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Robust state estimation in power systems using pre-filtering measurement data

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Abstract
State estimation is the foundation of any control and decision-making in power networks. The first requirement of a secure network is a precise and safe state estimator in order to make decisions based on an accurate knowledge of the network status. This paper introduces a new estimator that is capable of detecting bad data using few calculations without the need for repetitions and estimation residual calculations. The estimator is equipped with a filter formed in different times according to the Principal Component Analysis (PCA) of the measurement data. In addition, the proposed estimator employs the dynamic relationships of the system and the prediction property of the Extended Kalman Filter (EKF) in order to estimate fast and precise network states. Therefore, it makes the real-time monitoring of the power network possible. The proposed dynamic model also enables the estimator to estimate online the states of a large-scale system. The results obtained for the state estimation of the proposed algorithm for an IEEE 9 bus system shows that even in the presence of bad data, the estimator provides a valid and precise estimation of the system states, and tracks the network with an appropriate speed.

Keywords: *Bad Data, EKF, Outlier, PCA, Phasor Measurement Unit, Robust State Estimation.*

1. Introduction

Although several decades have passed since the emergence of state estimation in power grids, the dangerous consequences resulting from the control and decision-making based on inaccurate information of grid have caused the accuracy, reliability, and robustness of the estimation method to be among the fundamental challenges of the energy management system (EMS).

The popular state estimation techniques in power systems are static, and are mostly based on the weighted least squares (WLS) method. From the computational viewpoint, the quadratic-constant (QC) and least absolute values (LAV) techniques are faster than the conventional WLS estimator if they are implemented as the mathematical programming problems. These techniques can save up to 75% of the CPU time (compared with the WLS method). However, the mathematical programming formulation of some estimators (such as the least median of squares (LMS) and least trimmed of squares (LTS) approaches) involves the non-convexities and a significant number of binary variables, resulting in a higher computational burden. Regarding the estimation accuracy, the numerical simulations show that the least measurements rejected (LMR) and the quadratic-linear (QL) techniques provide an estimation accuracy level that is similar to that obtained using the WLS method [1].

Measurements providing the input data of the estimator may contain bad data due to the communication errors, systematic errors, incorrect wiring or infrequency of instrument calibration [2]. These estimators usually detect and identify bad data in the measurement data set by repeating a cycle of estimation of detection-elimination. It is rather time-consuming for large scale systems. On the other hand, the static state estimators are used to derive the control and monitoring functions that are associated with a power system operating under normal, slowly varying conditions, i.e. the slow changes in the state of the system or large changes on the long time scale but not with abrupt large changes on a very short time scale [3].

Bad-data identification in a power system state estimation plays an important role towards obtaining an unbiased state estimate. So far, many methods have been suggested to detect and eliminate bad data from a measurement dataset as the input of the state estimator.

A unified method for optimization of placement measuring devices used for a power system online monitoring by means of state estimation has been proposed in [4]. The proposed method can be suitable for the mixed measure system preserving state estimation observability and bad-data processing capability by employing numerical algorithms for observability checking, critical measurements, and critical couple identification. The node injection radix measurements and measurement categories were defined, and each measurement classification was determined by analysis of the column vectors of the coefficient matrix.

The member numbers of each measurement class can reveal the bad-data processing capability. Also the type number of measurements can be used for the observability analyzing [4].

In [5], a type of mismatch parameter such as the measurement residual has been introduced in the name of parity mismatches. The parity mismatches are employed for identification of gross errors in a given measurement set. The physical appeal of the parity mismatches enables one to adopt normalization, which improves the detectability of bad data in short lines.

Network changes or a temporary malfunction of the data acquisition system reduce data redundancy for state estimation. Redundancy of the measurement incorrectness can be specified by means of the presence of critical measurements and sets. In a majority of data validation techniques, the processing gross error is not possible in critical measurements and sets. In [6-8], several algorithms have been presented for detecting, identifying, and removing bad data in critical measurements. The basic idea in [7] converts the critical measurements to redundant measurements by placing PMUs for detecting bad data in them. Also in [8], Gou and Kavasseri have extended the idea to the critical pair, which is known to be undetectable if bad data appears in critical pairs.

Considering that there is not enough time for repeating and returning operations to detect bad data in the online monitoring, the pre-filter methods have been presented. Singh et al. have proposed a method for pre-filtering of state estimation based on wavelet analysis to detect bad data. Wavelet transform can be used to extract frequency information in the time domain by decomposing the signal with short scale of window for high frequency band, while with long window scale for low frequency band using the scale and shift technique, an important feature is used to identify the feature of a bad data and the reconstructed high frequency component to identify the abruptness in the measurement [9].

The application of Least Winsorized Square for tracking State Estimation (TSE) has been discussed in [2]. In the proposed estimator detection, identification of the anomalies such as the presence of bad data and sudden change in the load has been carried out. The asymmetry test, i.e. the skewness measure has been used in the reference. In this study, the problem of state estimation by the algorithm of JADE-adaptive differential evolution was used as an optimization tool to solve the power system state estimation. A method called Adaptive Partitioning State Estimation (APSE) has been employed in [10] for detection of the attack of bad-data injection. The essence of this method is based on two main ideas, as follow: 1) In order to improve the sensitivity of bad-data detection, the large power system is divided into several sub-systems. 2) The detection results are used to perform updating and repartitioning the sub-system in order to locate the bad data. In this method, the power system is mapped into a weighted undirected graph. In each sub-system, the Chi-squares test is used to detect the bad data. Detection and identification of the bad data are important not only in the conventional measured data but also in phasor measurements because these errors have a great impact on the estimated states in the power systems [11]. A detection method based on tracking the dynamics of measurement variations has been proposed in [12] to detect the attack of false-data injection. This method uses a measure called Kullback-Leibler Distance (KLD) to compute the distance between the two probability distributions obtained from variations in the measurement. When the falsified data is injected into the network, the probability distributions associated with the measurement variations take the deviation from the historical data, and therefore, lead to a greater KLD. The false-data detection issue has been considered as a matrix separation problem in [13]. In this study, a false-data detection algorithm was developed based on the separation of nominal power grid states and anomalies considering the inherent low dimensionality of temporal measurements of power system states and sparsity of the falsified data injection attacks. Finally, the problem was solved using the nuclear norm minimization and low rank matrix factorization. Also the Artificial Neural Network (ANN) learning process was used for pre-filtering the input data of the state estimators [14, 15]. In [15], a constructive ANN based on the Group Method of Data Handling (GMDH) has been designed by defining the normalized innovation factors. The learned ANN can be used as a pre-filter to perform a pattern analysis in order to identify both the topological and analogical errors. The need for the widespread information of possible network status and the time-consuming ANN learning process prevent the application of these methods to the real time state estimation.

