Large-Scale Power Systems State Estimation Using PMU and SCADA Data

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Abstract: **Power system monitoring and control relies on the result of dynamic state estimation. Installation of PMU in power grids in recent years makes it possible to study the dynamic properties of power system. However, it's hard to replace PMU on all buses with the conventional measurement of SCADA system in near future and there are lots of traditional measurements of SCADA system. Therefore, it is reasonable to use both measured data for estimation, control … purposes. This paper presents a hybrid dynamic state estimation algorithm by the PMU and SCADA measurements and since we have different measurements obtained by PMU and SCADA system with different sampling rates, we can apply data fusion methods to improve the estimation results.**

The hybrid method is examined on 14 buses IEEE power system and the results show estimation improvement by the hybrid approach.

Index Terms—Data fusion, Dynamic state estimation, Kalman filter, Phasor measurement unit, Synchronous generator

I. INTRODUTION

State estimation, introduced in 1969 by Fred Schweppe, is one of most important tools for the real-time monitoring of power systems [1]. Nowadays, it is executed in most energy control centres (EMS) [2].

Conventional state estimators use measurements gained from SCADA systems which are consisted of voltage magnitudes, real and reactive power flows and power injections, measured with one sample per second. SCADA system provides only steady, low sampling data from system.

The synchronized phasor measurement unit (PMU), developed in the 1980s, is considered to be one of the most important devices in the future of power systems. PMUs, can directly measure the voltage phasor at the installed bus and the current phasors of the associated lines with a high sampling rates such as 30 samples per second which has the ability to capture lower frequency system dynamics [3].

By fusing PMUs and SCADA measurements in power systems, limitation of SCADA system can be removed. PMU enables dynamic power system to be monitored on a more refine time scale [3-6].

In the past, in steady state studies efficient techniques are used for combining the accurate and reliable data of PMU with SCADA. It was observed that the hybrid algorithm improves the static state estimation performance [7-10], but previously no work has been done to combine the SCADA and PMU data for dynamic state estimation improvement.

Several methods have been applied to estimate the dynamic states of a single machine connected to an infinite bus [3-6, 11-13] but there is no research on large-scale power system state estimation.

In large scale power systems, we can apply both centralized and decentralized estimation algorithms. However, decentralized estimation algorithm can be applied easily in practice. Therefore, we choose decentralized algorithm for large scale systems. In this algorithm, the state of each subsystem is estimated considering the effect of often subsystems and an approximate model is defined for interactions [14-15].

In this paper, we exploit the data fusion algorithm to fuse the PMU and SCADA data in a large scale power system and the estimation algorithm is implemented locally in each subsystem.

This paper is organized as follows. In section II, the data fusion algorithm is presented. In section III, the decentralized state estimation is given. In section IV, the power system models, for multi-machine is described. In section IV, the algorithm is used for hybrid estimation of power systems. The result of simulation can be seen in section V. Finally, the conclusion is given in section VI.

II. DATA FUSION ALGORITHM

Data fusion is the process of combining information from different sources to obtain refined and complete description of states of the system [16].

Suppose that there are N sensors gathering measurements with different sampling rates. An example of time-scale map is shown in Fig. 1: one sensor gathers 6 samples in each data block, another one gathers 3 samples per block and the last one, gathers 1 sample per block.

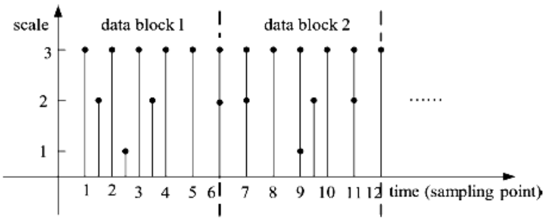

Fig. 1 Sampling time scale [16]

The dynamic model of system with N sensors is defined as follows [16]:

$$x(N,k+1) = A(N,k)x(N,k) + w(N,k) \tag{1}$$

$$z(i,k) = C(i,k)x(i,k) + v(i,k),\ i = 1,2,\ldots,N \tag{2}$$

The dynamic system is modelled at the finest sampling rate N, where $x(N,k) \in R^{n\times 1}$ is the state variable at the highest sampling rate at time k, $A(N,k) \in R^{n\times n}$ and $x(i,k)$ is the k-th state vector at scale i. $z(i,k) \in R^{q_i \times 1}(q_i \le n)$ is the k-th measurement observed by sensor i with sampling rate S_i. $C(i,k) \in R^{q_i \times N}$ is the measurement matrix.

