses in area i as well as at boundary buses of neighboring areas.

R_i : is area *i* measurement error covariance matrix,

$h_i(x_i)$: is the measurement function for area *i*.

Once each area estimates its own state vector x_i, then this will be sent along with all boundary measurements to the central coordinator. If the area has any PMU measurements, these measurements will also be communicated to the central coordinator. Note that, it is assumed that each area has sufficient measurement redundancy within its boundaries, so that bad data can be detected, identified and corrected by individual areas. The only bad data, which can not be properly processed, are those associated with the boundary measurements since they involve states of other areas. Any such bad data, which can not be identified by area estimators, will be detected and identified by the coordinator estimator.

Central coordinator will receive from each area the following information and measurements:

- Estimated state vector, $\hat{x}_i^b$ for the boundary buses internal to area *i*,
- Estimated state vector, $\hat{x}_i^{ext}$ for the boundary buses of the neighboring areas of area *i*,
- State covariance matrix for each area. This matrix is found by inverting the gain matrix associated with the WLS estimation of the area states,
- Boundary measurements from all areas,
- Any phasor measurements, z_{pmu} existing in any area.

The coordinator will then solve the following optimization problem, which is typically much smaller than any of the area state estimation problems:

$$\begin{aligned} &\text{Minimize } J_S = r_S^T R_S^{-1} r_S \\ &\text{Subject to } z_S = h_S(x_S) + r_S \end{aligned} \tag{2}$$

where:

$z_S = \left[z_u^T, z_{pmu}^T, \hat{x}^{b^T}, \hat{x}^{ext^T} \right]^T$, measurement vector used by the coordinator.

h_S: is the measurement function for the measurements used by the coordinator.

$x_S = [(x_1^b)^T, (x_2^b)^T, \ldots, (x_n^b)^T, \delta_1, \delta_2, \ldots, \delta_{n-1}]^T$: is the state vector estimated by the coordinator. It includes all area boundary bus voltages and the reference bus phase angle δ_i of each area, defined with respect to the *n*-th area reference bus in an *n*-area system.

z_u : is the boundary measurement vector, which includes the tie-line flows and injections incident at all boundary buses.

z_{pmu} : is the phasor measurements vector.

r_S : is the vector of residuals for measurements in z_S.

$\hat{x}^b = \left[\hat{x}_1^{b^T}, \hat{x}_2^{b^T}, \cdots, \hat{x}_n^{b^T} \right]^T$: boundary state variables estimated by individual area state estimators and treated as pseudo-measurements. Error covariance matrix for these pseudo-measurements is obtained from the covariance matrix of the states $R_{x,i}$ for individual areas. This matrix is equal to the inverse of the gain matrix associated with that area's WLS state estimator.

$\hat{x}^{ext} = \left[\hat{x}_1^{ext^T}, \hat{x}_2^{ext^T}, \cdots, \hat{x}_n^{ext^T} \right]^T$, similar to $\hat{x}^b$, except defined for the boundary buses of neighboring areas.

Noted that each area will communicate its state estimation results for its boundary states $\hat{x}^b, \hat{x}^{ext}$ and its state covariance matrix $R_{x,i}$ to the coordinator. In general a boundary bus may have two pseudo measurements associated with its state, one provided by the solution of its own state estimator and another provided by the neighbor's estimator. These will be treated as multiple measurements of the same quantity but having different variances provided by different area state estimators. Since individual estimators are not required to share any raw data with their neighbors, nor are they required to share any software or common database, this sort of distributed estimation scheme will be viable in the deregulated mega grid operation.

3 SIMULATION RESULTS

Above described distributed scheme is implemented and tested on simulated measurements for the IEEE 14 and 118 bus systems.

3.1 14-bus test system

A diagram of the 14-bus system showing its areas, tie lines and assumed PMU measurements is given in Figure 1.

