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Phasor Measurement Unit Based on Robust Dynamic State Estimation in Power Systems Using M-Estimators

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Abstract

This paper introduces the uses of Robust Dynamic State Estimation (RDSE) with Phasor Measurement Unit (PMU), The M-Estimators Quadratic Linear (QL) and Square Root (SR) Estimators have been used. For the solution of the M-estimators problem, Iteratively Re-weighted Least Squares Estimation (IRLS) method is applied. In this work, we used the Decoupled Current Measurement (DCM) method to include the Phasor Measurement Unit in Robust Dynamic State Estimation. The proposed method has been tested on standard data 30-bus testing system as a case study.

Keywords*: robust state estimation, DSE, PMU, energy management system*

1. Introduction

The power system can be operated in economic and secure with high reliability, if its state is known at the present time and next time, one step ahead for a known loading condition and network topology [1]. Static State Estimation (SSE) provides the information of system state of present time instant [2, 3]. Because the nature of the power system is not static, so, Dynamic State Estimation (DSE) can provide the information of system state of the current and next time instant (one step ahead) [4]. The DSE can predict the system state based on the previous state of the system, followed by a filtering process to provide the estimated state of the system [4-6]. In electric power system the prediction of the state variables at the next time interval, is very important for operation and control in both normal and abnormal conditions.

Most of the existing DSE methods at predicting and filtering step fail to determine the true behavior of the power system dynamics [4, 5], [7-9]. Moreover, the outlieris and Leverage points, which are created from the bad data points in the measurements, have a large influence on the state estimate. Therefore, M-Estimator concept is introduced to develop a robust dynamic state estimation method based on modeling the system dynamics for predicting and filtering step to improve the performance of the filter in presence of outliers [1, 2, 10, 11].

In state estimation, the state variable (bus voltage angle) is very important for estimating the state of the system. This voltage angle was not available by SCADA system as a measurement before. At recent time, PMUs able to provide the direct measurement of synchronized voltage phase angle as well as voltage magnitude and current phasor at the buses where it is installed, with addition to higher accuracy than the SCADA [12-14]. Therefore, many methods are proposed to install the PMUs in state estimation. In [15], Hybrid state estimation is proposed, in which a linear measurement model of traditional SE in terms of the voltage and current that provided by PMU measurements to form an augmented measurement vector resulting in a nonlinear state estimator. An alternative approach to include synchronized Phasor measurement in traditional state estimation is presented in [16]. A multilevel scheme and two stages of state estimator using PMUs is proposed in [17, 18]. In [19], an extensive review on the usage of PMUs is presented.

In this paper, a Robust Dynamic State Estimation (RDSE) is proposed with and without PMU, based on M-Estimators. Quadratic Linear (QL) and Square Root (SR) estimators are used. Iteratively Re-weighted Least Squares Estimation(IRLS) method is applied. A technique using DCM to add PMU in state estimation is used. For predicted and filtered state we used Holt's double exponential smoothing technique and EKF. The proposed method is applied to the standard data IEEE 30-bus as a case study [20].

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2. Mathematical Model

2.1. M-estimators

The Weighted Least Square (WLS) state estimation model can be found in [21].The M-estimators are a maximum likelihood estimator, minimize an objective function which represents the measurement residuals $\rho(r)$, subject to the constraints given by measurement equations [2].

$$\text{Min} \quad \sum_{i=1}^{m} \rho\left(r_i\right) \tag{1}$$

$$\text{Subject to} \quad z = h(x) + r \tag{2}$$

Where, $\rho(r)$ is a function represents the measurement residual r_i , Z is the vector of the measurements, x is the state variables and $h(x)$ is the measurement function.

2.2. Iteratively Re-weighted Least Squares Estimation (IRLS)

This method can suppress the bad data in the regular measurements, and also can avoid the impact of any existing of leverage measurements when they carry bad data [2].