Almost all approaches need a careful knowledge of the grid topology, i.e. Jacobian matrix for performing the bad-data detection (BDD) system. The BDD system is used to ensure the integrity of state estimation to filter the faulty measurements introduced by device malfunctions or malicious attacks. By contrast, Yu and Chin, in [16], have studied the general problem of blind false data injection attacks using the PCA approximation method without knowledge of the Jacobian matrix and the assumption regarding the distribution of state variables. This method is not capable of distinguishing right data with large deviation due to drastic changes in the network and the gross errors. However, it is appropriate to estimate the static mode, which is not applicable to the real time state estimation.

Nowadays, most supervisory control and data acquisition (SCADA) systems provide information on system trends. Recording functions allow operators to collect analogue values over selected time periods and to plot these values versus time as video displays in order to study the process trends. This has given a good insight into the modelling step.

This paper presents an algorithm by employing the record of measurement data and PCA technique that allows the state estimator to identify bad data without repeating estimation operations. As pointed out, the modern SCADA system can record information obtained from the network. With these information records, we can calculate the principal components of the network measurements in different time periods.

According to the proposed method, when the PCA pre-filter is used by the estimator, it can detect the outlier without too much time-consuming computations and repetition process. Also it becomes faster than the other bad-data detection algorithms. On the other hand, the pre-filter is a blocking outlier, so that it can prevent numerical instability in the estimation process due to significant errors that is a key element in most estimators. In addition, by employing the Kalman filter in the proposed estimator, the bad effect of noise (those having small amplitude errors) disappears. In conclusion, the proposed estimator has a fast calculation and an accuracy property as well as having robust against various bad data.

Section 2 describes, in detail, calculation of the principal data components based on information records, and section 3 explains its application to detect bad data. In order to describe the PCA pre-filter operation in details, the simple example of two-bus sub-system is presented in section 4. In section 5, the critical measurements are identified in order to prevent independent data in information matrix, and by suggesting appropriate places for PMUs, the critical measurements transform into the redundant ones. A comprehensive and appropriate pseudo-dynamic model for a wide power system is derived in section 6. Having a dynamic model of the network and measurement of filtered information, a dynamic estimator is introduced in section 7 using Extended Kalman Filter. Finally, in section 8, the proposed algorithm is implemented to assess the IEEE 9-bus system.

2. Principal component analysis

Principal Component Analysis (PCA) was first introduced by Pearson. It can be used to reduce the data dimensions from R^d to R^c with $c<d$, data clustering and feature extraction [17-19]. The principal components are orthogonal in R^c, and make up the axes of this space. Data is expressed in this method based on the similarities and differences. Moreover, a pattern can be found in data first, and based on this pattern, the information can be compressed by reducing the number of dimensions without losing the necessary information.

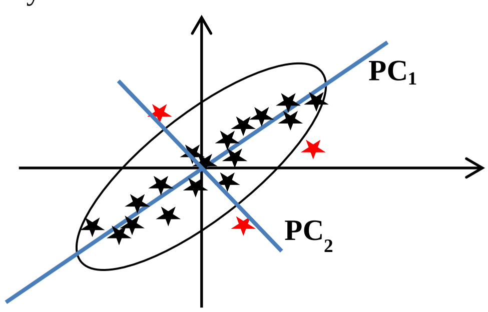

Figure 1. The 2D distribution of values around their principal components.

As shown in figure 1, for 2D data of principal components as PC_1 and PC_2 vectors, the majority of the data is scattered around the PC_1 vector. PC_1 is referred to as the first principal component (PC) of data. In addition, by choosing a permitted interval of principal components, the out-of-range data can be deleted. This technique will be used in the next sections in order to identify and delete the outlier.

To find the principal components, the covariance matrix of data variations around their means must first be formed. Now eigenvectors of the covariance matrix express the principal components, and the corresponding eigenvalues of each vector determine the priority of that component.

Consider matrix A_d, which is the matrix of data variations with zero means. Each column is the data related to a dimension (or a variable) [19-21]:

$$A_d = \begin{bmatrix} a_{1,1} & a_{1,2} & . & . & . & a_{1,m} \\ a_{2,1} & a_{2,2} & . & . & . & a_{2,m} \\ . & . & & & & \\ . & & . & & & \\ . & & & . & & \\ a_{k,1} & a_{k,2} & . & . & . & a_{k,m} \end{bmatrix} \quad (1)$$

Matrix Q, which is the covariance of matrix A_d, can be calculated as follows:

$$Q = \text{cov}(A_d)$$

$$= \begin{bmatrix} \text{cov}(a_1,a_1) & \text{cov}(a_1,a_2) & . & . & . & \text{cov}(a_1,a_m) \\ \text{cov}(a_2,a_1) & \text{cov}(a_2,a_2) & . & . & . & \text{cov}(a_2,a_m) \\ . & . & & & & \\ . & & . & & & \\ . & & & . & & \\ \text{cov}(a_m,a_1) & \text{cov}(a_m,a_2) & . & . & . & \text{cov}(a_m,a_m) \end{bmatrix}_{m\times m} \quad (2)$$

where:

$$a_j = [a_{1,j} \ \ a_{2,j} \ \ ... \ a_{k,j}]^T$$

$$\text{cov}(a_i, a_j) = \frac{\sum_{q=1}^{k} (a_{q,i} - \bar{a}_i)(a_{q,j} - \bar{a}_j)}{k-1}$$

Now, the principle components that are the same eigenvectors of Q can be expressed as:

$$PC = eigenvector(Q) = [PC_1 \ \ PC_2 \ \ .... \ PC_m] \quad (3)$$

in which, the order of vectors is determined by the corresponding eigenvalues. This means that most PCs are related to the largest eigenvalue.

To present data in the R^c space whose axes are orthogonal PC vectors, the unimportant principal components should simply be deleted and the PC matrix should be multiplied by the data matrix (A_d):

$$A_d^{\,projected\ to\ R^c} = PC^{reduced} \times A_d \quad (4)$$

where $PC^{reduced}$ is obtained by removing the unimportant principal components from PC, and $A_d^{\,projected\ to\ R^c}$ is the mapped data matrix into the selected principal component space.

3. BDD process

Except in particular cases, changes in the values of measurers are in a limited range, and there is harmony among the values of various measurers. In the proposed method, the pattern or principal components are found based on the measurement data obtained from several step times (whose accuracy must be verified). Based on this pattern, the current measurement values can be examined. If a datum is not located within the permitted range of principal components, it should be treated as suspicious data.

Consider the matrix $Data$ that includes k previous steps of m measurement data:

$$Data = \begin{bmatrix} Z_1^{(t-k)} & . & . & . & Z_{m-1}^{(t-k)} & Z_m^{(t-k)} \\ . & . & & & . & . \\ . & & . & & . & . \\ . & & & . & . & . \\ Z_1^{(t-2)} & . & . & . & Z_{m-1}^{(t-2)} & Z_m^{(t-2)} \\ Z_1^{(t-1)} & . & . & . & Z_{m-1}^{(t-1)} & Z_m^{(t-1)} \end{bmatrix} \quad (5)$$

The principal components can be calculated as follow:

$$\Delta Data = \left[Z_1 - \bar{Z}_1 \ \ Z_2 - \bar{Z}_2 \ \ ... \ \ Z_m - \bar{Z}_m\right] \quad (6)$$

$$Q = \text{cov}(\Delta Data) \quad (7)$$

$$PC = eignvector(Q) \quad (8)$$

where:

$$Z_i = [Z_i^{t-k} \ \ ... \ Z_i^{t-2} \ \ Z_i^{t-1}]^T, \ \bar{Z}_i = Mean(Z_i)$$

$$Z^t = [Z_1^t - \bar{Z}_1 \ \ .... \ \ Z_{m-1}^t - \bar{Z}_{m-1} \ \ Z_m^t - \bar{Z}_m]$$

To detect the bad data in the present measurement data, it is enough that Z^t is imaged on the important PCs by (4). If the projection of Z^t is not in the secure area, the data is contaminated with bad data. Note that the secure area can be determined by the projection of several authentic data measurement sets of previous step times.