The state space model based on each sensor i must be set up using the dynamic equations with N sensors formulized by (1) and (2). Therefore, it is assumed that the relation between $x(i,k)$ and $x(N,k)$ can be considered as follows [16]:

$$x(i,k) = (1/\tilde{M}_i)\sum_{l=0}^{\tilde{M}_i - 1} x(N, \tilde{M}_i k - l) \tag{3}$$

$$\tilde{M}_i = \prod_{j=i}^{N-1} n_j \qquad (i = 1,2,\ldots,N) \tag{4}$$

And the formultion of dynamic model based on each sensor i can be defined as follows [16]:

$$X_N(k+1) = A_N(k)X_N(k) + W_N(k) \tag{5}$$

$$Z_i(k) = C_i(k)X_N(k) + V_i(k) \tag{6}$$

In the following, the fusion estimation is given. Its assumed that $P_{i,N}(k|k)$ and $\hat{X}_{i,N}(k|k)$ are the estimation error covariance matrices and state estimation of $X_N(k)$ based on (3) and (4) using kalman filter. The equations for each sensor i are independent of each other. The optimal fusion estimation is obtained as follows:

$$\hat{X}(k|k) = \sum_{i=1}^{N} \alpha_{i,k} \hat{X}_{i,N}(k|k) \tag{7}$$

Where

$$\alpha_{i,k} = \left(\sum_{j=1}^{N} P_{i,N}^{-1}\right)^{-1} P_{i,N}^{-1}(k|k) \tag{8}$$

$$P(k|k) = \left(\sum_{i=1}^{N} P_{i,N}^{-1}(k|k)\right)^{-1} \tag{9}$$

Fig. 2 shows the kalman filter process based on sensor i and Fig. 3 describes the fusion estimation's algorithm.

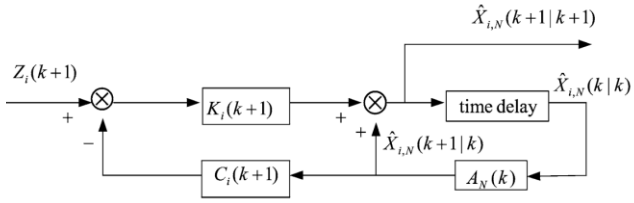

Fig. 2 Kalman filter based on sensor i. [16]

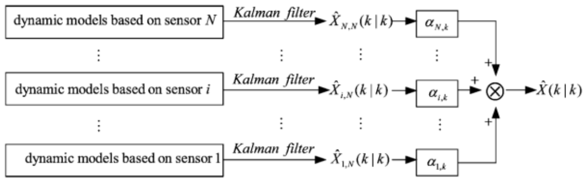

Fig. 3 Flowchart of multi-rate multisensory data fusion [16]

III. DECENTRALIZED STATE ESTIMATION

To estimate sates of a large-scale system, it is advised to design a decentralized state estimation algorithm. In [14], it is assumed that the large-scale system is decomposed to subsystems and for each subsystems, a local estimator is designed to estimate the interaction and states of the subsystems, using only the information from local quantities [14-15].