The objective function is expressed as:

$$\min \quad J\left(r\right) = \sum_{i=1}^{m} \rho\left(r_i\right) \tag{3}$$

Then,

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial r}\frac{\partial r}{\partial x} = 0 \Rightarrow \sum_{i=1}^{m} \frac{\partial p}{\partial r_i}.\frac{\partial r_i}{\partial x} = 0 \quad \Rightarrow \sum_{i=1}^{m} \Upsilon(ri).Hi = 0$$

$$\Rightarrow \sum_{i=1}^{m} \frac{\Upsilon(ri)}{ri} ri\ Hi = 0 \quad \Rightarrow \sum_{i=1}^{m} \Gamma(ri)\ ri\ Hi = 0 \quad \Rightarrow H^T \Gamma\left(z - h(x)\right) = 0 \tag{4}$$

By using Taylor approximation for $h(x) \approx h\left(x^k\right) + H\Delta x^k$ yields:

$$H^T \Gamma H\ \Delta x^k = H^T\ \Gamma\left(z - h\left(x^k\right)\right) \tag{5}$$

Where, $H_i = \frac{\partial h_i}{\partial x}$, $H^T = \left[h_1^T\ h_2^T\ \ldots h_m^T\right]$

$\Gamma_{ii} = \frac{\Upsilon(ri)}{ri}$ is a diagonal weight matrix. The elements of Γ_{ii} are determined as:

$$\text{For Quadratic linear estimator} \quad \Gamma_{ii} = \begin{cases} \frac{2}{\sigma_i^2} & \left|\frac{r_i}{\sigma_i}\right| \le \gamma \\ \frac{2\gamma\sigma}{r_i} sign(r_i) & otherwise \end{cases} \tag{6}$$

$$\text{For Square Root estimator} \quad \Gamma_{ii} = \begin{cases} \frac{2}{\sigma_i^2} & \left|\frac{r_i}{\sigma_i}\right| \le \gamma \\ \frac{2}{r_i}\sqrt{\frac{\gamma^3}{\sigma_i r_i}} & otherwise \end{cases} \tag{7}$$

γ is the tuning parameter whose values range between 1 and 4, specified by the users.

2.3 Decoupled Current Measurement (DCM) Method

In this method, the decoupled formulation of Weighted Least Square (WLS) is used [2, 14]. The current measurement which is measured by PMU is decoupled into active and reactive measurement and added to the WLS state estimation decoupled formula. Hence, the new formulation of the measurements set is written as:

$$Z_A = \begin{bmatrix} p_{ij} \\ p_i \\ \theta_i \\ I_{(ij)r} \end{bmatrix} \quad \& \quad Z_R = \begin{bmatrix} q_{ij} \\ q_i \\ V_i \\ I_{(ij)i} \end{bmatrix} \tag{8}$$

"Z_A" represent active measurements. "Z_R" is the reactive measurements. The subscripts "r" and "i" are the real and imaginary part of the phasor measurements.

The line current I_{ij} in line "ij" is calculated as in [16].

$$I_{(ij)r} = g_{ij}\left(V_i\cos\theta_i - V_j\cos\theta_j\right) - b_{ij}\left(V_i\sin\theta_i - V_j\sin\theta_j\right) - b_{i0}v_i\sin\theta_i \tag{9}$$

$$I_{(ij)i} = b_{ij}\left(V_i\cos\theta_i - V_j\cos\theta_j\right) + g_{ij}\left(V_i\sin\theta_i - V_j\sin\theta_j\right) + b_{i0}V_i\cos\theta_i \tag{10}$$

The series admittance between bus "i" and bus "j" is $y_{ij} = g_{ij} + jb_{ij}$, and the shunt admittance at bus "i" is $y_{i0} = jb_{i0}$.The nonlinear.

The Jacobin matrix of the phasor measurement is written as.

$\partial\theta_i \quad \partial\theta_j$

For active measurements $H_A = \begin{matrix} \partial\theta_i \\ \partial I_{(ij)r} \end{matrix} \begin{vmatrix} 1 & 0 \\ C_1 & C_2 \end{vmatrix}$ (11)

$\partial V_i \quad \partial V_j$

For reactive measurements $H_R = \begin{matrix} \partial V_i \\ \partial I_{(ij)i} \end{matrix} \begin{vmatrix} 1 & 0 \\ C_3 & C_4 \end{vmatrix}$ (12)

Where,

$$C_1 = \frac{\partial I_{(ij)r}}{\partial\theta_i}, \qquad C_2 = \frac{\partial I_{(ij)r}}{\partial\theta_j}, \qquad C_3 = \frac{\partial I_{(ij)i}}{\partial V_i}, \qquad C_4 = \frac{\partial I_{(ij)i}}{\partial V_j}$$

2.4. Robust Dynamic State Estimation with PMU

The basic model of DSE is given by:

$$x_{k+1} = F_k x_k + G_k + w_k \tag{13}$$

Where x_k is the state vector at instant k, x_{k+1} is the state vector at instant $(k+1)$, F_k is a function represents the state transition between two instants of time, and is an $(n\times n)$ diagonal matrix, G_k is a vector associated with trend behavior of the system of the state trajectory dimensional $(n\times 1)$ and w_k is white Gaussian noise with zero mean and covariance matrix Q.