It is possible in power systems for data to exceed the permitted range because of the sudden and large load changes or entering and exiting a large power plant or a line, and thus it is important to distinguish such changes from bad data. In view of the PMU data as authentic data, the PCA pre-filter is able to distinguish them. By removing the critical measurements, there is a correlation between all measurement data, only when the projected data go away from the principal components that are is bad data and are inconsistent with the other data.

4. Simple example of BDD process using PCA pre-filter

In this section, to describe the comprehensively of the PCA pre-filter operation, a simple example was presented. Consider the two-bus sub-system as a part of a power network, as shown in figure 2.

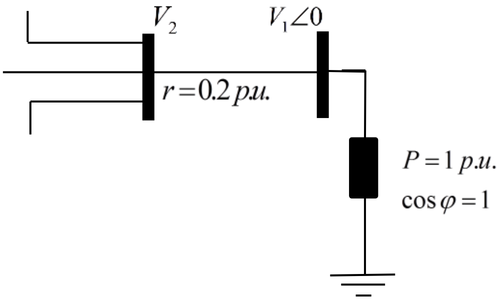

Figure 2. Two-bus sub-system.

The two voltmeters measuring and recording the voltage magnitudes of bus 1 and bus 2 during the various time steps are shown in figure 3.

As mentioned in the previous section, the principal components of data and the eigenvalues corresponding to them were calculated based on the history of measurement data, as follow:

$$Q=\text{cov}(\Delta Data)=10^{-3}\times\begin{bmatrix}0.109 & 0.089\\ 0.089 & 0.073\end{bmatrix}$$

$$PC=\begin{bmatrix}0.773 & -0.634\\ 0.634 & 0.7733\end{bmatrix}$$

in which they have been sorted based on their corresponding eigenvalues ($\lambda_1=0.1819\times10^{-3}$ and $\lambda_2=0.0005\times10^{-3}$).

As indicated in figure 4, the measurement data has been distributed around PC_1, which is an important component and corresponds to the largest eigenvalue. Assume that one bad data is received from the V_2 measurement at the 201$^{\text{th}}$ second (Figure 5).

As shown in figure 6, the penetrated outlier can be detected by considering an authorized area or distance from the principal components.

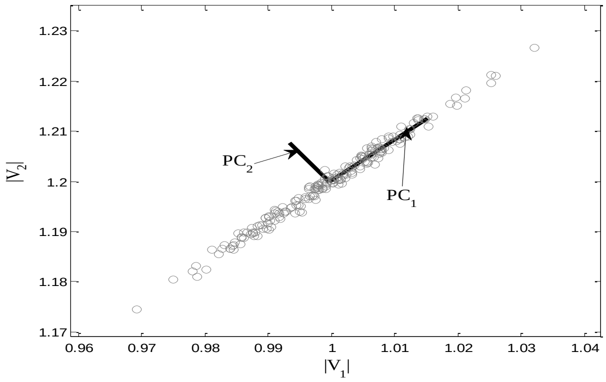

Figure 4. Measurement data and PCs.

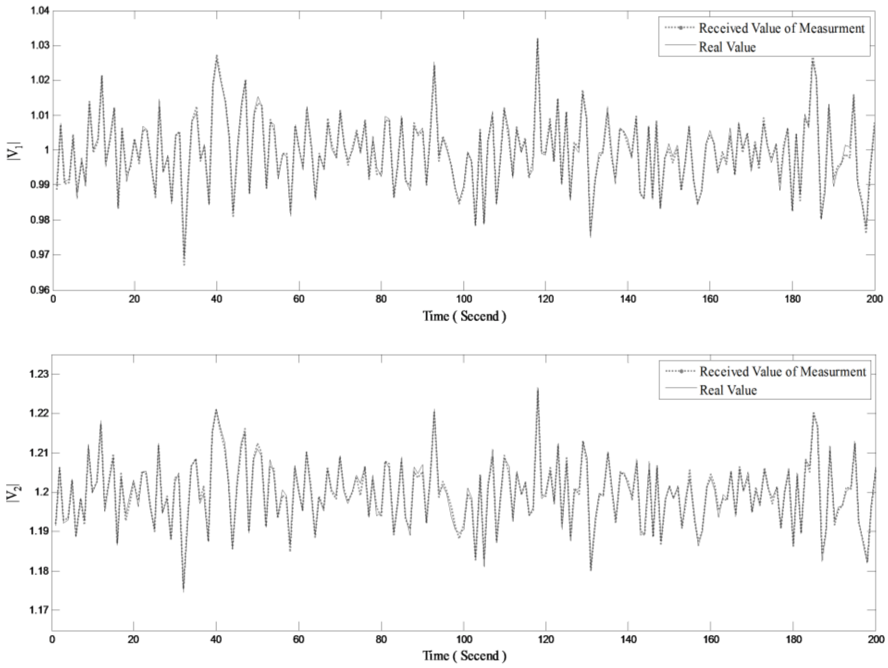

Figure 3. Received values of two measurements.

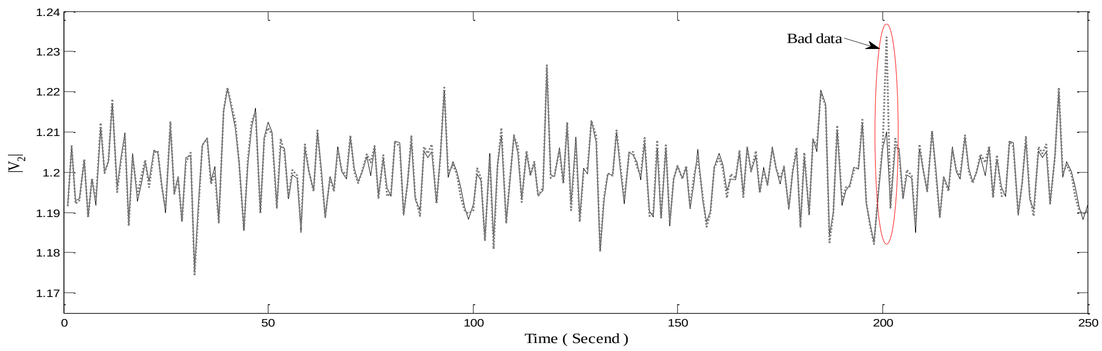

Figure 5. Falsified received measurement data of bus 2 with outlier.

