Real-time Hybrid State Estimation Incorporating SCADA and PMU Measurements

Kaushik Das, J. Hazra, Deva P. Seetharam, *Member, IEEE,* Ravi K. Reddi and A. K. Sinha, *Member, IEEE*

***Abstract*—This paper proposes a novel hybrid state estimation method using traditional SCADA (Supervisory Control And Data Acquisition) and newly deployed limited PMU (Phasor Measurement Unit) measurements. System states are estimated when a set of SCADA and/or PMU measurements come in. As PMU measurements come much faster (typically one sample in 20ms) than SCADA measurements (typically one sample in 10 seconds), in between two SCADA measurements, system states of PMU unobservable buses are interpolated using an interpolation matrix (H)live PMU measurements. In between two SCADA samples, if PMU measurements change significantly, pre-computed interpolation matrix (H) is compensated with a sensitivity change matrix (ΔH) and system states are estimated using the corrected interpolation matrix. In order to compute the ΔH, the method classified the measurement set into four sub-sets i.e. PMU measurements, SCADA measurements of PMU boundary buses with significant change, SCADA measurements adjacent to the selected boundary buses, and remaining SCADA measurements and run a modified weighted least square method with different weights corresponding to each sub-set of measurements. This compensation improves the estimation accuracy significantly. Effectiveness of the proposed scheme is evaluated on a number of IEEE benchmark test systems and evaluation results are presented in this paper.**

***Index Terms*—Phasor measurement unit, Synchrophasors, State Estimation, Linear State Estimation, Hybrid State Estimation, Observability**

I. Introduction

Phasor Measurement Units (PMUs) are now well accepted as measurement systems of choice by most power systems around the world [1]. As compared to SCADA measurements, PMU measurements are more accurate and of higher precision, thus play an important role in enhancing performance of state estimators [1]-[3]. However, being expensive, economic constraints do not allow PMUs to be installed in all the buses of a large power system. Traditionally PMUs are placed in gradual phases in large power systems. Thus, few PMU measurements along with the traditional SCADA measurements are available for state estimation. Since PMU data can be obtained as fast as one measurement per cycle, it is envisaged that the estimation should be real time and it should capture the dynamics of the system in the magnitude of milliseconds.

Several state estimation methods incorporating PMU measurements have already been proposed. For example, Bruno et al. [4], Hongga et al. [5], and Fang et al. [6] proposed direct state estimation methods using PMU measurements where the virtue of higher precision of PMU measurements is exploited. However, these methods could not take the advantage of faster data rate from PMUs as PMU measurements in between two SCADA measurements are dropped and hence could not track the system dynamics. Hui Xue et al.[7] and Jain et al. [8] improved above mention methods by predicting the change in SCADA measurements (due to slow change in load) while PMU measurements arrive. However these methods overlook the fast system dynamics trackable through PMU measurements. Meliopoulos et al.[9] and Farantatos et al.[10] suggested a distributed state estimator which estimates the states locally at substation level. This type of estimator requires the system to be completely observable through PMU. Cheng et al.[11] proposed a linear state estimator for mixed set of PMU measurements and traditional measurements. This estimator is unable to track system dynamics in any unobservable region through PMU. Nuqui et al.[12] suggested a hybrid state estimator where classical state estimator is incorporated along with the linear state estimator. However, this method also could not track system dynamics during fault or sudden change in load.

This paper proposes a novel hybrid state estimation algorithm combining conventional SCADA and limited PMU measurements. In between two SCADA measurements, when a set of PMU samples comes in, system states of PMU unobservable buses are interpolated from the live PMU data using a pre-computed interpolation matrix (H). This interpolation matrix is re-computed when both SCADA and PMU measurements arrive together. In between two SCADA measurements, if PMU measurements change significantly, pre-computed interpolation matrix (H) is compensated with a sensitivity change matrix (ΔH) and system states are estimated using the corrected interpolation matrix. In order to compute ΔH, proposed method classified the available measurement set (M) into four sub-sets i.e. PMU measurements ($A \subseteq M$), SCADA measurements of PMU boundary buses ($B \subseteq M$), SCADA measurements adjacent to boundary buses ($C \subseteq M$), and remaining SCADA measurements ($D \subseteq M$). A modified weighted least square method with differential weights ($W(A) > W(D) > W(C) > W(B)$) corresponding to each sub-set of measurements is run to estimate the states of the system. This differential weight factor improves the estimation accuracy significantly. Effectiveness of the proposed method is evaluated on a number of IEEE benchmark test systems and simulation results are presented in this paper.

Rest of the paper is organized as follows. Section II presents the partitioning of measurement set, Section III describes the proposed method, Section IV presents the simulation results and discussions and finally Section V concludes the work.