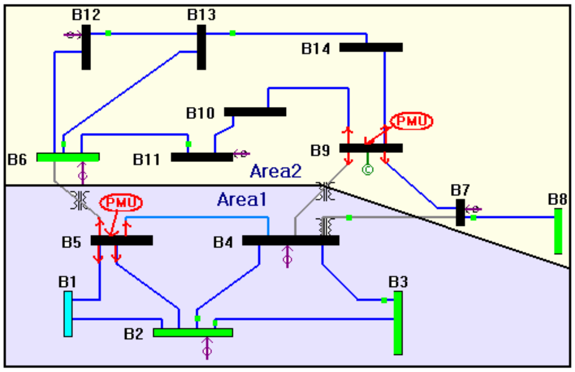

Figure 1: 14-bus system diagram showing its areas and measurements

In order to illustrate the distributed state estimation and bad data processing procedure, the power injection measurement at bus 6 in Area 2 is replaced by an incorrect value. Individual area estimators are then executed. Since the bad measurement appears in area 2, area 1 estimator will not be aware of this error. Area 2 estimator is expected to detect, identify and correct this bad measurement. However, since bad datum appears on a boundary measurement, which transforms into a critical measurement when area 2 estimator is executed, this bad measurement will go undetected by the area 2 estimator. Results of the largest normalized test run by area 2 are shown in Table 1. As evident from these results, all normalized residuals remain below the threshold of 3.0 falsely indicating no bad data.

BD identification	Sorted Normalized Residuals
Measurement/ R_n	Pflow(12,13)/ 2.01
	Pinj (12) / 1.87
	Pflow(6,13)/ 1.67
Eliminated meas.	No Bad Data Detected

Table 1: Normalized residuals obtained by area 2.

Next, the coordinator runs the central state estimation. At this stage, all boundary measurements are processed along with the results of individual area state-estimates. Area 2 state estimates will carry biases due to the undetected bad injection at bus 6.

Hence, in addition to the bad injection at bus 6, there are incorrectly estimated state variables associated with bus 5. Note that, since injection at bus 6 becomes critical for area 2 estimator, its bias will only affect the estimated state of bus 5, which is the external boundary bus for area 2. That is why, only state variables associated with bus 5 are estimated incorrectly by area 2. Table 2 shows the results obtained by the coordinator estimator during the bad data identification cycles. At the end of the fourth cycle, all bad data, namely the pseudo-measurements of estimated state of bus 5 and power injection at bus 6 are identified and eliminated.

3.2 118-bus test system

The 118-bus test system contains 9 areas of similar sizes. In order to test the distributed state estimation procedure, the state estimation of 118-bus system is carried out first by 9 areas separately and then their solutions are coordinated centrally. It is assumed that one PMU measurement is available in each area. The system diagram showing the areas, tie-lines and the measurements is given in Figure 2.

Treatment of bad data at area boundaries by the distributed estimation procedure is tested via simulations. A bad data is introduced in power injection at bus 23, which is a boundary bus for area 4. Detailed system topology and measurements around this boundary between areas 2 and 4 are shown in Figure 3. Note again that this boundary injection becomes critical when area 4 estimation is executed, due to the disregarding of injection measurements at the neighboring area buses.

The results of the normalized residual test for the area 4 estimator as well as the coordinator estimator are given in Tables 3 and 4. As evident from Table 3, area 4 estimator fails to detect bad data due to the criticality of the boundary injection at bus 23. As a result, incorrect estimates are obtained for the external boundary bus 22 by area 4. These estimates are then sent to the coordinator as pseudo-measurements, which are bad. Table 4 shows that the coordinator estimator detects and identifies all bad data including the bus injection at bus 23 as well as the bad pseudo-measurements of the state associated with bus 22 provided by area 4 estimator.

Coordinator Estimation (Sorted Normalized Residuals in Descending order)				
BD identif. cycle	1^{st}	2^{nd}	3^{rd}	4^{th}
Measurement/ R_n	External Pseudo Angle (5) / 129.14	Pinj (6) / 118.18	External Pseudo Voltage (5) /15.10	PMU Phasor Angle (14) / 2.62
	Pinj (6) / 114.03	Internal Pseudo Angle (6) / 96.49	Internal Pseudo Angle (6) / 1.39	PMU Phasor Angle (1) / 2.61
	Internal Pseudo Angle (6) / 90.37	Qinj (6) / 37.49	PMU Phasor Angle (1) / 1.25	Pinj (7) / 2.04
Eliminated meas.	External Pseudo Angle (5)	Pinj (6)	External Pseudo Voltage (5)	No More Bad Data

Table 2: Normalized residual test results for the coordinator estimator of the 14-bus system.

