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# State Estimation of Power System Using PMU Devices

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## Abstract

This paper explains the role of Phasor Measurement Units (PMUs) in estimating the state of energy systems and suggests a linear state estimator involving PMU current and voltage measurements for tracking the system state. The state estimator carries out the estimation process in two phases. The first phase uses the conventional SCADA measurements and applies the classical Weighted Least Square (WLS) approach for estimating the current system state, and the second phase corrects and tracks the system state using the PMU measurements in the subsequent intervals. It provides simulation results of the proposed method on IEEE 30 and 57 bus energy systems for exhibiting its superiority.

**Keywords**: State estimation, phasor measurement unit (PMU), weighted least square (WLS) estimation, SCADA.

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## 1. Introduction

State Estimation (SE) is a computational process of estimating the state of an energy system from the available real-time measurements. The measurements such as voltages, current flows, and bus powers, are measured through current transformers and voltage transformers, and transmitted through Supervisory Control And Data Acquisition (SCADA) systems at a rate of 2-4 samples per second to the control centre for estimating the system state for effective monitoring, and control in addition to ensuring safe, reliable, and economic operation of the modern energy management system. The synchrophasor technology introduced a new kind of measuring units, known as Phasor Measuring Units (PMUs), which are employed to obtain real-time voltage and current phasor measurements at a rate of 10-120 samples per second. As PMUs are so very expensive, they are placed only at selected locations and may not provide redundant measurements for enabling state estimation (SE). Both SCADA and PMU measurements are in general combined for performing the SE in energy systems [1].

Several approaches were suggested to optimally use the available SCADA and scarce PMU measurements for reconstructing the system state. Most of them were derived from the classical Weighted Least Square (WLS), Fast Decoupled WLS, and Weighted Least Absolute Value (WLAV) criterions [2]. The on-line execution of a robust SE algorithm was explained and its usability on a 400-node network was illustrated [3]. A WLS SE based on decomposition of singular value was proposed for ill-conditioned power systems [4]. An efficient least absolute value estimator using an iteratively reweighted least square method was presented [5]. A multi-objective optimal PMU placement was proposed using a fewer PMUs with a view of bringing down the uncertainty in voltage magnitude estimation and lending guidance for static voltage compensator [6]. A corrective action scheme was discussed to decrease the curtailment of wind energy and the excessive-load on the power lines [7]. A simple decentralized derivative-free dynamic SE scheme for a power system was developed [8]. A Cubature Kalman filter based tracking SE involving synchronized phasor measurements from PMUs was developed [9]. A quick network parameter error correction scheme was suggested based on detection of parameter errors [10]. The performance of SE in electric cyber-physical system model considering the false data attacks was assessed [11].

A forecasting-supported state estimator was proposed to follow the states of an energy network [12]. The motivations and engineering values of dynamic SE were revealed, and a set of probable applications depending on dynamic SE was discussed [13]. An analytical equation was derived for examining the covariance of vigorous least absolute value dynamic SE using influence function approximation [14]. A robust SE method involving PMUs was suggested for detecting online-attacks [15]. An ideal distribution system SE technique based on the data lent by smart meters for aiding voltage control strategies in actual time was discussed [16]. A dynamic SE method based on Kalman filtering was suggested and applied to a doubly fed induction generator-based wind generator model [17]. A load disturbance identification and enhancement scheme that functions with other dynamic SE methodologies was developed [18]. A PMU based bad data identification scheme was suggested with a view of improving the PMU data quality [19]. An original systematic proposal that merged stochastic activity network's numerical computation and modelling was suggested for investigating the reliability of the 5G-based Wide Area Measurement Systems [20]. A WLS linear algorithm involving SCADA and PMU measurements was outlined for performing SE of power systems with bad data detection scheme [21]. A 3-phase SE based on an artificial neural networks and PMU measurements was suggested for distribution networks [22].

Most of the existing approaches combine both SCADA and PMU measurements together into a single set and solve the SE problem, but the SCADA and PMU measurements are obtained at different rates of 2-4 samples/second (sub-second time frames) 10-120 samples/second respectively. It will be good and realistic, if both measurements are dealt independently. The SCADA measurements can be used for static SE and PMU measurements can be used for correcting/tracking the systems state in the subsequent instants. This article therefore develops a new realistic tracking SE method that adopts the classical WLS approach using SCADA measurements and a correction scheme involving PMU measurements for tracking the system state. The developed method has been studied on the standard IEEE 14 and 30 bus power systems, and the results presented.