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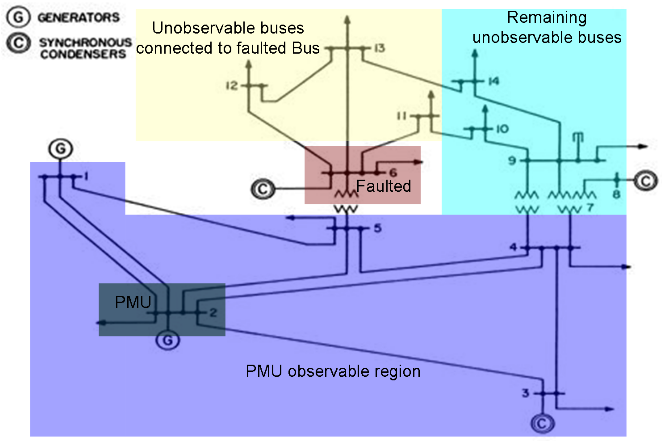

Fig. 1. Partition of measurement

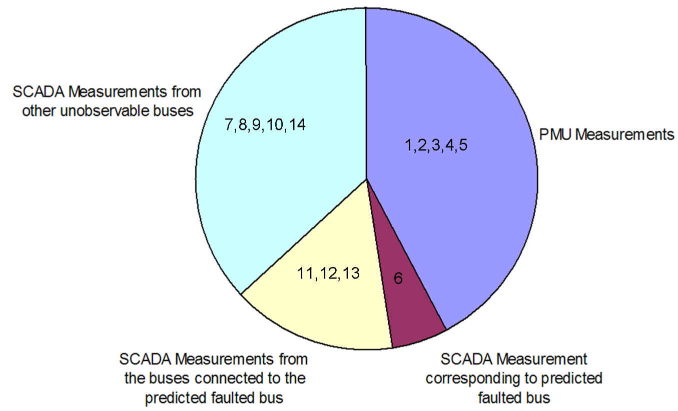

Fig. 2. Weights for sub-sets

II. Partitioning of Measurement Set

In order to improve the estimation accuracy during disturbance, proposed method partitioned the measurement set into four subsets based on disturbance location. The concept is illustrated using the IEEE 14 bus test system as shown in Figure 1. Let us assume that the system is completely observable through SCADA measurements and there is only one PMU at bus 2. Hence, the system is partially observable (buses 1, 2, 3, 4 and 5) through PMU. Now consider a fault occurs at bus 6 in between two sets of SCADA measurements. Hence, this fault will only be reflected in PMU measurements close to the fault. In this case sates of PMU observable bus 5 will change most as this is the closest observable bus of the fault. Hence PMU unobservable bus 6 connected to 5 will be treated as disturbance location. If multiple buses are connected to bus 5, all the buses directly connected to it will be considered as disturbance location. As last SCADA measurement of bus 6 is no more valid, least weight is given to the bus 6 SCADA measurement in the WLS estimation. Similarly, states of all the buses connected to bus 6 will also change to some extent, hence SCADA measurements of buses 11 and 12 will also be given lower weight. Remaining set of SCADA measurements (7, 8, 9, 10, 13 and 14) can be given a moderate weight as they may not change for the given fault. Being highly accurate and live, highest weight is given to the set of PMU observable buses (e.g. 1, 2, 3, 4 and 5). An example weight factors for these four subsets are presented in figure 2.

III. Proposed State Estimation

In this paper, a novel Linear State Estimation (LSE) method is proposed based on LSE formulation developed by Nuqui [12]. In the proposed method, a interpolation matrix H is computed when both SCADA and PMU measurements comes in together and in between two SCADA measurements when a set of PMU measurement comes in, states are recomputed directly using the interpolation matrix and the new set of PMU measurements. In case PMU measurements change significantly, interpolation matrix (H) is compensated by a factor called sensitivity change of interpolation matrix (ΔH) and states are computed. H is recomputed as soon as a new set of SCADA measurements becomes available. This helps to track the system dynamics more accurately. The mathematical model of the proposed method is demonstrated as follows:

Let, a set of buses (O) is observable through PMUs whereas another set of buses (U) is unobservable through PMUs. The vector of observable buses consists of PMU placed buses and buses directly connected to PMU buses. LSE interpolates the voltages of unobserved buses from the observed ones. The relationship between the vector of complex voltages of unobserved buses E_U and the vector of complex voltages of observed buses E_O is derived as follows [12]:

Nodal equations in a power system form can be written as:

$$[I_{BUS}] = [Y_{BUS}] \,.\, [E_{BUS}] \tag{1}$$

Where, I_{BUS} is bus injection vector, Y_{BUS} is bus admittance matrix, and E_{BUS} is node voltage vector. The bus admittance matrix Y_{BUS} is partitioned into four sub-matrices, one each corresponding to self admittance of observable and unobservable buses and two corresponding to the mutual admittances of the lines connected between observable and unobservable buses as follows:

$$\begin{bmatrix} I_O \\ I_U \end{bmatrix} = \begin{bmatrix} Y_{OO} & Y_{OU} \\ Y_{UO} & Y_{UU} \end{bmatrix} \cdot \begin{bmatrix} E_O \\ E_U \end{bmatrix} \tag{2}$$

At a particular operating point, the injections I_U at the unobserved buses U is modeled as equivalent load admittances. If N_u be number of unobserved buses, the current injections I_U at the unobserved buses are expressed as:

$$[I_U] = [(P_i - jQ_i)/E_i^*] \,, i = 1, 2, ..., N_U \tag{3}$$

The equivalent load admittance vector Y_U follows from the relationship $Y = I/E$.