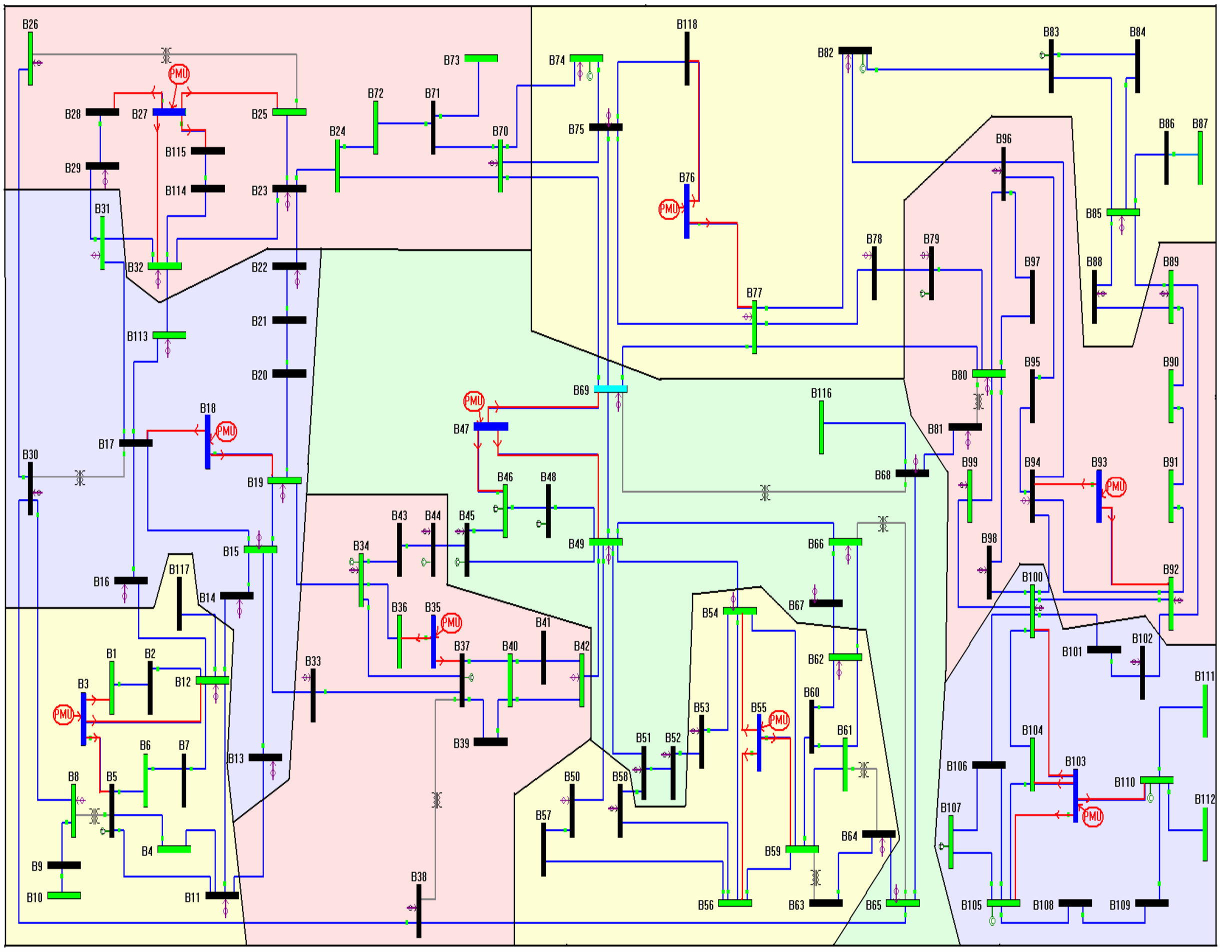

Figure 2: 118-bus system diagram showing its areas and measurements

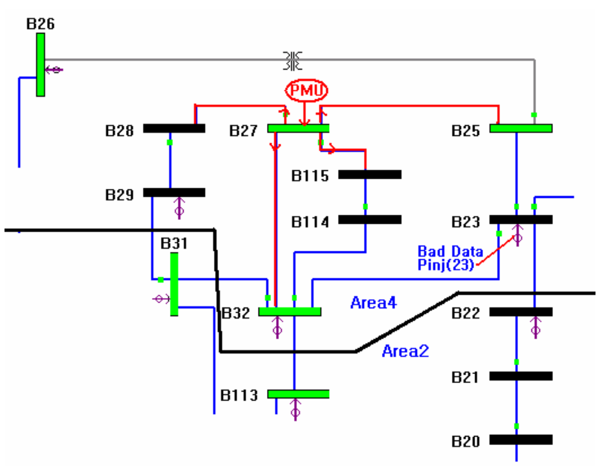

Figure 3: Magnified view of the boundary between areas 2 and 4.

Sorted Normalized Residuals	
BD identification cycle	1st
Measurement/ R_n	Pinj(29)/ 1.15
	Pflow(32,31)/ 1.14
	Pflow(28,29)/ 1.13
Eliminated meas.	No Bad Data

Table 3: Results of area 4 estimation.

Sorted Normalized Residuals				
BD identification cycle	1st	2nd	3rd	4th
Measurement/ R_n	External Pseudo Angle(22) / 135.12	Pinj (23) / 115.60	External Pseudo Voltage (22) /6.64	Internal Pseudo Angle (53) /2.45
	Pinj (23) / 114.84	Internal Pseudo Angle (23) /109.90	Internal Pseudo Voltage (22) /3.20	Internal Pseudo Angle (19) /2.27
	Internal Pseudo Angle(23) / 108.20	Internal Pseudo Angle (22) / 31.73	Pinj (16) / 3.16	Pinj (75) / 2.24
Eliminated meas.	External Pseudo Angle(22)	Pinj (23)	External Pseudo Voltage (22)	No More Bad data

Table 4: Results of coordinator estimator for the 118-bus system.

4 IMPLEMENTATION CONSIDERATIONS

The proposed multi-area estimation scheme assumes that the individual area estimators have sufficient internal measurement redundancy to detect and identify bad data appearing in their internal measurements and their non-critical boundary measurements. Each area estimator may or may not be able to estimate the states associated with its external boundary buses depending upon the availability of proper boundary measurements. If some or all of the external boundary buses are unobservable for a given area, that area will simply not provide the estimated pseudo-measurements for its external bus state variables to the coordinator. The coordinator not only estimates the unknown phase differences between individual area reference buses, but also facilitates bad data detection and identification for certain boundary measurements. These are the measurements that can not be processed by individual area estimators because they become critical when used in isolation by their respective area estimators. If bad data are detected by the coordinator, the identified bad boundary measurement will be flagged and the corresponding area estimator will be notified. This will lead to another estimation cycle which will only involve the affected area estimator and the coordinator. Also note that, even though the availability of PMU measurements will greatly facilitate the estimation of the phase angles between individual area reference buses, they are not necessary for the proposed estimation scheme to work. In the total absence of PMU measurements, the area boundary measurements will still provide the necessary information for the solution of the multi-area coordinated state estimation problem.

5 CONCLUSIONS

This paper describes a distributed state estimator which is to be used by mega grid state estimation. The main advantage of the distributed set up is that individual area state estimators can operate independently and do not have to share network data or measurements with any neighbors. Coordination is accomplished via a central coordinator, such as an ISO, which receives state estimation solutions from individual areas and coordinates them. It also carries out bad data processing function in order to detect missed bad data by individual area estimators due to the reduced redundancy at area boundaries during individual area estimations.

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