The parameters F_k and G_k are calculated using Holt's double exponential smoothing method [7, 22].

For predicted state, Let $\hat{x}_k$ and Ψ_k be the estimated state at a time k and its covariance matrix, at time $(k+1)$, the predicted state vector $\tilde{x}_{k+1}$ and its covariance matrix M_{k+1} can be obtained by:

$$\tilde{x}_{k+1} = F_k \hat{x}_k + G_k \tag{14}$$

$$M_{k+1} = F_k \Psi_k F_k^T + Q_k \tag{15}$$

$$M_{A_{k+1}} = F_{A_k} \Psi_{A_k} F_{A_k}^T + Q_{A_k} \quad \text{and} \quad M_{R_{k+1}} = F_{R_k} \Psi_{R_k} F_{R_k}^T + Q_{R_k} \tag{16}$$

For filtering state, now we obtained the new measurements z_{k+1} at the instant of time $(k+1)$. Based on the data at a time k the forecasted state vector at the instant of time $(k+1)$ will then be filtered to obtain the estimated state x_{k+1} at the instant of time $(k+1)$ with its estimated error's covariance Ψ_{k+1}. By using EKF , the objective function minimizes the residuals of the measurements and error in the state vector. Hence, the objective function for active measurements and reactive measurements at the next time (k+1) is given by:

$$J_A(\theta) = \left|Z_A - h_A(\tilde{\theta})\right|^T \Gamma_A \left|Z_A - h_A(\tilde{\theta})\right| + \left|\theta - \tilde{\theta}\right|^T M_A^{-1} \left|\theta - \tilde{\theta}\right| \tag{17}$$

$$J_R(V) = \left|Z_R - h_R(\tilde{V})\right|^T \Gamma_R \left|Z_R - h_R(\tilde{V})\right| + \left|V - \tilde{V}\right|^T M_R^{-1} \left|V - \tilde{V}\right| \tag{18}$$

Note that, the time index $(k+1)$ has been omitted to simplify the notation.

$$\hat{\theta}_{k+1} = \tilde{\theta}_{k+1} + K_{A_{k+1}} \left|Z_{A_{k+1}} - h_A(\tilde{\theta}_{k+1})\right| \tag{19}$$

$$\hat{V}_{k+1} = \tilde{V}_{k+1} + K_{R_{k+1}} \left|Z_{R_{k+1}} - h_R(\tilde{V}_{k+1})\right| \tag{20}$$

$$K_{A_{k+1}} = \Psi_{A_{k+1}} H_{AA_{k+1}}^T \Gamma_{A_{k+1}} \tag{21}$$

$$\Psi_{A_{k+1}} = \left|H_{AA_{k+1}}^T \Gamma_{A_{k+1}} H_{AA_{k+1}} + M_{A_{k+1}}^{-1}\right|^{-1} \tag{22}$$

Where K is called the gain matrix.

3. The Simulation Analysis

3.1. Description of Simulation

In this paper, IEEE 30-bus test system is used to evaluate the performance of the proposed method. The load curve at each bus was composed of a linear trend and random fluctuation (jitter). For simulating the dynamic nature of the system, the simulation is carried out over a period of 20 time sample intervals. During each interval, the load per bus is increased by a constant change of 5% for all buses with a constant power factor, so that the reactive power followed the active power. The true values of measurements were obtained by the load flow. The simulated measurements were obtained by adding a normally distributed error function with zero mean and standard deviation. In this work, Holt's double parameter linear exponential smoothing method for predicting state is used. For filtering state we used the EKF[23].The tuning parameter γ of the M-Estimators is chosen to be 2.5 for the both QL and SR estimators. The parameters of α and β for state prediction are chosen to be 0.7 and 0.435, while the elements of Q is fixed at 10^{-6}.

3.2. Performance Indices

The average performance indices for voltage magnitudes and voltage angles is given by:

$$\varepsilon_{v\_pre} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\left(v'_{i_{pre}} - v'_{i_{true}}\right)}{v'_{i_{true}}}\right| \times 100\% \tag{23}$$

$$\varepsilon_{\theta\_pre} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\left(\theta'_{i_{pre}} - \theta'_{i_{true}}\right)}{\theta'_{i_{true}}}\right| \times 100\% \tag{24}$$

ε_{v_pre} and ε_{θ_pre} represent the absolute predicted error as a percentage ratio, of the voltage magnitudes and voltage angles, v_{true} and θ_{true} are the true value of voltage magnitude and angle and v'_{pre} and θ'_{pre} are transposed of the predicted voltage magnitude and voltage angle.