$$[Y_U] = [Y_L] = [(P_i - jQ_i)/|E_i|^2] \,, i = 1, 2, ..., N_U \tag{4}$$

Where, Y_L is a diagonal matrix of size $N_U * N_U$. With the current injections at the unobserved buses converted into admittances, the original matrix equation (2) now becomes

$$\begin{bmatrix} I_O \\ ---- \\ 0 \end{bmatrix} = \begin{bmatrix} Y_{OO} & | & Y_{OU} \\ ---- & - & ---- \\ Y_{UO} & | & Y_T \end{bmatrix} . \begin{bmatrix} E_O \\ ---- \\ E_U \end{bmatrix} \quad (5)$$

Where,

$$Y_T = Y_{UU} + Y_L \quad (6)$$

Performing the indicated operation on the lower row of matrix equation (5) yields

$$0 = Y_{UO}.E_O + Y_T.E_U \quad (7)$$

Which when solved for E_U will now express the relationship between the vector of PMU unobservable buses with the vector of PMU observable buses. Hence,

$$E_U = -Y_T^{-1}.Y_{UO}.E_O \quad (8)$$

Let us denote the number of observed buses to be N_O and number of unobserved buses to be N_U. The product $Y_T^{-1}.Y_{UO}$ is a sparse matrix with admittance elements of dimension $N_U X N_O$. Let us define this product to be H

$$H = -Y_T^{-1}.Y_{UO} \quad (9)$$

Yielding our model for interpolation of unobserved buses in matrix form,

$$E_U = H.E_O \quad (10)$$

If there is any change in configuration or power flow in between the arrival of next set of PMU measurements, then the above stated linear state estimator has to be updated. Any set of interpolation coefficients H calculated using (9) assumes a reference operating point, say '0'. That is,

$$H^0 = -(Y_T^0)^{-1}.Y_{UO} \quad (11)$$

Any deviation in operating point will create errors in the following interpolation equation.

$$E_U = H^0.E_O \quad (12)$$

A method of updating the interpolators H as the system changes its operating point can be found as given below:

$$H = -(Y_{UU} + diag[S_U^*/|E_U|^2])^{-1}.Y_{UO} \quad (13)$$

as,

$$Y_T = Y_{UU} + diag[S_U^*/|E_U|^2] \quad (14)$$

Then we have the aforementioned expression of the interpolation coefficients. From (9), we get

$$Y_T.H = -Y_{UO} \quad (15)$$

Taking the differential of both sides of this matrix equation yields,

$$\Delta Y_T.H + Y_T.\Delta H = 0 \quad (16)$$

Which when solved for ΔH yields

$$\Delta H = -Y_T^{-1}\Delta Y_T H \quad (17)$$

Now from (14), the differential of Y_T is,

$$\Delta Y_T = \left(diag\left[S_U^{'*}/|E_U^{'}|^2 - S_U^{0*}/|E_U^0|^2\right]\right) \quad (18)$$

Where, $S_U^{'}$ is the injection of unobservable buses at the present configuration, S_U^0 is the injection of unobservable buses at the initial operating configuration, $E_U^{'}$ is the voltage of unobservable buses at the present configuration, E_U^0 is the voltage of unobservable buses at the initial operating configuration. Since Y_{UU} is a constant matrix of Y_{BUS} elements, ΔY_{UU} is 0. Finally, we have the following expression for the change in the value of the interpolation coefficient matrix H.

$$\Delta H = -(Y_T^0)^{-1}.\left(diag\left[S_U^{'*}/|E_U^{'}|^2 - S_U^{0*}/|E_U^0|^2\right]\right).H \quad (19)$$

Which expresses the relationship between the incremental (sensitivity) changes in the interpolation coefficient matrix with change in injected power at a unobservable bus. Hence, the interpolation formula for unobserved buses becomes

$$E_U = (H + \Delta H).E_O \quad (20)$$

From the equation (20) it can be observed that when traditional measurements and PMU measurements arrive simultaneously, admittance matrix can be recomputed based on topology and state information and thereby, H can be updated to calculate E_U. But, PMU measurements can be obtained as fast as every cycle, while other SCADA measurements get updated every 2-10 seconds.

So, inorder to calculate ΔH only when PMU measurements arrive, voltage magnitude and power injection of unobservable buses are predicted since, ΔH is a function of power injection and voltage magnitude of unobservable buses for the present configuration, i.e.

$$\Delta H = f(S_U^{'}, |E_U^{'}|) \quad (21)$$

Both $S_U^{'}, |E_U^{'}|$ can be obtained with the help of a modified weighted least square algorithm as explained below:

With the knowledge of PMU observable bus voltage vector for present configuration and PMU unobservable bus voltage vector for previous operating configuration, the change in power flow for the lines are calculated. If the maximum change is found to be greater than a pre specified value then change in configuration (disturbance) can be inferred. In case of disturbance, the states are updated using modified weighted least square subroutine as follows:

Let, x = state vector of the system (bus voltage and power angle), n = number of states = $2N - 1$, for N bus system, z = measurement vector, $z \epsilon R^m$, m = number of measurements; $m > n$, η = measurement noise vector, whose elements are usually assumed to be independent Gaussian random variables with zero mean.