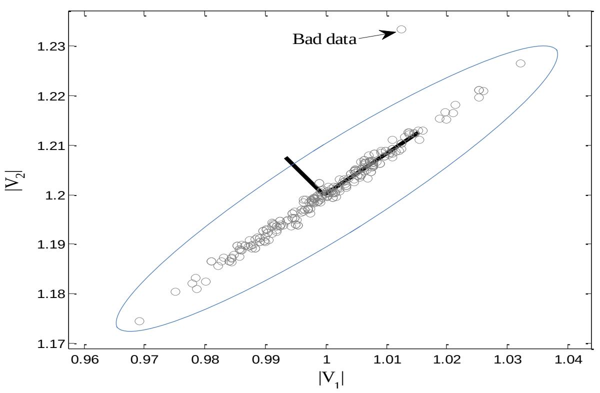

Figure 6. Bad data and its distance from PCs.

5. PMUS placement to enable BDD

This section describes the placement of PMUs in order to convert all the critical measurements into redundant ones. The benefit of having this new measurement configuration is that the system will no longer be vulnerable to the loss of any of the previous critical measurements, and now that they are no longer critical, if they carry bad data, they can be detected. The procedure can be formulated as a two-step solution involving the following stages:

1) Identification of critical measurements;

2) Finding the optimal set of PMU candidates that can transform each critical measurement into a redundant one.

The measurement set can be divided into two groups: 1) critical measurements 2) non-critical or redundant measurements. A measurement is known as "a critical measurement" if its removal leads to an observable system to become unobservable. The critical measurements can be identified by either topological or numerical methods [22].

Consider an observable network with n states and m measurements. Select n measurements, so that the network will be observable only with them. In other words, their corresponding Jacobian matrix must be full rank. This set of n measurements is called the "essential measurements". Such a set is, in general, not unique, yet contains all the critical measurements. Arrange the set measurement such that the essential measurements are first in the measurement vector. The linearized measurement equations will be [23]:

$$\begin{bmatrix} H_1 \\ H_2 \end{bmatrix}.[X]=\begin{bmatrix} Z_1 \\ Z_2 \end{bmatrix} \tag{9}$$

where, H_1, Z_1 and H_2, Z_2 correspond to the essential and non-essential measurements, respectively. By the Peters-Wilkinson [24] factorization, (9) can be re-written as:

$$\begin{bmatrix} H_1 \\ H_2 \end{bmatrix}=\begin{bmatrix} L_1 \\ M_2 \end{bmatrix}.[U] \tag{10}$$

where, L_1 is an $n\times n$ lower triangular matrix, M_2 is a $(m-n)\times n$ rectangular matrix, and U is an $n\times n$ upper triangular matrix.

Substituting (10) into (9):

$$Z_1=L_1.U.X \tag{11}$$

$$Z_2=M_2.U.X \tag{12}$$

and replacing $U.X=L_1^{-1}Z_1$:

$$Z_2=T.Z_1 \tag{13}$$

where, $T=M_2.L_1^{-1}$.

Equation (13) shows the linear dependency among the non-essential and essential measurements. Hence, a Z_1 element will be critical if the corresponding T column is null. To find the optimal set of PMUs, first consider that one PMU is available. Then look for a bus to install PMU where no column of T is null. If this target is not achievable with a PMU, add one to the number of PMU. This process will continue until no column of T is null. In fact, this scheme converts the critical measurements into the redundant ones.

6. Power system pseudo-dynamic model

The relations between active power injection (P_i), reactive power injection (Q_i), active power flow in lines (P_{ij}), and reactive powers flow in lines (Q_{ij}) can be stated as (14)-(17):

$$f_I = |V|_i \sum_{j=1}^{N} |V_j| (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) - P_i = 0 \quad (14)$$

$$f_{II} = |V_i| \sum_{j=1}^{N} |V_j| (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) - Q_i = 0 \quad (15)$$

$$\begin{aligned} f_{III} &= |V_i^2| (g_{si} + g_{ij}) \\ &- |V_i V_j| (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) - P_{ij} = 0 \end{aligned} \quad (16)$$

$$\begin{aligned} f_{IV} &= -|V_i^2| (b_{si} + b_{ij}) \\ &- |V_i V_j| (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) - Q_{ij} = 0 \end{aligned} \quad (17)$$

where:

$G_{ij} + jB_{ij}$ is the ij^{th} element of the complex bus admittance matrix,

$g_{ij} + jb_{ij}$ is the admittance of the series branch connecting buses i and j,

and $g_{si} + jb_{si}$ is the admittance of the shunt branch connected at bus i.

$\bar{V} = [\theta_2 \ \theta_3 \ .... \ \theta_N \ |V_1| \ |V_2| \ .... |V_N|]^T$ and $\theta_{ij} = \theta_i - \theta_j$.

Now, consider function F, as follows:

$$F(\bar{V}, [P_i \, Q_i \, P_{ij} \, Q_{ij}]^T) = [f_I \ \ f_{II} \ \ f_{III} \ \ f_{IV}]^T \quad (18)$$

Regarding the definition for F, it can be written as:

$$\Delta F(\bar{V}, [P_i \, Q_i \, P_{ij} \, Q_{ij}]^T) = 0 \quad (19)$$

Considering the modeling errors and uncertainties, it can be written, practically, as:

$$\Delta F(\bar{V}, [P_i \, Q_i \, P_{ij} \, Q_{ij}]^T) = e(t) \quad (20)$$

where, $e(t)$ is a Guassian white noise with a zero mean.

Regarding the fact that F is a function of $\bar{V}$ and $[P_i \, Q_i \, P_{ij} \, Q_{ij}]^T$, (20) can be extended to the first derivative with a good approximation by the Taylor expansion, as follows:

$$\begin{aligned} &\frac{\partial F}{\partial \bar{V}} \Delta \bar{V} + \\ &\frac{\partial F}{\partial [P_i \, Q_i \, P_{ij} \, Q_{ij}]^T} [\Delta P_i \, \Delta Q_i \, \Delta P_{ij} \, \Delta Q_{ij}]^T = e(t) \end{aligned} \quad (21)$$

Let $J_V = \frac{\partial F}{\partial \bar{V}}$, and based on (14)-(17):

$$\frac{\partial F}{\partial [P_i \, Q_i \, P_{ij} \, Q_{ij}]^T} = -I_{N \times N} \quad (22)$$

Therefore, we have:

$$J_V \, \Delta \bar{V} - I \, [\Delta P_i \, \Delta Q_i \, \Delta P_{ij} \, \Delta Q_{ij}]^T = e(t) \quad (23)$$

Since in the state estimation of power systems state variables are voltage magnitude and voltage angle of bus, it can be written as:

$$X(t) = \bar{V}(t) = [\theta_2 \ \theta_3 \ .... \ \theta_N \ |V_1| \ |V_2| \ .... \ |V_N|]^T \quad (24)$$

Furthermore, considering power changes as inputs:

$$U(t) = [\Delta P_i \, \Delta Q_i \, \Delta P_{ij} \, \Delta Q_{ij}]^T \quad (25)$$

Equation (23) can be re-written as follows:

$$\Delta X = J_V^{-1} U(t) + J_V^{-1} e(t) \quad (26)$$

or in standard form:

$$X(t+1) = A(t) \, X(t) + B(t) U(t) + w(t) \quad (27)$$

where, $A(t) = I_{N \times N}$ and $B(t) = J_v^{-1}(t)$, and $w(t) = J_V^{-1} e(t)$ is the noise process that is assumed to be drawn from a zero mean normal distribution with covariance Q ($w(t) \sim N(0, Q)$).