3. Results and Analysis

In this paper, the proposed method is applied to 30-bust under normal operating conditions, and tested with and without PMU, where a single PMU has been added to every bus at each experiment. It also compared with the traditional WLS state estimation method. The weight of the PMU measurements is fixed at 100 times the normal SCADA measurement for all buses.

Table 1. The Average Results of the Various Estimators without PMU

Estimation method	Predicted Error%		Filtered Error %	
	Voltage	Angle	Voltage	Angle
QL	0.1854	1.0313	0.1739	0.9403
SR	0.1869	1.0165	0.1753	0.9268
WLS	0.3960	2.2864	0.3712	2.0806

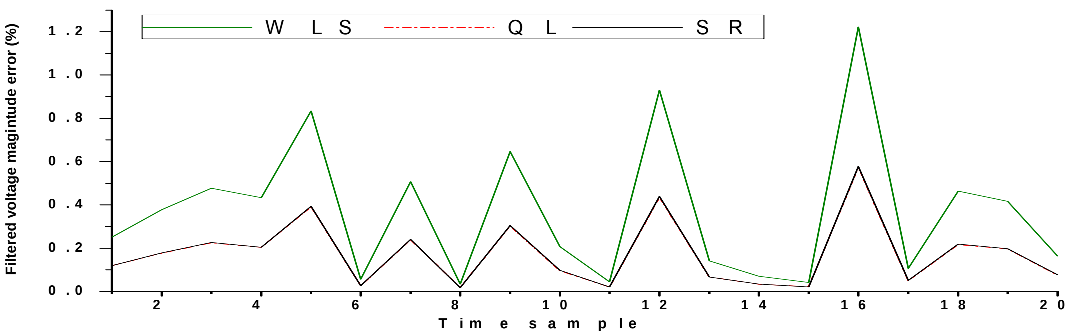

Figure 1. Performance Index of the IEEE 30-bus Test System for Estimated Voltage Magnitude

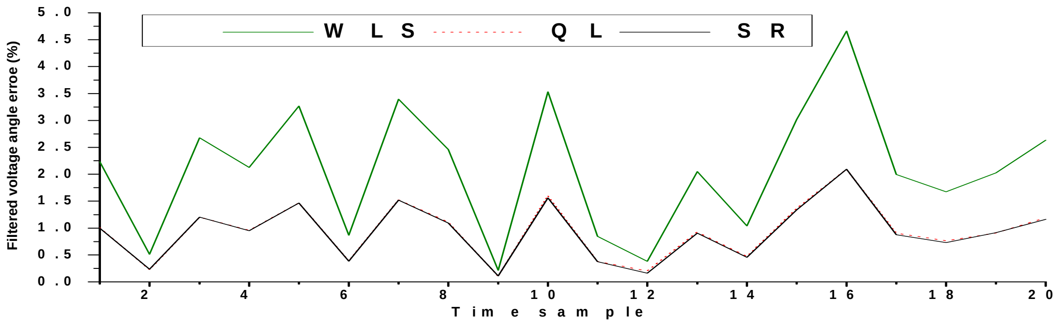

Figure 2. Performance Index of the IEEE 30-bus Test System for Estimated Voltage Angle

Table 1 shows a comparative study of the average results of the estimators at normal operation without PMU. Whereas it shows that, the use of robust M-estimators is better than the use of WLS estimator, because these M-estimators are designed for automatically detecting the bad measurements and suppressing their influences on the state estimate.

Figure 1 and Figure 2 represent the performance characteristics for the average error of voltage magnitude and voltage angle at the filtered state over a period of 20 time sample intervals.