In this WLS algorithm, normal traditional measurements corresponding to unobservable regions through PMU measurements are considered along with the PMU measurements in order to obtain complete topological observability of the system. Then,

$$z = h(x) + \eta \quad (22)$$

Where, h(x) is a nonlinear vector function of x. Objective function in WLS method is the weighted sum of squared error; it can be defined as,

$$J(x) = [z - h(x)]^T.R^{-1}.[z - h(x)] \quad (23)$$

Where, h(x) is equivalent to estimated measurement, R is the covariance matrix of measurement errors which are assumed to be uncorrelated.

Expanding (23) in Taylor series and neglecting second and higher order terms, we get

$$J(x) = [\Delta z - h(\Delta x)]^T.R^{-1}.[\Delta z - h(\Delta x)] \tag{24}$$

which in iterative form can be written as,

$$J(x^k) = [\Delta z^k - h(\Delta x^k)]^T.R^{-1}.[\Delta z^k - h(\Delta x^k)] \tag{25}$$

where,

$$\Delta x^k = x^k - x^{k-1} \tag{26}$$

$$\Delta z = z - h(x^k) \tag{27}$$

x^k = state vector at the k^{th} iteration P^k = Jacobian matrix $\delta h(x)/\delta x$ with $P_{ij}^k = \delta h_i/\delta x_j|_{x=x_k}$ At the optimum point, $\nabla J(x) = 0$, which yields

$$\Delta x^k = (P^{kT} R^{-1} P^k)^{-1} P^{kT} R^{-1} \Delta z^k \tag{28}$$

Weight factors for the above WLS method is selected as follows: If the line corresponding to the maximum change in power flow is connected to any PMU unobservable bus (say bus 'a') then SCADA measurements corresponding to bus 'a' is given very low weight. Further, SCADA measurements corresponding to all buses connected to bus 'a' are also given lower weight.

Equation (28) is solved iteratively by initializing the states with the last estimated values. This reduces computational time as compared to traditional WLS method where flat start is considered. State vector x is updated, until all elements of Δx becomes less than a pre-specified convergence limit.

The flowchart in Figure 3 shows the implementation steps of the above proposed method. It can be observed from the flowchart that when the SCADA data arrive, based on the classical state estimator and topology processor (both not shown in the figure) results, Y_{BUS} is recalculated to calculate H matrix. Whereas, when the PMU measurements arrive, power flow is calculated in all the lines using present PMU measurements and previous instant's state estimation results for PMU unobservable buses to judge on the change of configuration in the present instant. If there is not much change in configuration (maximum power flow change less than a threshold value), linear state estimation is run based on present PMU measurements, else H matrix is updated by running a modified Weighted Least Square algorithm. Based on this new value of H, unobservable regions' voltages are calculated.

IV. Simulation Results

Performance of the proposed state estimation methods is evaluated on IEEE 30 bus and IEEE 118 bus system. It is assumed that both the systems are completely observable through SCADA whereas some buses are unobservable through PMUs. For simulations, SCADA data were generated using a conventional Fast Decoupled power flow program, whereas PMU data were generated using a time domain transient stability program. To simulate real scenario, 2% random error is incorporated in the SCADA data. However, being highly accurate true values from transient stability analysis are used as PMU measurements. The set of available SCADA measurements is formed by selecting measurement data randomly ensuring the observability and the redundancy of 1.6. For IEEE 30 bus system, 5 PMUs were placed at buses 2, 6, 10, 15, and 25 as shown in Figure 4 and for IEEE 118 bus system 16 PMUs were placed at buses 8, 15, 26, 30, 38, 45, 52, 57, 63, 68, 74, 81, 90, 99, 108, and 117 based on observability analysis. For simulation, it is considered that PMU measurements arrive at an interval of 20ms, whereas SCADA measurements arrive at an interval of 4s. The algorithm is coded in C programming language in the environment of Visual C++ in 32 bit Windows OS platform with 2.10 GHz Intel Core 2 Duo processor.

To illustrate the effectiveness of the proposed method, for IEEE 30 bus system a temporary (0.1 s) three phase to ground fault is simulated at bus 13 which is unobservable through PMUs as shown in Figure 4. When PMU measurements come, power flow through all the lines connected between any observable and unobservable buses are calculated. For the given fault, it was found that power flow on line 12-13 changes significantly ($> 10\%$) from the last estimation. Hence, unobservable bus 13 is treated as faulted bus. Though in this case detected faulted bus is actually faulted bus, this may not happen in all cases. Any unobservable bus connected to an observable bus and close to the faulted bus may also be detected as faulted bus when depth of observability is low. Based on detected faulted bus, dynamic weight factors are selected for different set of measurements. For example, SCADA measurement corresponding to faulted bus, 13 will be given least weight, SCADA measurements for buses (4, 12) directly connected to the faulted bus will be given low weight, remaining SCADA measurements will be given moderate weight and the PMU measurements will be given the highest weight. With such weights, states are estimated using WLS.