Function F should be in a way that J_V, or in other words, Jacobian matrix of function F is full rank and reversible. This condition can be satisfied by choosing power injection measurements and power flow measurements by which the power system is observable.

Up to here, the system was modeled well. Now it is time to write the output equations, or, in other words, the relationship between the measurements and the system state. Since the values obtained from the network measurements (conventional measurements and PMUs) are a function of magnitude and angle of voltage in the network, the measurement equations can be written as follows:

$$Z(t) = h(X(t)) + v(t) \quad (28)$$

where:

$Z = [Z_C \ Z_P]^T$,

$Z_C = [P_{Injection} \ P_{Flow} \ Q_{Injection} \ Q_{Flow} \ |V|_C]^T$,

$Z_P = [\theta_{V,P} \ \ |V|_P \ \ \theta_{I,P} \ \ |I|_P]^T$

Z_C is the value related to the conventional measurements including the measurement of active power injection from buses ($P_{Injection}$),measurement of active power flow in lines (P_{Flow}),measurement of reactive power injection from buses ($Q_{Injection}$),measurement of reactive power flow in lines (Q_{Flow}), and measurement of bus voltage magnitude ($|V|_C$), respectively.

Z_P is the value related to PMUs, which, according to the first method presented in [25], includes measurement of voltage angle of buses ($\theta_{V,P}$), measurement of voltage magnitude buses (

$|V|_P$), current angle measurement of the lines connected to the bus equipped with PMU ($\theta_{I,P}$), and measurement of the current magnitude of lines connected to the bus ($|I|_P$), respectively.

$h(\bullet)$ is a non-linear function representing the relationship between the measurements and the state variables.

$v(t)$ is the measurement noise, which is assumed to be zero mean Gaussian white noise with covariance R ($v(t) \sim N(0,R)$).

$R = diag\left[\sigma_1^2 \quad \sigma_2^2 \quad .... \quad \sigma_{N_M}^2\right]$, σ_i is the i^{th} standard deviation, and N_M is the total number of measurements.

7. Dynamic state estimation by EKF

As stated earlier, although many methods have been presented for the dynamic state estimation, the Kalman filter-based methods are more popular because they are easier and more accurate to be conducted. Furthermore, the results achieved from such methods are more reliable. Many articles have been presented so far on applying the Kalman filter to the dynamic state estimation since it was discussed first (1960). EKF is an efficient recursive algorithm used for state estimation in non-linear systems. The mathematical nature of this algorithm is based on minimizing the squared error covariance between the real states and the estimated ones. The main idea of this estimator is to use the estimation of X vector as the nominal trajectory in the linearized Kalman filter [26]. In other words, while performing estimation operations, the $\overline{X}$ set (vector of nominal trajectory) is assumed to be equal to $\hat{X}$ in the linearized Kalman filter. It is regarded as a smart bootstrap method of state estimation. X is estimated using a nominal trajectory, and the resulting value is used as the nominal trajectory. Consider (27) and (28) as the state equation and output equation of a system:

$$\begin{cases} X(t+1) = A(t)\,X(t) + B(t)U(t) + w(t) \\ Z(t) = h(X(t)) + v(t) \end{cases} \quad (29)$$

In order to perform EKF for the presented model, the following steps should be implemented up to the considered time ($t_{\max}$).

1. The initialization for state vector $X(t_0)$, estimation-error covariance P_0, and enough number of repetitions for each time step ($K_{\max}$).
2. $k \leftarrow 0$, $\hat{X}_k \leftarrow \hat{X}(t)$.
3. Compute the values for Jacobian matrix h for the state vector values:

$$C_k = \left.\frac{\partial h(X(t))}{\partial X(t)}\right|_{X(t)=\hat{X}_k} \quad (30)$$

4. Update $B_k = J_V^{-1}\Big|_{X(t)=\hat{X}_k}$ values.
5. Compute the Kalman gain value, as follows [26]:

$$K_k = P_k\, C_k^T \left(C_k\, P_k\, C_k^T + R\right)^{-1} \quad (31)$$

6. Predict the state vector value using the following relation [26]:

$$\hat{X}_{k+1} = A\,\hat{X}_k + B_k\,U(t) + K_k\left[Z(t) - h(\hat{X}_k)\right] \quad (32)$$

7. Update the estimation-error covariance matrix, as follows [26]:

$$P_{k+1} = A\left(I - K_k\, C_k\right)P_k\, A^T + Q \quad (33)$$

8. If $k+1 < k_{\max}$, then $k \leftarrow k+1$, and go to step 3.
9. $\hat{X}(t+t_S) \leftarrow \hat{X}_{k+1}$ and $P_0 \leftarrow P_{K+1}$.
10. If $t+t_s < t_{\max}$, then $t \leftarrow t+t_S$, and go to step 2.

8. Simulation results

Consider the IEEE 9-bus system in figure 7. According to the method presented in section 5, the most suitable place for a PMU to detect bad data is bus 8. Now consider that the network loads changes randomly and that one of the conventional measurers includes both the outlier and the data with intense changes resulting from load changes. Table 1 represents some of the eigenvalues of the covariance matrix and the corresponding eigenvector (principal components of the measurement data). As the table shows, from order 8 onwards, the eigenvalues are insignificant. This indicates that the similarity between the imaged measurement data on PC is great, namely correlation between the data is high. Figure 8 shows the received data from some of the measurements.The received measurement data contains both data with the intense variations due to changes in load or generation and outlier. At the 380th second, the outlier penetrated by measured data of the active power flow from bus 4 to bus 9. The results of state estimation for voltage magnitude and angle of buses 4 and 9 are presented in figures 9 and 10. These figures show the estimation errors for both estimators, which increase to keep out the Kalman filter trajectory from the real trajectory of the system at the intense change moments. These errors are damped as soon as the coupling real system trajectory and Kalman filter trajectory are performed.