The large-scale system S, composed of N subsystems S_i (i=1… N) is considered as follows:

$$S_i = \begin{cases} \dot{x}_i = A_{ii}x_i + h_i + B_i u_i + G_i w_i \\ y_i = C_i x_i + v_i \end{cases}, \qquad i = 1,\ldots,N \tag{10}$$

Where, h_i is the interaction of other subsystems.

$$h_i = \sum_{j=1, j\ne i}^{N} A_{ij} x_j \tag{11}$$

The goal of this method is designing an estimator for each subsystem to estimate the interaction from other subsystem, h_i, and the state of i-th subsystem. In this method, a basic dynamic model is defined for the main system and a dual model which describes the dynamic model of each subsystemsis considered for theinteraction effects [14].

The dynamic model of large-scale system for the main and dual systems are:

$$\begin{aligned} \dot{x}_i &= A_{ii}x_i + h_i + B_i u_i + G_i w_i \\ y_i &= C_i x_i + v_i \end{aligned} \tag{12}$$

$$\begin{aligned} \dot{\tilde{x}}_i &= \tilde{A}_i \tilde{x}_i + A_{hi} x_i + \tilde{B}_i \tilde{u}_i + \tilde{G}_i \tilde{w}_i \\ h_i &= \tilde{C}_i \tilde{x}_i \end{aligned} \tag{13}$$

Where $x_i \in R^{n_i}$ is the state vector of i-th subsystem and $u_i \in R^{p_i}$ is it's control function. $w_i \in R^{g_i}$ is the disturbance and $v_i \in R^{q_i}$ is the measurement noise, which are assumed to be bounded. A_{ii}, B_i, C_i and G_i describe the dynamic of the isolated i-th subsystem.

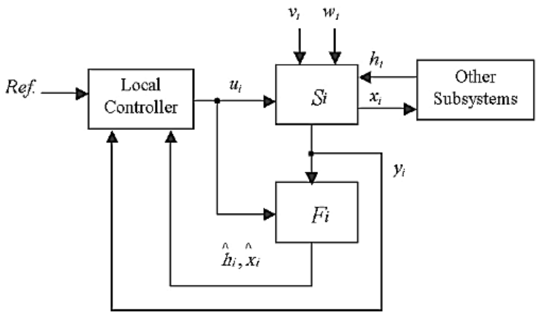

Fig. 4 State and interaction estimation diagram at i-th subsystem[14]

A_{ij} describes the interaction matrix from the j-th subsystem, which are assumed to have appropriate dimension and the model (13) shows the dynamics of the interaction system [14].

In [14], the following estimator is defined for the system (Fig. 4).

$$\begin{aligned}
\dot{\hat{x}}_i &= A_{ii}\hat{x}_i + \hat{h}_i + K_1(y_i - C_i\hat{x}_i) + B_i u_i \\
\dot{\xi}_i &= M\xi_i + N\hat{x}_i + K_2(y_i - C_i\hat{x}_i) \\
\hat{h}_i &= E\xi_i \\
y_i &= C_i x_i + v_i
\end{aligned} \tag{14}$$

Where, K_1 and K_2 are filter gains and E, M, N, are appropriately dimensioned design matrices which substitute for the dynamics of the interactions [14].

$$E = \rho I \tag{15}$$

$$N = \rho^{-1}\tilde{C}_i A_{hi} \tag{16}$$

$$M = \tilde{C}_i \tilde{A}_i \tilde{C}_i^{\perp} \tag{17}$$

IV. POWER SYSTEM MODEL

The model of a large-scale power system composed of n generators interconnected through a transmission network can be defined as follows [17-19]:

$$\begin{cases}
\dot{\delta}_i(t) = \omega_i(t) \\
\dot{\omega}_i(t) = -\dfrac{D_i}{J_i}\cdot\omega_i(t) + \dfrac{1}{J_i}(P_{mi} - P_{ei}(t)) \\
\dot{E}'_{qi}(t) = \dfrac{1}{T'_{doi}}(E_{fi}(t) - E_{qi}(t))
\end{cases} \tag{18}$$