Estimated states of the faulted bus 13 and a remote bus 30 (not directly connected to faulted bus) are presented in Figure 5 and Figure 6, respectively. Proposed estimation is compared with estimation method in [12] and with the true value obtained from time domain transient stability solution. From Figure 5, it is clear that proposed estimation is much better than the method in [12] and is very much close to the actual. However, for any remote bus as shown in Figure 6, both the methods can accurately estimate the system states.

For IEEE 118 bus test system, two case studies were made. In the first case, a three phase temporary (0.1s) fault is simulated at bus 18 and in the second case 60 MW load at bus 18 is suddenly thrown off for few seconds. Estimated states for bus 18 in both the cases are presented in Figure 7 and Figure 8, respectively. Though bus 18 is unobservable through PMU, in both cases proposed estimation is much better than [12] and very close to the actual.

For any system, if unobservable buses are far from PMU observable buses, it is expected to have lower estimation accuracies depending on their distance with respect to nearest

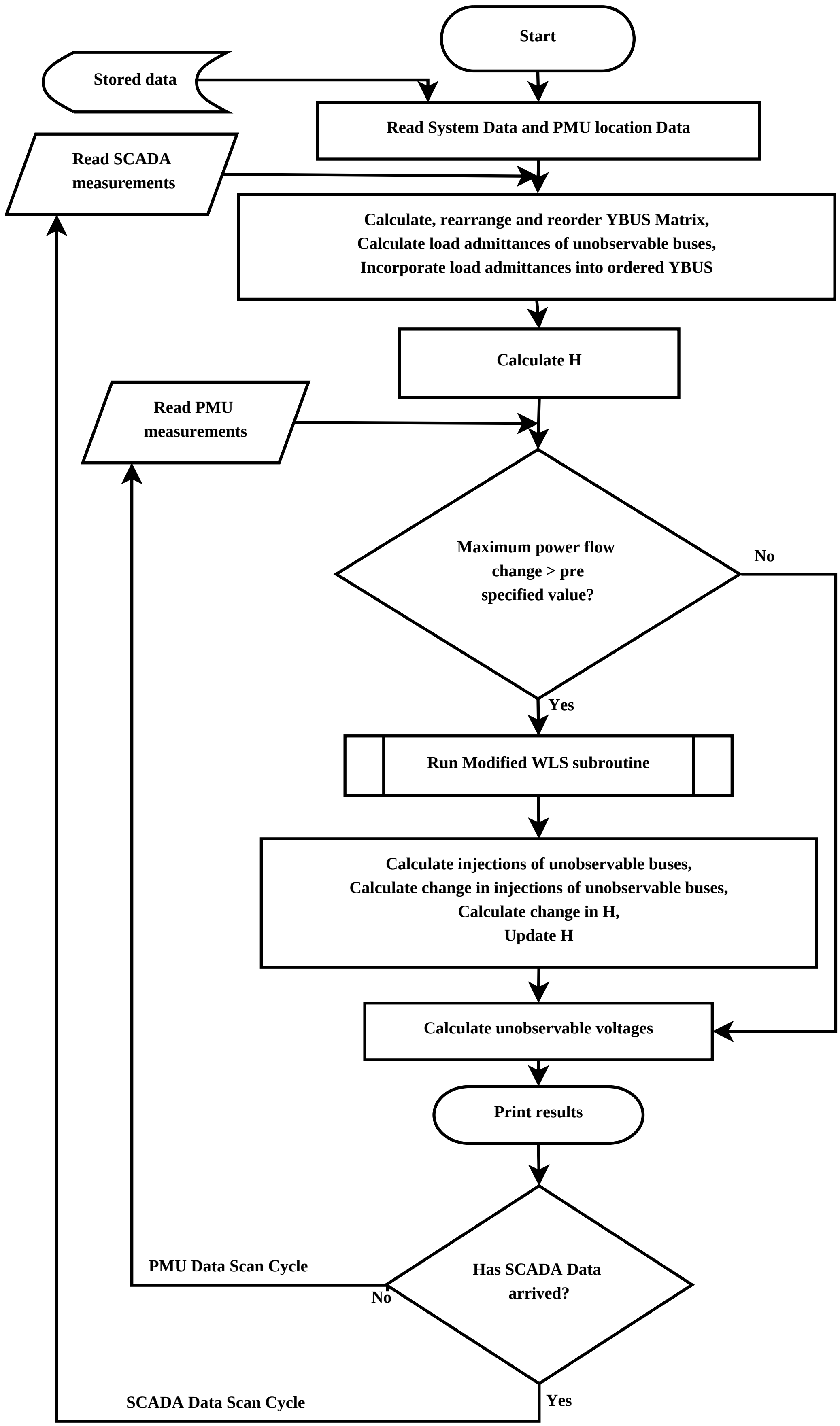

Fig. 3. Flowchart for the proposed Hybrid State Estimation

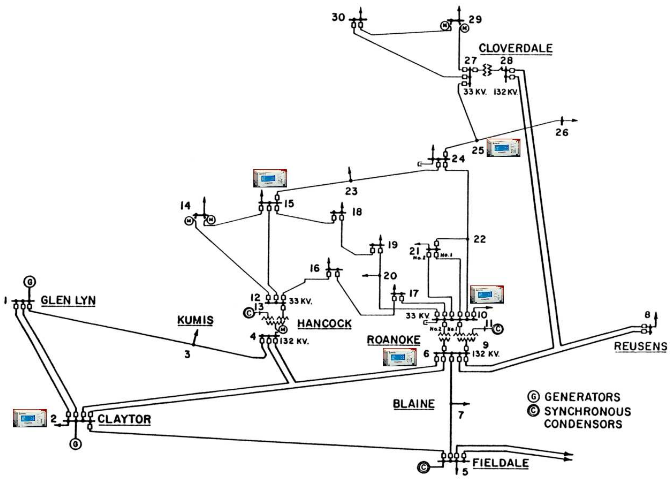

Fig. 4. IEEE 30 bus test system

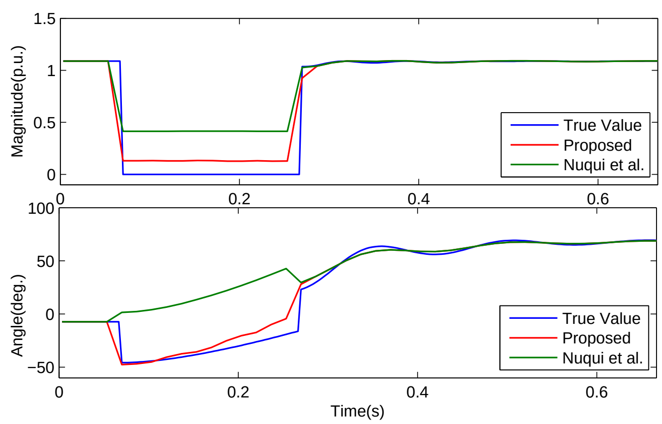

Fig. 5. Voltage and phase angle for bus 13 of IEEE 30 bus system for a 3 phase fault on bus 13

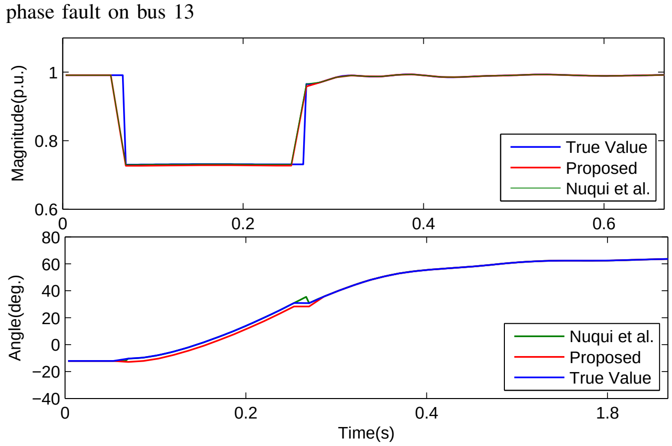

Fig. 6. Voltage and phase angle for bus 30 of IEEE 30 bus system for a three phase fault on bus 13

PMU observable bus. This is reasonable because changes in states in those unobservable buses may not be reflected in the PMU measurements. In order to verify the estimation accuracy in such cases, system states were estimated for disturbances at various tier of unobservability, where tier of unobservability is defined as the maximum of all the minimum distances of buses

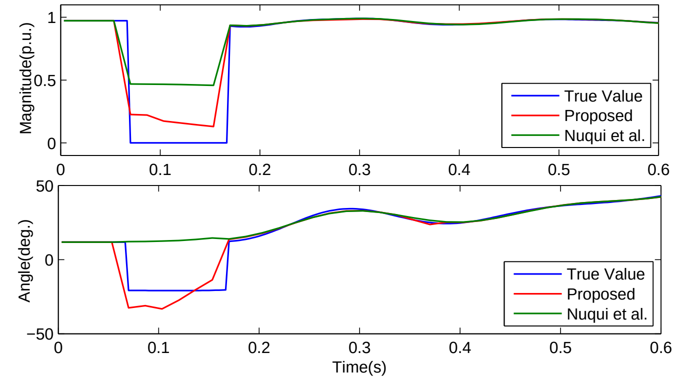

Fig. 7. Voltage and phase angle for bus 18 of IEEE 118 bus system for a 3 phase fault on bus 18

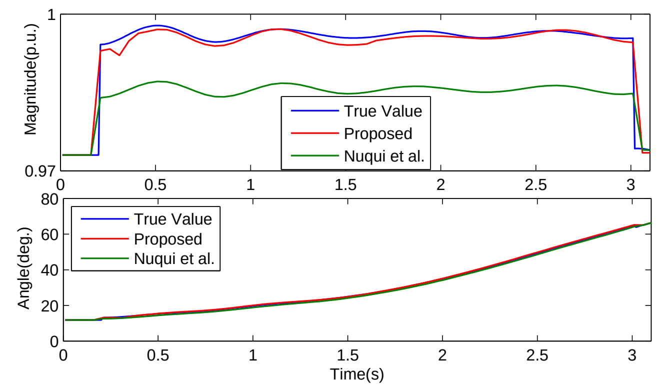

Fig. 8. Voltage and phase angle for bus 18 of IEEE 118 bus system for load thrown off at bus 18