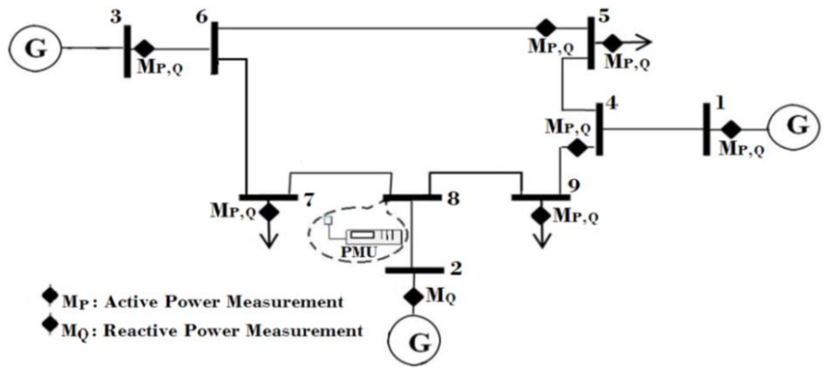

Figure 7. Single line diagram of IEEE-9 bus test system.

Table 1. PCs of under study system measurements.

Order	1 th	2 th	3 th	4 th	5 th	6 th	7 th	8th	9th	23th
Eigen value	0.3993	0.0055	0.0029	0.0013	0.0002	0.0001	0.0001	0.0	0.0	0.0
Principal Component	-0.2926	-0.0013	0.3267	-0.2145	0.0490	-0.1870	-0.0326	-0.0477	0.1671	-0.2218
	-0.3657	-0.0569	0.2010	-0.0663	0.0067	0.0776	-0.2093	0.0122	-0.0800	-0.0279
	-0.0957	-0.0603	-0.1147	0.1216	-0.0445	0.1590	-0.0709	-0.0089	-0.0553	-0.0657
	0.1870	0.3737	0.0798	0.4095	0.1431	0.1594	0.2882	0.1052	-0.1216	-0.1494
	0.1942	0.2074	-0.3737	-0.4146	-0.3149	-0.1474	0.1067	0.0256	0.1336	-0.0310
	0.3502	-0.4673	-0.1080	0.1377	0.1583	-0.1671	0.0238	-0.1552	0.1480	-0.1869
	-0.1116	-0.3119	0.1219	-0.2324	0.0239	-0.2053	-0.1591	0.1516	-0.0959	0.0214
	0.0786	0.0698	0.1977	0.1841	0.1648	-0.0296	0.1177	0.0932	-0.0326	0.1233
	-0.0957	-0.0603	-0.1147	0.1216	-0.0445	0.1590	-0.0709	-0.0089	-0.0553	0.7748
	0.1797	0.2193	-0.2893	-0.1044	-0.1926	-0.0028	0.1340	0.0349	-0.0090	-0.0507
	-0.1824	0.1669	-0.0942	-0.1721	-0.1878	0.0848	-0.0854	-0.0662	0.0033	-0.2274
	0.1768	-0.3062	-0.2016	-0.0208	-0.0249	-0.0403	-0.1044	0.0539	-0.1257	0.0885
	0.1734	-0.1610	0.0936	0.1585	0.1832	-0.1268	0.1282	-0.2091	0.2737	-0.1011
	-0.1810	0.3106	0.2048	0.0179	0.0251	0.0183	0.1265	-0.1993	0.2631	0.0762
	-0.3393	-0.0986	-0.2315	-0.0492	0.1403	-0.2157	0.4832	-0.2864	-0.4878	0.0208
	-0.2641	-0.0910	-0.0498	0.2181	-0.1855	-0.3914	0.3690	0.1732	-0.0337	-0.0182
	0.1157	0.2816	0.1015	0.1550	-0.0993	-0.7238	-0.2415	-0.0460	0.0496	0.2060
	0.1028	0.1457	-0.0190	-0.4781	0.6702	-0.0780	0.1808	0.2953	0.0729	0.1882
	0.2164	-0.1531	0.4388	-0.2296	-0.3684	0.0792	0.3831	-0.2086	0.1290	0.2962
	-0.1732	-0.1736	-0.0389	0.1397	-0.1777	0.0129	0.2156	0.6966	0.3363	-0.0064
	0.1555	-0.1151	0.2771	-0.1758	-0.1343	0.1283	0.2509	0.0485	-0.2056	-0.1297
	0.2791	0.0882	0.3051	-0.0303	-0.1238	-0.1073	-0.1522	0.3060	-0.5578	-0.0640
	0	0	0	0	0	0	0	0	0	0

However, the dynamic estimator without pre-filter can remove the effect of noise using the Kalman filter, although estimation of all states is effected by the outlier, and represents invalid estimation results, as indicated in figure 9. As shown in figure 10, the proposed estimator can trace the network states fast and accurately. Also this estimator can identify and eliminate the outlier by analyzing the principal components of the measurement data and evaluating the outlier distances from PCs. This property leads to the proposed estimator operations to be reliable and safe even with various amplitude of variation data and outlier. Also the simulation results indicate that the proposed algorithm is able to distinguish the outlier from the correct data with intense changes in the network.

9. Conclusion

Estimation of the network state is the first and most fundamental function in controlling and operating the power system. However, an inaccurate or delayed state estimation might lead to heavy damages because of the EMS wrong decision. Therefore, a method was presented in this paper that is robust against bad data, precise, fast, and simultaneous. In the proposed method, the outlier is immediately deleted by the pre-filter based on PCA of the measurement data. Moreover, this pre-filter is able to distinguish the outlier from non-normal data caused by sudden and large changes in the network. The results of the simulation show that by employing the Kalman Filter, the estimator is also secure against small amplitude errors. It should be noted that PC determination of different regimes in the network is performed once for several hours. Also it can be found by a separate processor, so the calculation burden on the estimator is dispelled. In addition, the dynamic model for the proposed estimator does not require dynamic parameters of load and generator, and given a high estimation speed, this estimator is able to properly real-time track a large scale network state.