$$V_{q_i} = E'_{q_i} - x_{d_i}\left(\sum_{j=1}^{n} E'_{q_j}(t)\left(G_{ij}\sin(\delta_{ij}) - B_{ij}\cos(\delta_{ij})\right)\right) \tag{19}$$

$$V_{d_i} = x_{q_i}\left(\sum_{j=1}^{n} E'_{qj}(t)\left(B_{ij}\sin(\delta_{ij}(t)) + G_{ij}\cos(\delta_{ij}(t))\right)\right) \tag{20}$$

$$P_{e_i} = \sum_{j=1}^{n} E'_{q_i}E'_{q_j}\left(B_{ij}\sin(\delta_{ij}) + G_{ij}\cos(\delta_{ij})\right) \tag{21}$$

The linearized model is:

$$\begin{aligned}
\dot{x}_i(t) &= A_i x_i(t) + B_i u_i(t) + \sum_{j=1,\, j\neq i}^{n} H_{ij}x_j \quad , i = 1\cdots n \\
y_i &= \begin{bmatrix} dV_t \\ dP_t \end{bmatrix} = C_i x_i + \sum_{j=1,\, j\neq i}^{n} L_{ij}x_j
\end{aligned} \tag{22}$$

$$x_i = \begin{bmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \end{bmatrix} = \begin{bmatrix} \Delta\delta_i \\ \Delta\omega_i \\ \Delta E'_{qi} \end{bmatrix}, u_i = \begin{bmatrix} u_{1i} \\ u_{2i} \end{bmatrix} = \begin{bmatrix} \Delta E_{fi} \\ \Delta P_{mi} \end{bmatrix}, y_i = \begin{bmatrix} V_t \\ P_t \end{bmatrix} \tag{23}$$

$$A_i = \begin{bmatrix} 0 & 1 & 0 \\ \dfrac{1}{J_i}\sum\limits_{j=1, j\neq i}^{n} E'_{qio}\cdot E'_{qjo}\cdot GS_{ijo} & -\dfrac{D_i}{J_i} & -\dfrac{2G_{ii}E'_{qio}}{J_i} - \dfrac{1}{J_i}\sum\limits_{j=1, j\neq 1}^{n} E'_{qjo}\cdot BS_{ijo} \\ -\dfrac{(x_{di} - x'_{di})}{T'_{doi}}\sum\limits_{j=1, j\neq i}^{n} E'_{qjo}\cdot BS_{ijo} & 0 & -\dfrac{1}{T'_{doi}} + \dfrac{(x_{di} - x'_{di})}{T'_{doi}}B_{ii} \end{bmatrix} \tag{24}$$

$$H_{ij} = \begin{bmatrix} 0 & 0 & 0 \\ -\dfrac{1}{J_i}E'_{qio}E'_{qjo}\cdot GS_{ijo} & 0 & -\dfrac{1}{J_i}E'_{qio}\cdot BS_{ijo} \\ \dfrac{(x_{di} - x'_{di})}{T'_{doi}}E'_{qjo}\cdot BS_{ijo} & 0 & -\dfrac{(x_{di} - x'_{di})}{T'_{doi}}\cdot GS_{ijo} \end{bmatrix} \tag{25}$$

In the above equations $GS_{ijo} \overset{\Delta}{=} G_{ij}\sin(\delta_{ijo}) - B_{ij}\cos(\delta_{ijo})$,

$BS_{ijo} \overset{\Delta}{=} B_{ij}\sin(\delta_{ijo}) + G_{ij}\cos(\delta_{ijo})$.

$$B_i = \begin{bmatrix} 0 & 0 \\ 0 & 1/J_i \\ 1/T'_{doi} & 0 \end{bmatrix} \tag{26}$$