from nearest observable bus. For example, PMU observable buses are in tier 0, buses directly connected to PMU observable buses are in tier 1 and so on. Three case studies were simulated on IEEE 118 bus test system. In the first case, PMUs were placed in such a way that all buses will be within tier 3, for the second case additional PMUs were placed to make all buses within tier 2 and in third case few more PMUs were placed to make the system observable within tier 1. For 118 bus test system, initially 4 PMUs were placed at buses 17, 49, 85 and 94 to make it observable up to tier 3. For the next case 6 more PMUs were placed at buses 9, 12, 23, 34, 71 and 105 and for the third case 5 more PMUs were placed at buses 28, 63, 68, 77 and 110. A temporary (0.1 s) three phase to ground fault was simulated on bus 4 which is in tiers 3, 2, and 1 for cases 1, 2, and 3, respectively. Estimated states for each case are presented in Figure 9, Figure 10, and Figure 11, respectively. It can be observed from Fig. 9- Fig. 11 that the estimated results are more accurate for 1^{st} tier observability as compared to 2^{nd} tier or 3^{rd} tier cases. However, estimated results for 2^{nd} tier and 3^{rd} tier are also very close to true value. This shows that even if very few PMUs are placed strategically, proposed estimation will provide reasonably accurate results.

Similarly, a simulated scenario is generated where the load is thrown off on bus 4 which is in tiers 3, 2, and 1 for

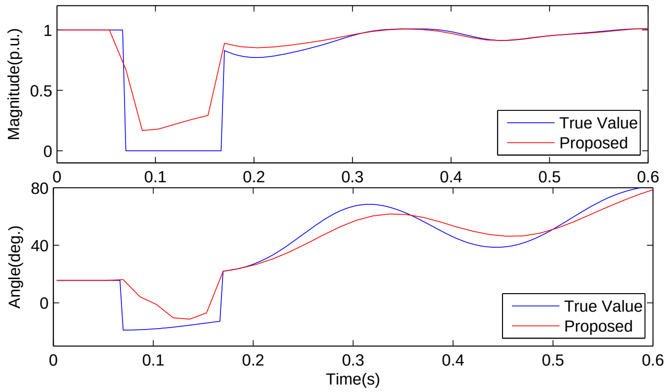

Fig. 9. Voltage and phase angle of bus 4 (at 3rd tier) for a fault in IEEE 118 bus system

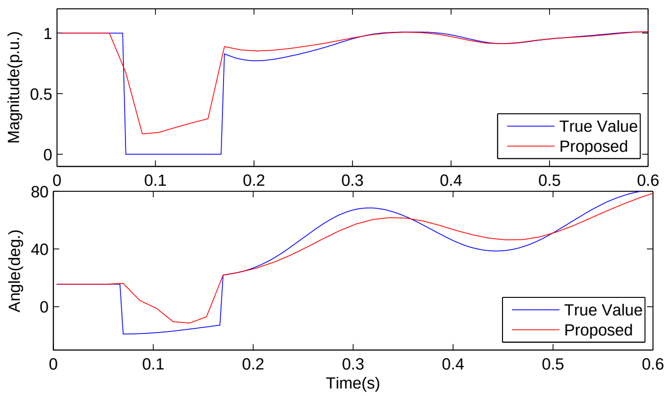

Fig. 10. Voltage and phase angle of bus 4 (at 2nd tier) for a fault in IEEE 118 bus system

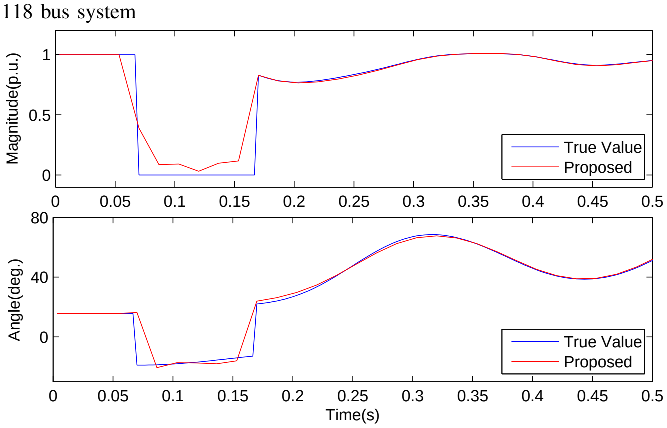

Fig. 11. Voltage and phase of bus 4 (at 1st tier) for a fault in IEEE 118 bus system

cases 1, 2, and 3, respectively. Estimated states for each case are presented in Figure 12, Figure 13, and Figure 14, respectively. As expected, it can be observed from Fig. 12-Fig. 14 that the estimated results are more accurate for 1^{st} tier observability as compared to 2^{nd} tier or 3^{rd} tier cases. In this case also, estimated results for 2^{nd} tier and 3^{rd} tier are also very close to true value. This shows that even if very few PMUs are placed strategically, proposed estimation will provide reasonably accurate results.