Section 2 explains the proposed SE method, section 3 presents the simulation results and section 4 concludes.

## 2. Proposed Method

The proposed method has two phases of estimation. The first phase performs conventional SE using SCADA measurements, and the second phase corrects the estimated state using PMU measurements, thereby tracking the system state in the subsequent instants.

### 2.1. SE with SCADA measurements

In this phase, the classical WLS method processes the SCADA measurements and estimates the system state in polar form. The nonlinear functions, $s(x^{polar})$, connecting the measurements $M$ and the state vector, $x^{polar} = V\angle\theta$, with errors, $e$, can be written as:

$$M = s(x^{polar}) + e \tag{1}$$

The variance ${\sigma_j}^2$ indicates the uncertainty of the concerned measurements. A large variance represents that the concerned measurement is inaccurate. The measurement error covariance matrix can be written by Eq. (2)

$$C = \begin{bmatrix} {\sigma_1}^2 & & & \\ & {\sigma_2}^2 & & \\ & & \ddots & \\ & & & {\sigma_{nM}}^2 \end{bmatrix} \tag{2}$$

where $nM$ denotes the number of measurements.

As the errors $e$ are modelled by Gaussian noise, the measurements $M$ represent Gaussian distribution with mean $s(x^{polar})$ and covariance $C$. The probability density function of $M$ is expressed as:

$$f(M) = \frac{1}{(2\pi)^{nM/2}|C|^{1/2}} \times exp\left\{-\frac{1}{2}[M - s(x^{polar})]^T C^{-1}[M - s(x^{polar})]\right\} \tag{3}$$

The intend of the SE is to estimate the system state that maximizes the probability of the true value being equal to the measured quantity, that is, the system state maximizes the probability density function of Eq. (3).

The exponential function within the braces of Eq. (3) is equivalent to the reduction of the quadratic term as in Eq. (4).

$$\text{Minimize } CF = \frac{1}{2}[M - s(x^{polar})]^T C^{-1}[M - s(x^{polar})] \tag{4}$$

$$= \sum_{j=1}^{nM} \frac{1}{2} \frac{\{M_j - s_j(x^{polar})\}^2}{{\sigma_j}^2} \tag{5}$$

where

$CF$ is the cost function to be minimized.

$M$ is a set of measurements

$s(x^{polar})$ is the set of measurement functions

$C$ is the diagonal covariance matrix in terms of the variance ${\sigma_j}^2$ of the measurements.

Eq. (5), representing the maximum likelihood criterion, lowers the net squared errors weighted by the measurement accuracy ${\sigma_j}^{-2}$, and is generally referred to as the WLS estimation. The solution of this equation provides an estimate $x^{polar}$ that should satisfy the following condition:

$$\frac{\partial CF}{\partial x^{polar}} = S^T C^{-1}[M - s(x^{polar})] = 0 \qquad (6)$$

where $S = \partial s(x^{polar})/\partial x^{polar}$ represents partial derivatives of $s(x^{polar})$ with respect to state variables $(x^{polar})$, referred to as Jacobian Matrix.

Newton's technique is applied for solving Eqs. (4) and (6) as:

$$(S^T C^{-1} S)\Delta x^{polar} = S^T C^{-1} \Delta M \qquad (7)$$

$$x^{polar}(t+1) = x^{polar}(t) + \Delta x^{polar} \qquad (8)$$

where $\Delta M = M - s(x^{polar})$ is the measurement mismatch vector.

A SE solution is obtained by iteratively solving Eqs. (7) and (8) for $x^{polar}$ until $|\Delta x^{polar}|$ becomes less than a small tolerance value, say 0.001. Once converged, the values given by Eq. (8) is the estimated system state $(x^{polar}(t+1))$.