Table 2. The Percentage of the Average Error in Voltage Magnitude and Angle using QL Estimator

Location Of PMU	Predicted Error%		Filtered Error %		Location Of PMU	Predicted Error%		Filtered Error %	
	Voltage	Angle	Voltage	Angle		Voltage	Angle	Voltage	Angle
NO PMU	0.1854	1.0313	0.1739	0.9403	16	0.0833	0.4810	0.0614	0.2771
2	0.0721	0.4717	0.0464	0.2415	17	0.0911	0.4479	0.0687	0.2260
3	0.0737	0.4821	0.0513	0.2719	18	0.0923	0.4711	0.0704	0.2611
4	0.0701	0.4751	0.0495	0.2625	19	0.0968	0.4634	0.0759	0.2487
5	0.0700	0.6030	0.0431	0.4544	20	0.0902	0.446	0.0685	0.2302
6	0.0737	0.4433	0.0500	0.2130	21	0.0856	0.4542	0.0634	0.2336
7	0.0731	0.4990	0.0501	0.3024	22	0.0882	0.4537	0.0666	0.2364
8	0.0775	0.4967	0.0540	0.3028	23	0.0944	0.5168	0.0770	0.3408
9	0.0778	0.45374	0.0535	0.2357	24	0.0824	0.4757	0.0606	0.2585
10	0.0785	0.4602	0.0521	0.2399	25	0.0795	0.5120	0.0602	0.3187
11	0.0998	0.4579	0.0808	0.2457	26	0.0775	0.5756	0.0569	0.4277
12	0.0682	0.49579	0.0412	0.3058	27	0.0749	0.4904	0.0487	0.2800
13	0.0740	0.5247	0.0547	0.3573	28	0.0722	0.5122	0.0491	0.3163
14	0.0794	0.5184	0.0598	0.3427	29	0.0729	0.5610	0.0500	0.3972
15	0.0854	0.4897	0.0630	0.2900	30	0.0749	0.5986	0.0526	0.4526

Table 3. The Percentage of the Average Error in Voltage Magnitude and Angle using SR Estimator

Location Of PMU	Predicted Error%		Filtered Error %		Location Of PMU	Predicted Error%		Filtered Error %	
	Voltage	Angle	Voltage	Angle		Voltage	Angle	Voltage	Angle
NO PMU	0.1869	1.0165	0.1753	0.9268	16	0.0799	0.4789	0.0579	0.2726
2	0.0715	0.4846	0.0453	0.2644	17	0.0908	0.4435	0.0684	0.2311
3	0.0718	0.4841	0.0489	0.2733	18	0.0925	0.4676	0.0707	0.2583
4	0.0705	0.4730	0.0497	0.2576	19	0.0971	0.4598	0.0762	0.2475
5	0.0692	0.5887	0.0422	0.4319	20	0.0909	0.4466	0.0690	0.2362
6	0.0734	0.4487	0.0499	0.2150	21	0.0867	0.4515	0.0641	0.2377
7	0.0726	0.5127	0.0496	0.3241	22	0.0896	0.4482	0.0678	0.2388
8	0.0745	0.4975	0.0496	0.3048	23	0.0949	0.4647	0.0734	0.2530
9	0.0765	0.4548	0.0514	0.2411	24	0.0841	0.4608	0.0622	0.2467
10	0.0783	0.4578	0.0515	0.2410	25	0.0810	0.4717	0.0596	0.2574
11	0.0989	0.4510	0.0793	0.2405	26	0.0785	0.5496	0.0568	0.3933
12	0.0678	0.5039	0.0411	0.3163	27	0.0727	0.4808	0.0448	0.2669
13	0.0733	0.5208	0.0540	0.3497	28	0.0696	0.5100	0.0454	0.3146
14	0.0772	0.5149	0.0566	0.3374	29	0.0714	0.5424	0.0480	0.3717
15	0.0798	0.4893	0.0568	0.2862	30	0.0735	0.5791	0.0506	0.4268

Table 2 and Table 3 show the performance of proposed method for IEEE 30-bus with and without PMU. It is obvious from these results the influences of the PMU in RDSE, where about (50% - 75%) improvement of estimated voltage magnitude. On the other hand, the improvement in the voltage angle is about (42% - 77%) for both QL and SR method. These results also prove the accuracy of DCM technique for including PMU in DSE.

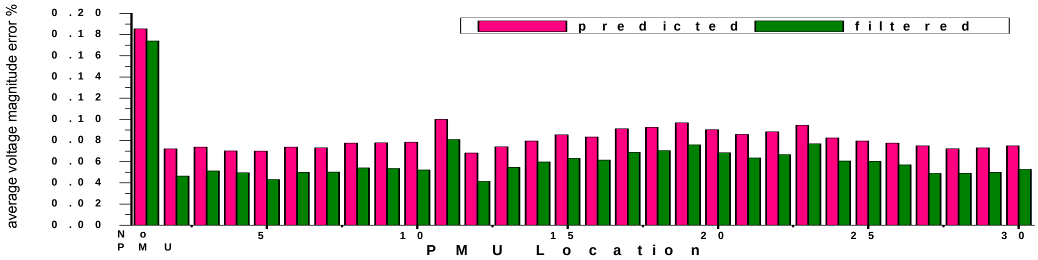

Figure 3. The Percentage of the Average Error in Voltage Magnitude using QL Estimator