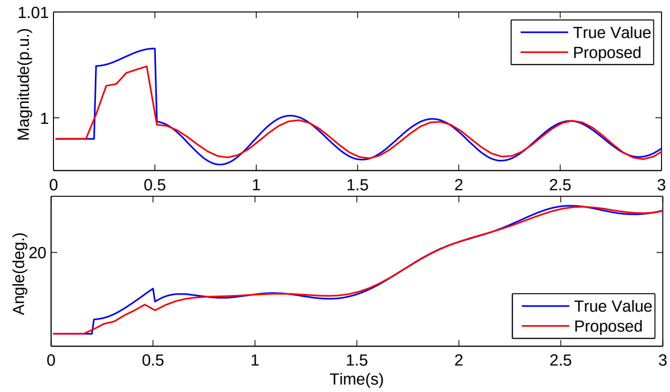

Fig. 12. Voltage and phase angle of bus 4 (at 3rd tier) for load change in IEEE 118 bus system

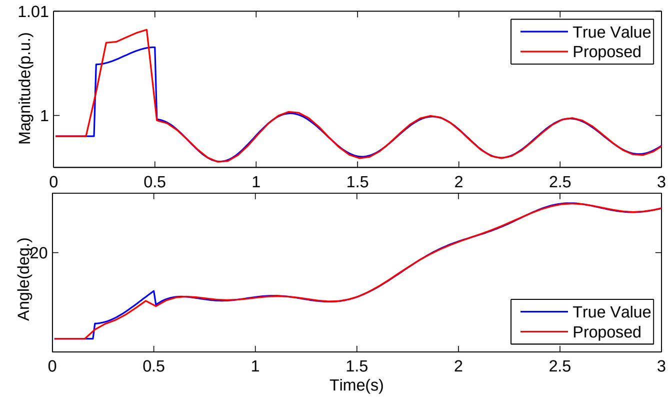

Fig. 13. Voltage and phase angle of bus 4 (at 2nd tier) for load change in IEEE 118 bus system

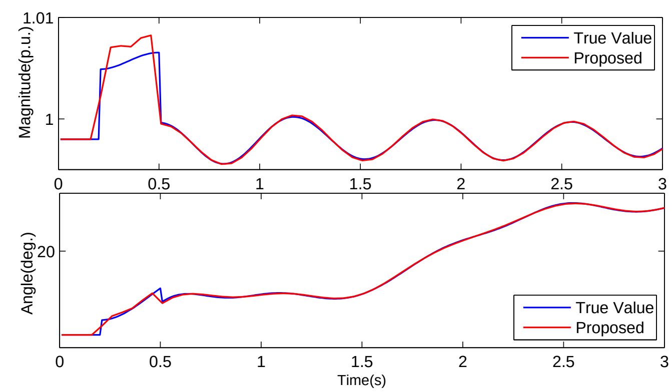

Fig. 14. Voltage and phase of bus 4 (at 1st tier) for load change in IEEE 118 bus system

Computational efficiency of the proposed method is compared with the traditional methods and experimental results are presented in Table I. It can be seen from the Table I that proposed method takes more time than LSE due to additional computation. However, computation time requirement is much less compared to the traditional WLS state estimator. It is also clear that with the increase in system size computational speed up of the proposed method increases significantly compared to conventional WLS.

TABLE I
EXECUTION TIME COMPARISON OF STATE ESTIMATION TECHNIQUES

IEEE system	No. of PMUs	Time required			Speed-up
		LSE	WLS	Proposed	
30bus	4	0.03ms	6.1ms	2.1ms	2.9
118bus	16	0.07ms	72ms	13ms	5.54

V. Conclusion

This paper presented a novel hybrid state estimation technique combining SCADA and PMU measurements. The simulation results presented clearly show that the proposed state estimation technique could accurately track the system dynamics even in the presence of a disturbance in the unobservable part of the system. Simulation results also show that with strategic placing of PMUs, proposed method could estimate the system states using minimum number of PMUs within reasonable accuracy and could estimate the states as frequent as PMU sampling rate. Hence, this estimation technique could be utilized for faster control actions such as transient stability analysis, FACTS devices control, voltage stability analysis, etc.

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VII. Biography

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Ravi Kiran Reddi received his M.Tech(Master of Technology) in Power System Engineering from Indian Institute of Technology, Kharagpur in 2011. His thesis was on Real Time Large Signal Rotor Angle Stability using Synchrophasor Measurements. From July, 2011, he is working with BHEL Corporate Research and Development. His research interest includes Power system protection, Substation Automation, Grid Stability Control using HVDC, Wide Area Monitoring and Control of Power Systems Using Synchrophasor Measurements, Smart Grid.

Avinash K. Sinha joined IIT Kharagpur in 1984, where he is currently a Professor in the department of Electrical Engineering. He was head of this department from 2007-2010. He was a Visiting Professor at Washington State University, Pullman (2001-2002 and 2011). He received IBM Open Collaborative Faculty Award for the years 2010 and 2011. At IIT Kharagpur he is leading the Power Systems group and his team has developed a digital simulator for power systems. His research interests include Power System Analysis, Simulation of Power System Dynamics, AI Applications to Power Systems, Synchro-phasor applications to power Systems.