## 2.2. Correction with PMU measurements

Though the estimated system state $(x^{polar})$ from Eq. (8) represents the current system state, it is considered as pseudo measurements $(\mathrm{V}^{pseudo})$ in the subsequent instant, and combined with the PMU voltage $(\mathrm{V}^{pmu})$ and current $(\mathrm{I}^{pmu})$ measurements to form a new measurement set in polar form $(M^{polar})$.

$$M^{polar} = [\mathrm{V}^{pseudo}, \mathrm{V}^{pmu}, \mathrm{I}^{pmu}]^T \qquad (9)$$

To derive a non-iterative SE process, all the measurements must be converted into rectangular form $(M^{rect})$ using a transformation matrix $(K)$.

$$M^{rect} = [K][M^{polar}]^T \qquad (10)$$

where,

$$K = \begin{bmatrix} \cos\theta_1 & 0 & 0 & -|V_1|\sin\theta_1 & 0 & 0 \\ 0 & \cos\theta_2 & 0 & 0 & -|V_2|\sin\theta_2 & 0 \\ 0 & 0 & \vdots & 0 & 0 & \vdots \\ \sin\theta_1 & 0 & 0 & |V_1|\cos\theta_1 & 0 & 0 \\ 0 & \sin\theta_2 & 0 & 0 & |V_2|\cos\theta_2 & 0 \\ 0 & 0 & \vdots & 0 & 0 & \vdots \end{bmatrix} \qquad (11)$$

$|V_1|, |V_2|, \ldots\ldots |V_n|$ denote the voltage magnitudes.

$\theta_1, \theta_2, \ldots\ldots \theta_n$ represent voltage angles.

The error covariance matrix $(C^{pseudo})$ of pseudo measurements must also be converted into rectangular form using Eq. (12).

$$C^1 = K \cdot C^{pseudo} \cdot K^T \qquad (12)$$

Similarly, the error covariance matrix of PMU measurements must also be converted into rectangular form using Eq. (13).

$$C^2 = K \cdot C^{pmu} \cdot K^T \qquad (13)$$

Thus, the new covariance matrix $(C')$ can be formed as:

$$C' = \begin{bmatrix} C^1 & 0 \\ 0 & C^2 \end{bmatrix} \qquad (14)$$

WLS algorithm for this new measurement set and covariance matrix can be formed as:

$$(S'^T C'^{-1} S')\Delta x^{rect} = S'^T C'^{-1} \Delta M^{rect} \qquad (15)$$

where $S' = \partial s'(x^{rect})/\partial x^{rect}$ represents the new Jacobian Matrix containing the partial derivatives of measurement functions $s'(x^{rect})$ of the measurement set $(M^{rect})$ with respect to state variables $(x^{rect})$.

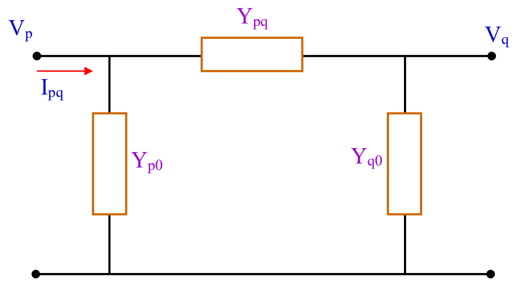


**Fig. 1:** π - model of a transmission line

In the Jacobian matrix $(S')$, the elements corresponding to $\mathrm{V}^{pseudo}$ and $\mathrm{V}^{pmu}$ are simply 0's and 1's, while the Jacobian elements corresponding to $\mathrm{I}^{pmu}$ can be derived from the π - model of a transmission line as in Fig. 1.

The line current $(I_{pq})$ can be written as

$$I_{pq} = V_p Y_{po} + (V_p - V_q) Y_{pq} \qquad (16)$$

where

$V_p$ and $V_q$ are the p-th and q-th bus voltages respectively.

$Y_{pq}$ denotes the admittance $(G + jB)$ of the transmission line connected between buses p and q.

$Y_{po}$ is the half line charging admittance $(G_{po} + jB_{po})$.

The above equation in terms of rectangular coordinates can be written as:

$$\begin{bmatrix} I_{pq}^{real} \\ I_{pq}^{imag} \end{bmatrix} = \begin{bmatrix} (G + G_{po}) & -(B + B_{po}) & -G & B \\ (B + B_{po}) & (G + G_{po}) & -B & -G \end{bmatrix} \begin{bmatrix} V_p^{real} \\ V_p^{imag} \\ V_q^{real} \\ V_q^{imag} \end{bmatrix} \qquad (17)$$

where the superscripts $real$ and $imag$ denote the real and imaginary parts of the concerned variable.