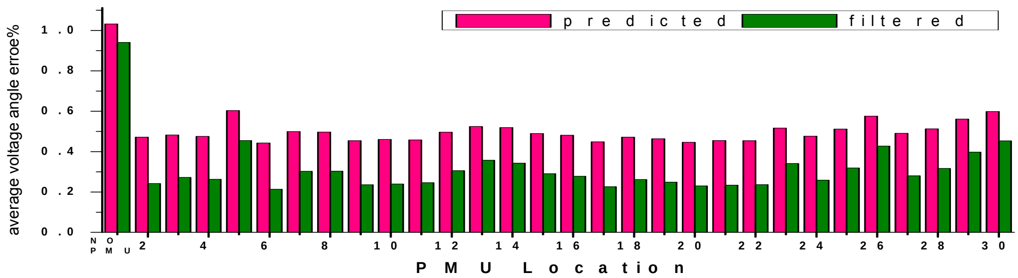

Figure 4. The Percentage of the Average Error in Voltage Angle using QL Estimator

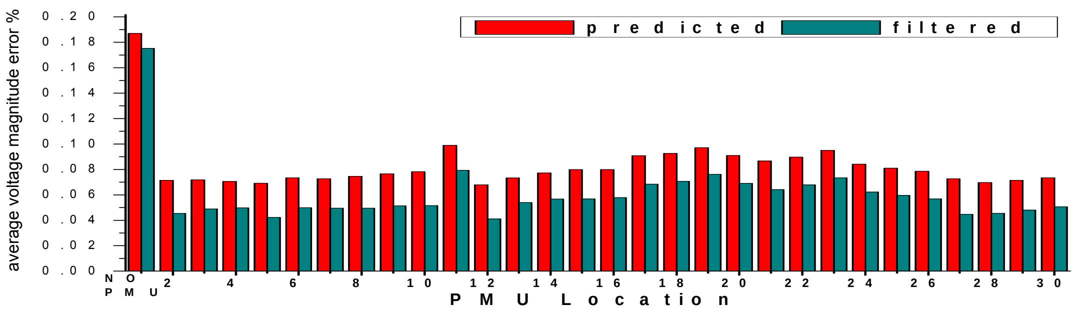

Figure 5. The Percentage of the Average Error in Voltage Magnitude using SR Estimator

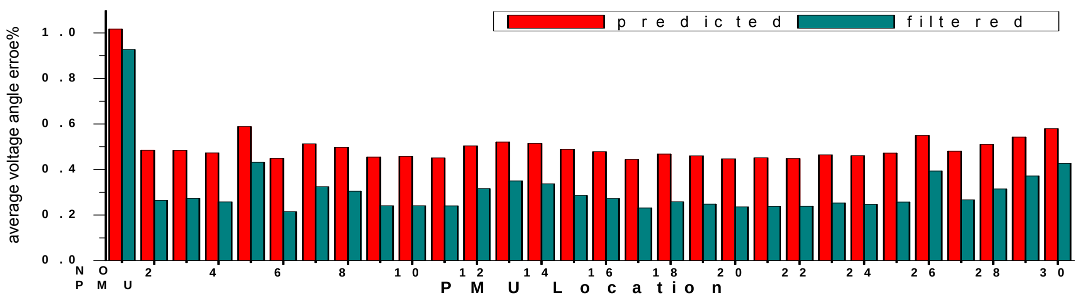

Figure 6. The Percentage of the Average Error in Voltage Angle using SR Estimator

Figures 3, 4, 5 and 6 display the variations of the percentage of the estimated errors when the PMU is included individually at each bus. It can be seen that, the importance of the PMU to improve the accuracy of the estimator. Additionally, further improvements at the predicted and filtered state that obtained by the PMU are shown.

4. Conclusion

Regards to the above results, we conclude that the uses of the robust M-Estimators are the perfect solution for Wide Area Measurement System, with high robustness and efficiency relative to a WLS state estimator. Furthermore, the uses of the robust M-Estimators improve the predicting and filtering states. Also the results show the advantages of the Decoupled Current Measurement method for including PMU in Dynamic State Estimation, which improves the quality of the estimator then upgrades the system reliability.

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