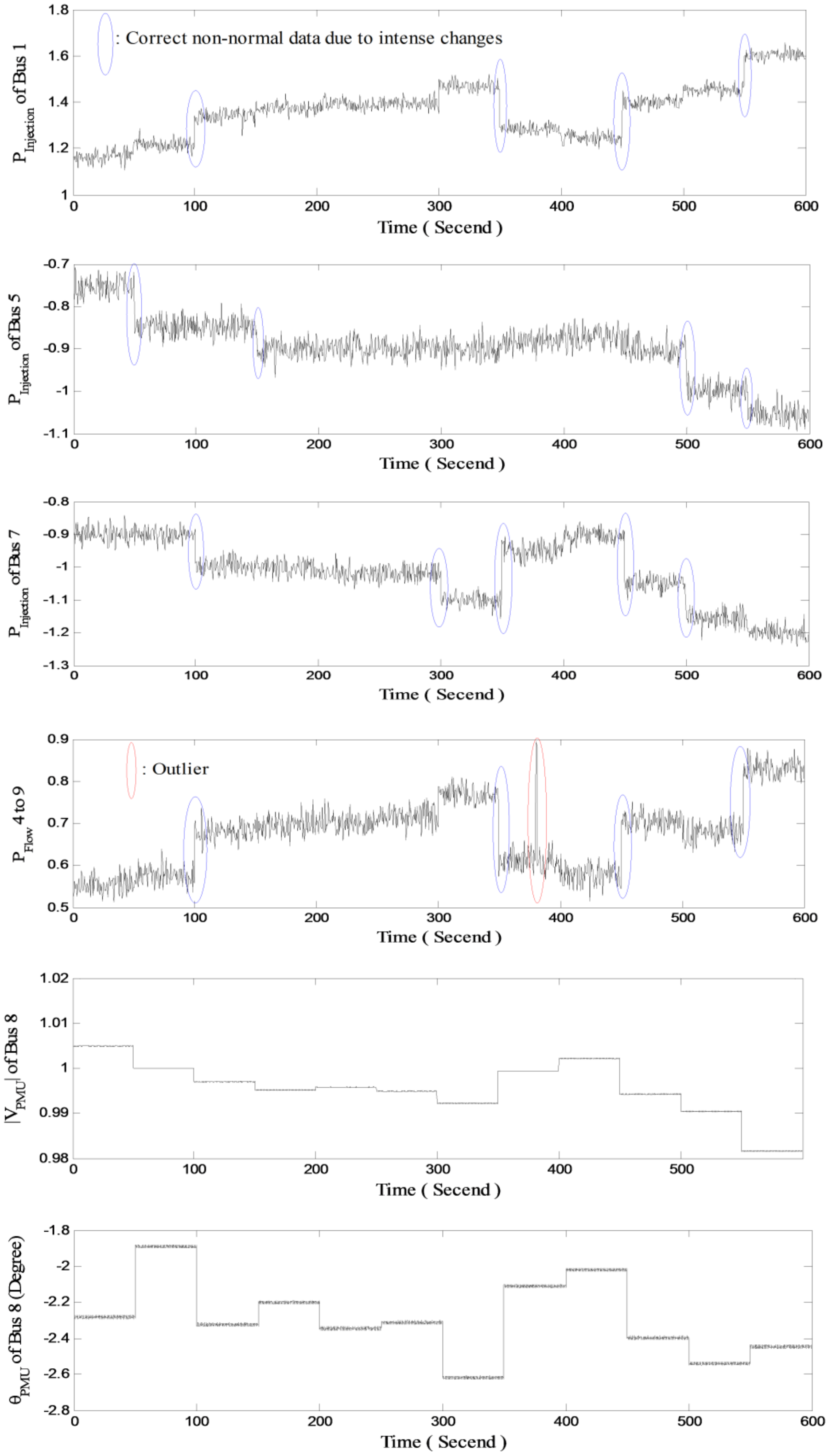

Figure 8. Some understudied system measurement data: conventional measurements and PMU.

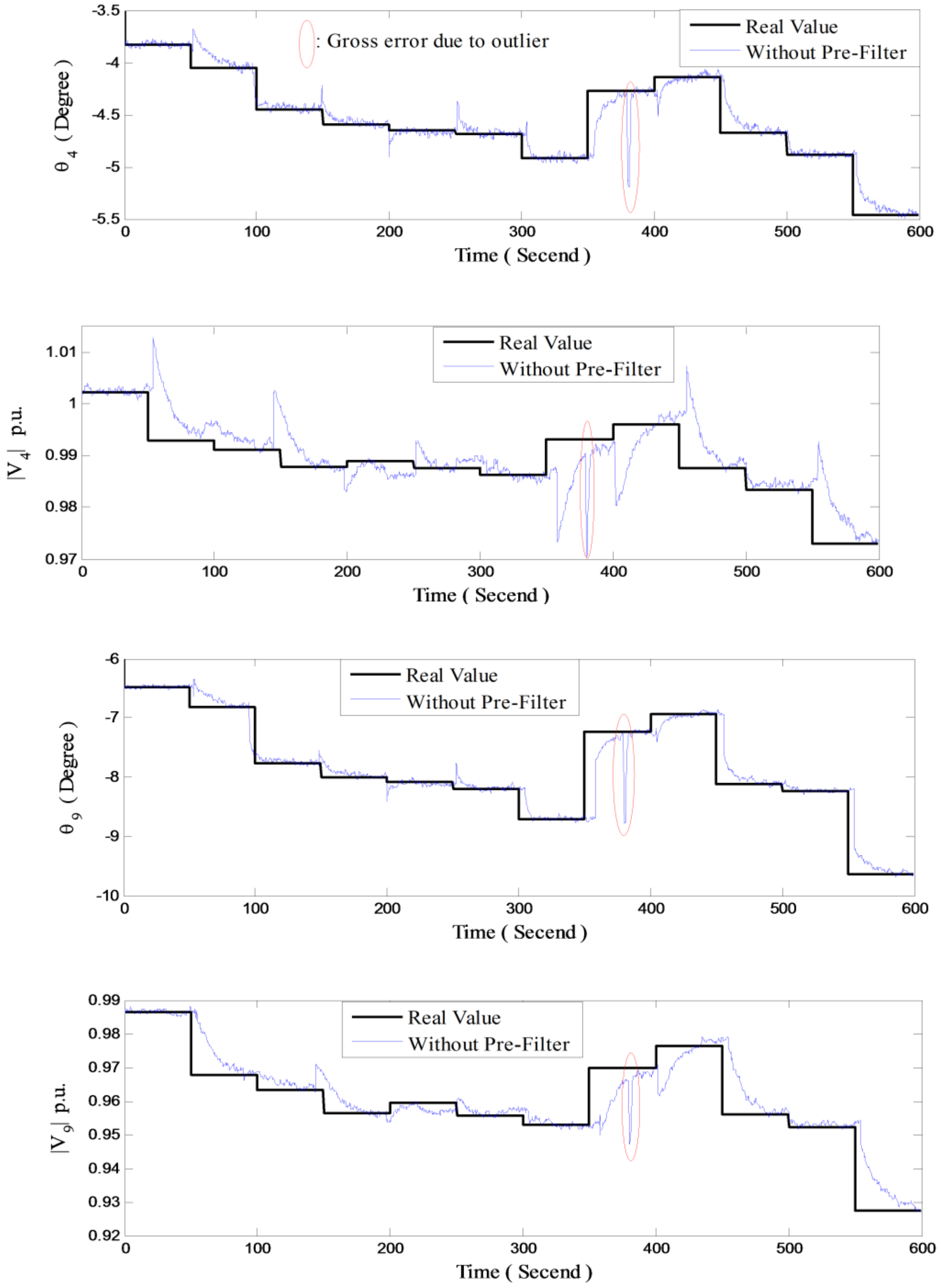

Figure 9. Some state estimation results without pre-filter.