The partial derivatives of Eq. (17) with respect to real and imaginary parts of voltages yield constants only in terms of conductance and susceptance of the transmission lines.

Therefore, the resulting Jacobian matrix $(S')$ contains only constant terms, that is they have only 0's, 1's, susceptance, and conductance of transmission lines, and makes Eq. (15) linear and non-iterative. This equation is solved for $\Delta x^{rect}$, and the state vector is updated using Eq. (18).

$$x^{rect} = x^{rect} + \Delta x^{rect} \qquad (18)$$

## 2.3. Algorithm

1. Obtain the SCADA measurements.
2. Solve Eqs. (7) and (8) iteratively. $x^{polar}$ is the system state.
3. Obtain the real-time PMU measurements.
4. Combining $x^{polar}$ and PMU measurements as a single set of measurements, solve Eq. (15) for $\Delta x^{rect}$.
5. Update the system state using Eq. (18). $x^{rect}$ is the current system state.
6. Repeat steps (3)-(5) in the subsequent instants for continuously updating/tacking the system state, till the next

SCADA measurements are available. If SCADA measurements are available, go to step (1).

## 3. Simulation results

The proposed SE method was studied on IEEE-14 and -30 bus power systems [23]. The power flow was carried out and a small percent (1-10%) of random noises were added to obtain the noisy SACDA and PMU measurements, whose locations were chosen to evenly spread across the system to ensure observability of the system.

- The estimated system state at the end of two phases of both systems are given in Tables 1 and 2 for 14 and 30 bus systems respectively.
- Figs. 2 & 3 displays voltage angle estimate errors using SCADA and PMU measurements respectively for 14 bus system.
- Figs. 4 & 5 displays voltage magnitude estimate errors using SCADA and PMU measurements respectively for 14 bus system.
- Figs. 6 & 7 displays voltage angle estimate errors using SCADA and PMU measurements respectively for 30 bus system.
- Figs. 8 & 9 displays voltage magnitude estimate errors using SCADA and PMU measurements respectively for 30 bus system.

The Figs. 2-9 clearly indicate that there is significant reduction error components with PMU measurements in the subsequent estimation process. This reduction in estimation errors clearly indicate that the estimate is more accurate and refined in the subsequent estimation process with PMU measurements for both the systems. It is also seen that the accuracy of the SE method slightly lowers with increase in the system size.

**Table 1:** Estimated Solution for 14 bus system

| Bus No | True | | Estimated State without PMU (Phase-1) | | Estimated State with PMU (Phase-2) | |
|---|---|---|---|---|---|---|
| | Voltage Magnitude (p.u.) | Voltage Angle (degree) | Voltage Magnitude (p.u.) | Voltage Angle (degree) | Voltage Magnitude (p.u.) | Voltage Angle (degree) |
| 1 | 1.0600 | 0.0000 | 1.0068 | 0.0000 | 1.0584 | 0.0000 |
| 2 | 1.0450 | -4.9891 | 0.9899 | -5.5265 | 1.0451 | -5.0258 |
| 3 | 1.0100 | -12.7492 | 0.9518 | -14.2039 | 1.0046 | -12.7546 |
| 4 | 1.0132 | -10.2420 | 0.9579 | -11.4146 | 1.0083 | -10.2142 |
| 5 | 1.0166 | -8.7601 | 0.9615 | -9.7583 | 1.0118 | -8.7264 |
| 6 | 1.0700 | -14.4469 | 1.0185 | -16.0798 | 1.0700 | -14.4443 |
| 7 | 1.0457 | -13.2368 | 0.9919 | -14.7510 | 1.0457 | -13.2372 |
| 8 | 1.0800 | -13.2368 | 1.0287 | -14.7500 | 1.0800 | -13.2371 |
| 9 | 1.0305 | -14.8201 | 0.9763 | -16.5125 | 1.0305 | -14.8206 |
| 10 | 1.0299 | -15.0360 | 0.9758 | -16.7476 | 1.0299 | -15.0364 |
| 11 | 1.0461 | -14.8581 | 0.9932 | -16.5397 | 1.0461 | -14.8553 |
| 12 | 1.0533 | -15.2973 | 1.0009 | -17.0203 | 1.0533 | -15.2946 |
| 13 | 1.0466 | -15.3313 | 0.9940 | -17.0583 | 1.0466 | -15.3285 |
| 14 | 1.0193 | -16.0717 | 0.9647 | -17.8967 | 1.0193 | -16.0727 |