Usually, the terminal voltage and active power are chosen as outputs of the power system. Each generator output depends directly on both the local generator states and the states of others generator. The linearized output equations are as follows:

$$C_{v_{d_i}} = \begin{bmatrix} x_{q_i}\sum\limits_{\substack{j=1 \\ j\neq i}}^{n} E'_{q_j}\left(B_{ij}\cos(\delta_{ij}(t)) - G_{ij}\sin(\delta_{ij}(t))\right) \\ 0 \\ x_{q_i}G_{ii} \end{bmatrix}^T \tag{27}$$

$$L_{v_{d_{ij}}} = \begin{bmatrix} x_{q_i}\left(E'_{q_i}\left(G_{ij}\sin(\delta_{ij}(t)) - B_{ij}\cos(\delta_{ij}(t))\right)\right) \\ 0 \\ x_{q_i}\left(B_{ij}\sin(\delta_{ij}(t)) + G_{ij}\sin(\delta_{ij}(t))\right)_{q_i} \end{bmatrix}^T \tag{28}$$

$$C_{v_{q_i}} = \begin{bmatrix} -x_{d_i}\sum\limits_{\substack{j=1 \\ j\neq 1}}^{n} E'_{q_j}\left(G_{ij}\cos(\delta_{ij}(t)) + B_{ij}\sin(\delta_{ij}(t))\right) \\ 0 \\ 1 + x_{d_i}B_{ii} \end{bmatrix}^T \tag{29}$$

$$L_{v_{q_{ij}}} = \begin{bmatrix} x_{d_i}\left(E'_{q_j}\left(G_{ij}\cos(\delta_{ij}(t)) + B_{ij}\sin(\delta_{ij}(t))\right)\right) \\ 0 \\ x_{q_i}\left(B_{ij}\cos(\delta_{ij}(t)) - G_{ij}\sin(\delta_{ij}(t))\right) \end{bmatrix}^T \tag{30}$$

$$C_{P_{e_i}} = \begin{bmatrix} \sum_{\substack{j=1 \\ j\neq 1}}^{n} E'_{q_i} E'_{q_j} \left(B_{ij} \cos(\delta_{ij}(t)) - G_{ij} \sin(\delta_{ij}(t)) \right) \\ 0 \\ 2G_{ii} E'_{q_i} + \sum_{\substack{j=1 \\ j\neq 1}}^{n} E'_{q_j} \left(B_{ij} \sin(\delta_{ij}(t)) + G_{ij} \cos(\delta_{ij}(t)) \right) \end{bmatrix}^T \quad (31)$$

$$L_{P_{e_{ij}}} = \begin{bmatrix} E'_{q_i} E'_{q_j} \left(G_{ij} \sin(\delta_{ij}(t)) - B_{ij} \cos(\delta_{ij}(t)) \right) \\ 0 \\ E'\left(B_{ij} \sin(\delta_{ij}(t)) + G_{ij} \sin(\delta_{ij}(t)) \right)_{q_i} \end{bmatrix} \quad (32)$$

V. ALGORITHM FOR HYBRID ESTIMATION OF LARGE SCALE POWER SYSTEMS

In this paper, we extend the method for data fusion algorithm that it is described in section II to a large scale system model.

Consider the large scale system mode, we can see that the interaction term h_i is appeared in (21) while in (1) it is not seen. The model will be similar to (1) and it is possible to apply the method of section II for its data fusion.

It's assumed that we have 2 sources or sensors with different sampling rates, PMU and SCADA, to estimate the dynamic sates of multi-machine power system. In this power system, suppose that SCADA measures terminal voltage V_t and terminal active power P_t and PMU measures terminal voltage V_t.