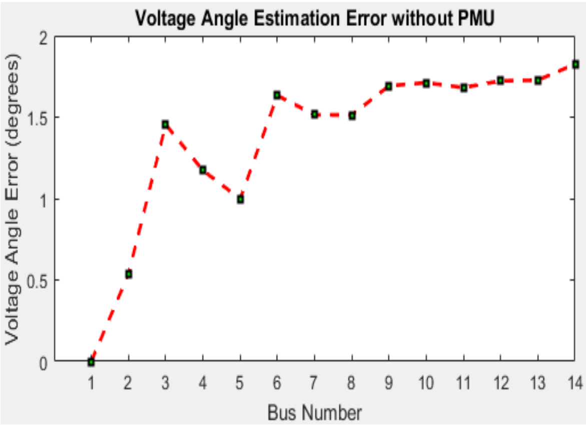


**Fig. 2:** Voltage angle estimation errors with SCADA measurements for 14 bus system.

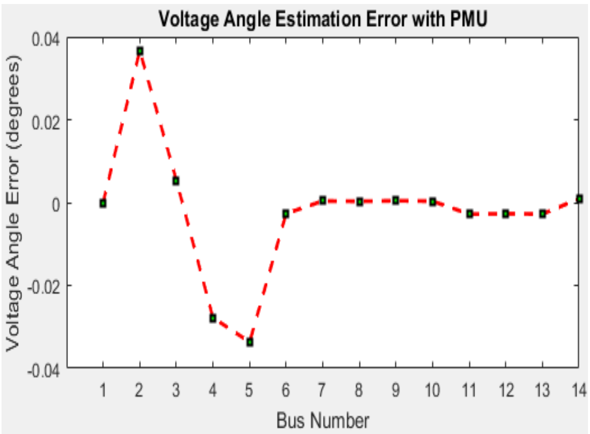


**Fig. 3:** Voltage angle estimation errors with PMU measurements for 14 bus system.

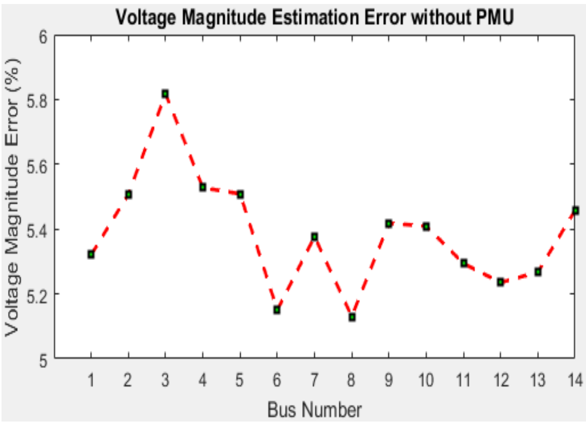


**Fig 4:** Voltage magnitude estimation errors with SCADA measurements for 14 bus system

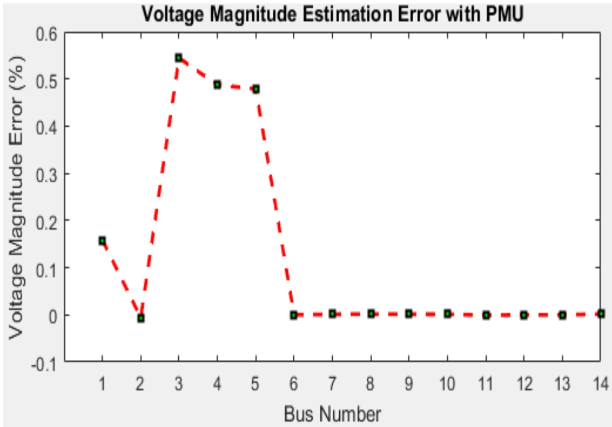


**Fig 5:** Voltage magnitude estimation errors with PMU measurements for 14 bus system

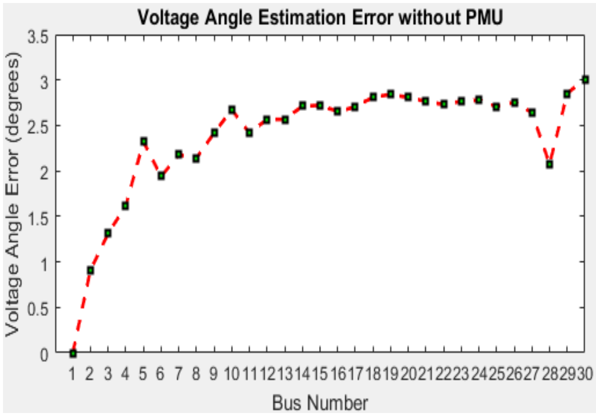


**Fig. 6:** Voltage angle estimation errors with SCADA measurements for 30 bus system.

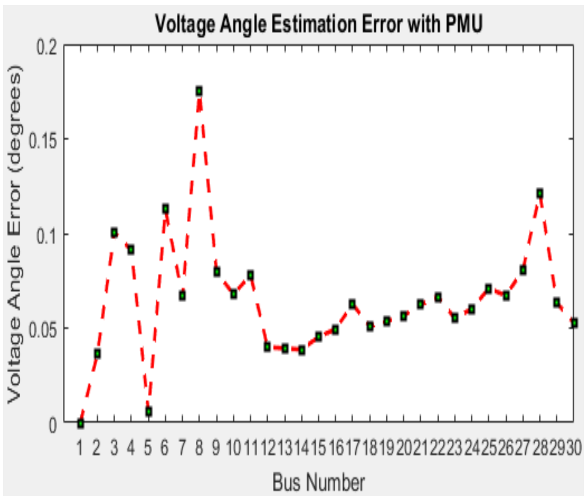


**Fig. 7:** Voltage angle estimation errors with PMU measurements for 30 bus system.

**Table 2:** Estimated Solution for 30 bus system

| Bus No | True | | Estimated State without PMU (Phase-1) | | Estimated State with PMU (Phase-2) | |
|---|---|---|---|---|---|---|
| | Voltage Magnitude (p.u.) | Voltage Angle (degree) | Voltage Magnitude (p.u.) | Voltage Angle (degree) | Voltage Magnitude (p.u.) | Voltage Angle (degree) |
| 1 | 1.0600 | 0.0000 | 0.9865 | 0.0000 | 1.0574 | 0.0000 |
| 2 | 1.0430 | -5.3543 | 0.9700 | -6.2635 | 1.0430 | -5.3904 |
| 3 | 1.0196 | -7.5308 | 0.9474 | -8.8420 | 1.0234 | -7.6313 |
| 4 | 1.0104 | -9.2840 | 0.9384 | -10.9021 | 1.0141 | -9.3750 |
| 5 | 1.0100 | -14.1738 | 0.9335 | -16.4941 | 1.0101 | -14.1795 |
| 6 | 1.0096 | -11.0581 | 0.9395 | -12.9975 | 1.0152 | -11.1708 |
| 7 | 1.0020 | -12.8649 | 0.9287 | -15.0443 | 1.0054 | -12.9316 |
| 8 | 1.0100 | -11.8193 | 0.9449 | -13.9608 | 1.0201 | -11.9941 |
| 9 | 1.0392 | -14.0644 | 0.9667 | -16.4813 | 1.0424 | -14.1441 |
| 10 | 1.0215 | -15.6706 | 0.9472 | -18.3445 | 1.0248 | -15.7384 |
| 11 | 1.0820 | -14.0644 | 1.0093 | -16.4813 | 1.0821 | -14.1425 |
| 12 | 1.0496 | -15.1245 | 0.9746 | -17.6918 | 1.0517 | -15.1645 |
| 13 | 1.0710 | -15.1245 | 0.9954 | -17.6918 | 1.0711 | -15.1638 |
| 14 | 1.0320 | -16.0018 | 0.9559 | -18.7137 | 1.0344 | -16.0404 |
| 15 | 1.0251 | -16.0084 | 0.9491 | -18.7299 | 1.0277 | -16.0537 |
| 16 | 1.0304 | -15.6251 | 0.9555 | -18.2800 | 1.0331 | -15.6746 |
| 17 | 1.0188 | -15.8687 | 0.9441 | -18.5714 | 1.0219 | -15.9313 |
| 18 | 1.0114 | -16.6067 | 0.9352 | -19.4195 | 1.0144 | -16.6575 |
| 19 | 1.0066 | -16.7658 | 0.9306 | -19.6063 | 1.0097 | -16.8193 |
| 20 | 1.0095 | -16.5502 | 0.9339 | -19.3581 | 1.0127 | -16.6068 |
| 21 | 1.0082 | -16.2178 | 0.9328 | -18.9821 | 1.0115 | -16.2801 |
| 22 | 1.0120 | -15.9811 | 0.9372 | -18.7111 | 1.0156 | -16.0477 |
| 23 | 1.0085 | -16.2294 | 0.9331 | -18.9957 | 1.0118 | -16.2845 |
| 24 | 0.9991 | -16.3007 | 0.9231 | -19.0788 | 1.0030 | -16.3609 |
| 25 | 1.0032 | -16.0720 | 0.9270 | -18.7784 | 1.0082 | -16.1429 |
| 26 | 0.9852 | -16.5038 | 0.9070 | -19.2593 | 0.9904 | -16.5709 |
| 27 | 1.0145 | -15.6559 | 0.9395 | -18.2962 | 1.0202 | -15.7365 |
| 28 | 1.0078 | -11.7163 | 0.9398 | -13.7910 | 1.0143 | -11.8374 |
| 29 | 0.9944 | -16.9077 | 0.9177 | -19.7604 | 1.0003 | -16.9710 |
| 30 | 0.9828 | -17.8067 | 0.9051 | -20.8172 | 0.9888 | -17.8592 |