In this section, the data fusion method of section II is extended to be applied on the large scale system model. The algorithm is given below:

1. Model the large scale power system by model (12)
2. According to estimation model of each subsystem as (14), consider $x_{A_i} = \begin{bmatrix} x_i \\ \xi \end{bmatrix}$ which shows the state of the augmented state of each subsystem considering both its states and the states related to the interaction effects.
$$\dot{x}_{A_i} = \begin{bmatrix} \dot{x}_i \\ \dot{\xi}_i \end{bmatrix} = \begin{bmatrix} A_i & E \\ N & M \end{bmatrix} \begin{bmatrix} \hat{x}_i \\ \xi_i \end{bmatrix} + B_i u_i \quad (33)$$
$$y_i = C_i x_i + v_i$$
3. Assume E, M and N as (15) - (17)
4. Using data fusion algorithm, the dynamic model in finest sampling time α and the measurement equation for both PMU and SCADA assuming that the sampling time of SCADA is α times larger than PMUs is defined as follow:

$$X_\alpha(k+1) = A_\alpha(k) X_\alpha(k) + W_\alpha(k) \quad (34)$$

$$Z_{PMU}(k) = C_{PMU}(k) X_\alpha(k) + V_{PMU}(k) \quad (35)$$

$$Z_{SCADA}(k) = C_{SCADA}(k) X_\alpha(k) + V_{SCADA}(k) \quad (36)$$

5. The whole model of each subsystem is (34) – (36). Apply the data fusion technique of section II to estimate the states of this model.

In this section, hybrid state estimation by using data fusion algorithm and PMU and SCADA measurements calculated. In next section simulation results for multi-machine is described.

VI. SIMULATION RESULTS

In this paper, we choose IEEE-14 buses system as the large scale system, that it can be seen in Fig. 5.

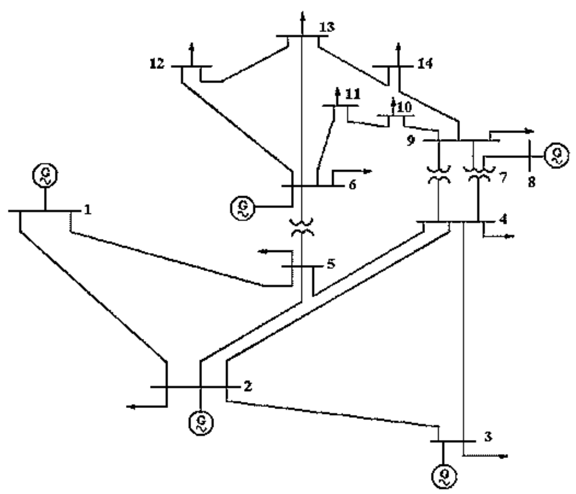

Fig. 5 IEEE 14 bus power system

This system has 5 generators on 1, 2, 3, 6 and 8 buses. If each generator and the related connected branches are considered as a subsystem, this large scale system will have 5 subsystems and each subsystem has its own dynamical model. The third order model is considered for describing the model of each generator.

The purpose of this paper is to estimate the dynamic states of power system. At first, PMU measurements are used to estimate the dynamic states of power system. Then, PMU and SCADA data are combined using the proposed algorithm in section V.

A. Dynamic estimation using PMU measurements

For 14 buses IEEE power system model, the estimate of voltage and active power for generator bus 1 considering the interference effects from other buses are shown in Fig. 6 and 7 for the centralized and decentralized cases, respectively.

B. Dynamic estimation using PMU and SCADA measurements

In this part, centralized and decentralized estimation results for multi-machine can be seen. First, we used the centralized model of power system that is described in section IV and used data fusion technique to estimate the sates of it. Then, by decentralizing centralized model of power system and dividing the system into five subsystems, again we used data fusion technique to fuse

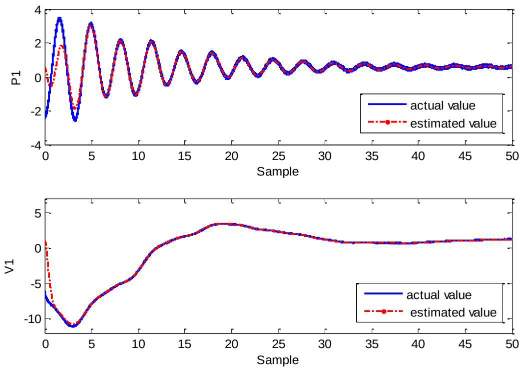

Fig. 6 Centralized dynamic states estimation with kalman filter and using PMU measurements in multi-machine power systems