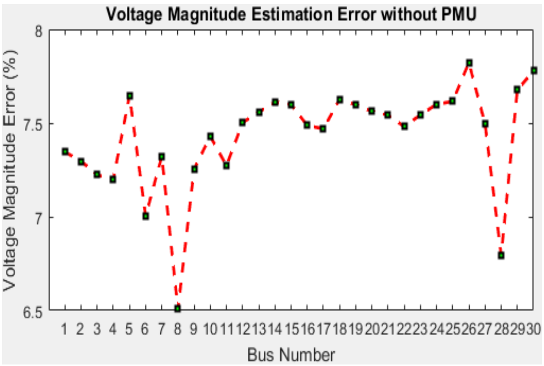


**Fig 8:** Voltage magnitude estimation errors with SCADA measurements for 30 bus system

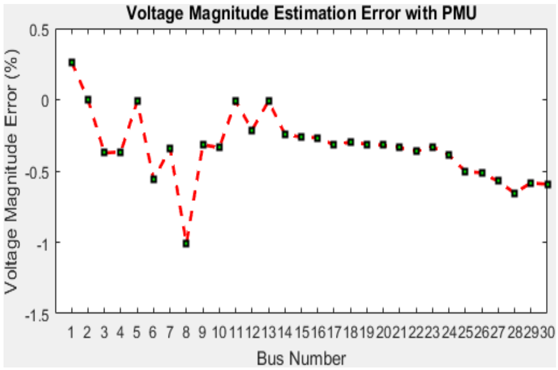


**Fig 9:** Voltage magnitude estimation errors with PMU measurements for 30 bus system

## 4. Conclusion

The proposed SE algorithm involving two phases was developed with SCADA and PMU measurements. The first phase considered only the SCADA measurements and estimated the system state. The second phase transformed the phase-1 results as pseudo measurements, and combined with the PMU measurements and corrected the previous system state through a non-iterative solution process. The second phase continuously tracks the system state in real-time according to the continuously available PMU measurements. The study of the proposed algorithm on two standard IEEE systems revealed the following:

- The phase-1 estimation process is iterative and takes more time for estimation, as Jacobian and gain matrices must be recomputed during the iterative process.
- The phase-2 equations are linear due to constant Jacobian and gain matrices, and the solution process is non-iterative. Moreover, the Jacobian and gain matrices can be made readily available for a given system with a given set of PMU measurements at the beginning of the estimation process, and need not be computed during the solution process, thereby lowering the computation time.
- The voltage angle and magnitude errors are getting corrected and reduced in the subsequent estimation process with PMU measurements, compared to that of the initial estimation with SCADA measurements.
- The inclusion of PMU measurements does not introduce any complexity in the SE process.
- The accuracy of the SE method slightly lowers with increase in system size.

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