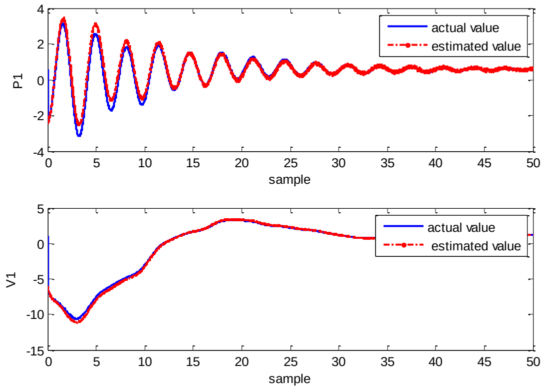

Fig. 7 Decentralized dynamic states estimation with kalman filter and using PMU measurements in multi-machine power systems

the measurements of PMU and SCADA system. We assume that the ratio between rate of sampling of PMU and SCADA is α=50 and this means that for every 50 data that is measured by PMU, 1 data can be measured by SCADA.

The results of this two part can be seen in Fig. 8 and 9 moreover the mean square error of estimation is given in TABLE I and II to compare the estimation results in hybrid and non-hybrid cases.

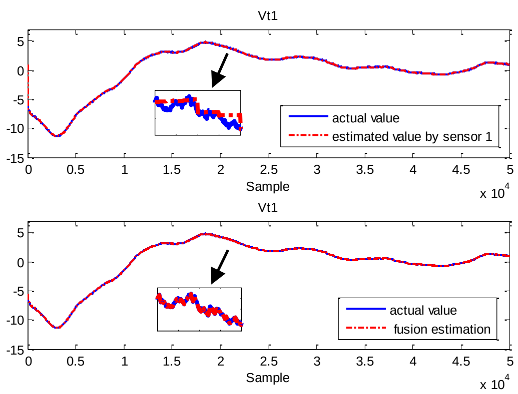

Fig. 8 Centralized dynamic states estimation with data fusion and using PMU and SADAC measurements in multi-machine power system

TABLE I
RESULTS OF ESTIMATION WITH PMU MEASUREMENTS AND HYBRID MEASUREMENTS

Index	*Value*
MSE (Estimation by PMU)	0.023
MSE (Fusion Estimation)	4.813e-005

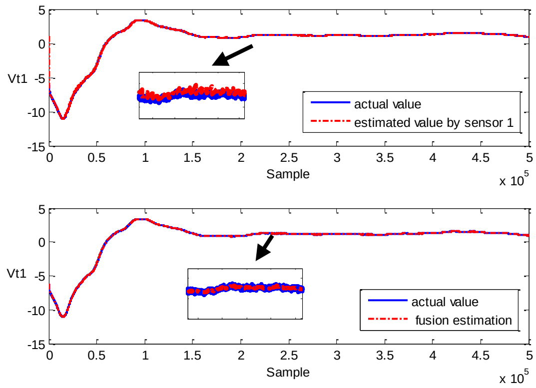

Fig. 9 Decentralized dynamic states estimation with data fusion and using PMU and SADAC measurements in multi-machine power system

TABLE II
RESULTS OF ESTIMATION WITH PMU MEASUREMENTS AND HYBRID MEASUREMENTS

Index	*Value*
MSE (Estimation by PMU)	0.0616
MSE (Hybrid Estimation)	1.24e-004

VII. CONCLUSION

Dynamic state estimation can be performed by using PMU's data, but it could not be possible to replace PMU in all buses of a network in near future and there are lots of data measured by SCADA systems. Therefore, in this paper we decide to combine measurements of PMU and SCADA to have a more accurate estimation.

The measurements of this to sensor, have different sampling rates and the data fusion technique is used to fuse the measurements. The results on a sample 14 bus power system show that hybrid measurements will improve the accuracy of the estimation.

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