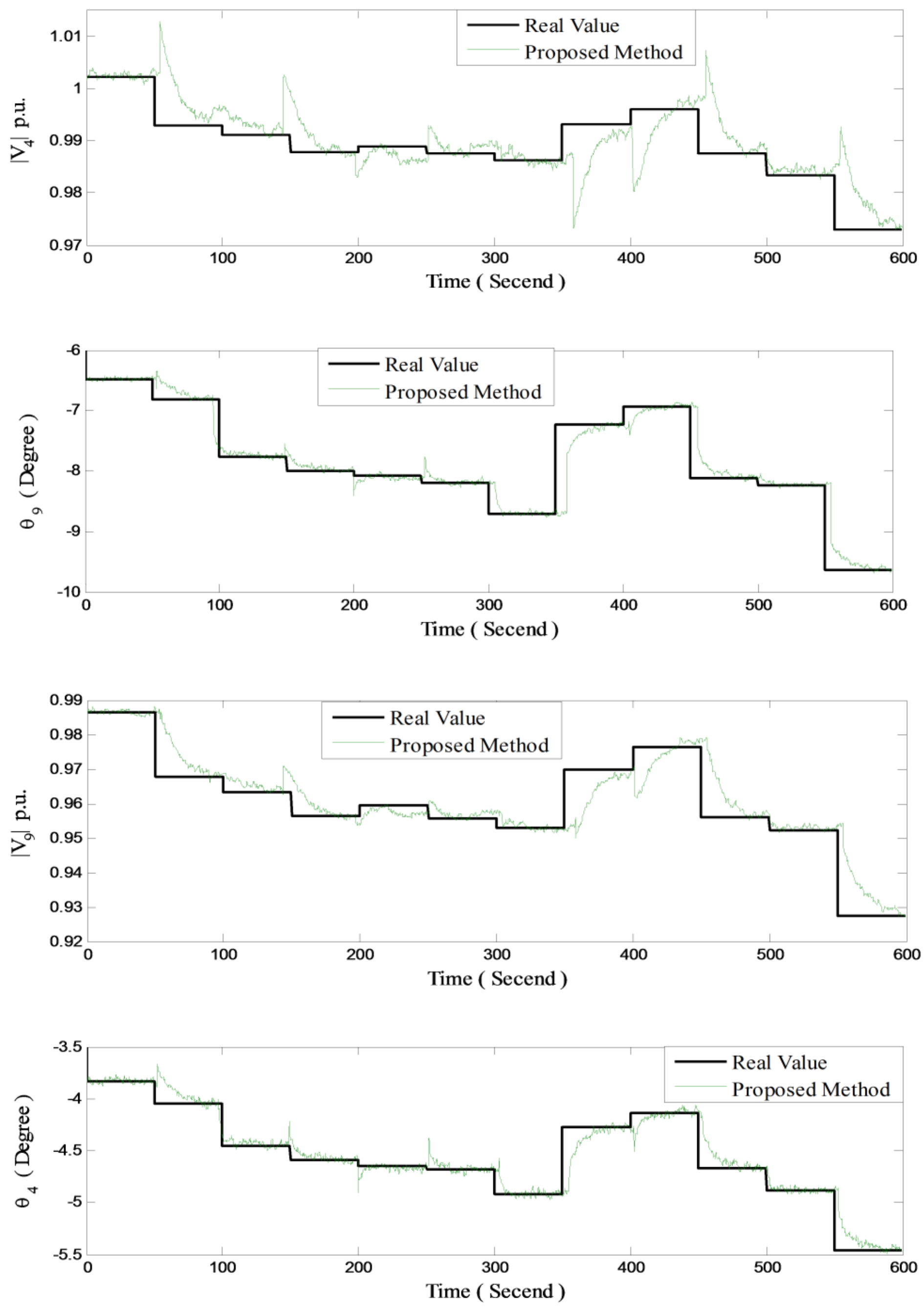

Figure 10. Some state estimation results with pre-filter.

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Appendix

Relation between elements of matrix J_V and C :

$$J_V = \frac{\partial F}{\partial \overline{V}} = \begin{bmatrix} \frac{\partial P_i}{\partial \theta} & \frac{\partial P_i}{\partial |V|} \\ \frac{\partial Q_i}{\partial \theta} & \frac{\partial Q_i}{\partial |V|} \\ \frac{\partial P_{ij}}{\partial \theta} & \frac{\partial P_{ij}}{\partial |V|} \\ \frac{\partial Q_{ij}}{\partial \theta} & \frac{\partial Q_{ij}}{\partial |V|} \end{bmatrix} \quad (34)$$

$$C = \frac{\partial h}{\partial X} = \begin{bmatrix} \frac{\partial P_i}{\partial \theta} & \frac{\partial P_i}{\partial |V|} \\ \frac{\partial P_{ij}}{\partial \theta} & \frac{\partial P_{ij}}{\partial |V|} \\ \frac{\partial Q_i}{\partial \theta} & \frac{\partial Q_i}{\partial |V|} \\ \frac{\partial Q_{ij}}{\partial \theta} & \frac{\partial Q_{ij}}{\partial |V|} \\ \frac{\partial |V|_C}{\partial \theta} & \frac{\partial |V|_C}{\partial |V|} \\ \frac{\partial \theta_{V,P}}{\partial \theta} & \frac{\partial \theta_{V,P}}{\partial |V|} \\ \frac{\partial |V|_P}{\partial \theta} & \frac{\partial |V|_P}{\partial |V|} \\ \frac{\partial \theta_{I,P}}{\partial \theta} & \frac{\partial \theta_{I,P}}{\partial |V|} \\ \frac{\partial |I|_P}{\partial \theta} & \frac{\partial |I|_P}{\partial |V|} \end{bmatrix} \quad (35)$$

$$\frac{\partial P_i}{\partial \theta_i} = \sum_{j=1}^{N} V_i V_j (-G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) - V_i^2 B_{ii} \quad (36)$$

$$\frac{\partial P_i}{\partial \theta_j} = V_i V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \quad (37)$$

$$\frac{\partial P_i}{\partial |V_i|} = \sum_{j=1}^{N} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) + V_i G_{ii} \quad (38)$$

$$\frac{\partial P_i}{\partial |V_j|} = V_i (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) \quad (39)$$

$$\frac{\partial Q_i}{\partial \theta_i} = \sum_{j=1}^{N} V_i V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) - V_i^2 G_{ii} \quad (40)$$

$$\frac{\partial Q_i}{\partial \theta_j} = V_i V_j (-G_{ij} \cos\theta_{ij} - B_{ij} \sin\theta_{ij}) \quad (41)$$

$$\frac{\partial Q_i}{\partial |V_i|} = \sum_{j=1}^{N} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) - V_i B_{ii} \quad (42)$$

$$\frac{\partial Q_i}{\partial |V_j|} = V_i (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij}) \quad (43)$$

$$\frac{\partial P_{ij}}{\partial \theta_i} = V_i V_j (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) \quad (44)$$

$$\frac{\partial P_{ij}}{\partial \theta_j} = -V_i V_j (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) \quad (45)$$

$$\frac{\partial P_{ij}}{\partial |V_i|} = -V_j (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) + 2(g_{ij} + g_{si}) V_i \quad (46)$$

$$\frac{\partial P_{ij}}{\partial |V_j|} = -V_i (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) \quad (47)$$

$$\frac{\partial Q_{ij}}{\partial \theta_i} = -V_i V_j (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) \quad (48)$$

$$\frac{\partial Q_{ij}}{\partial \theta_j} = V_i V_j (g_{ij} \cos\theta_{ij} + b_{ij} \sin\theta_{ij}) \quad (49)$$

$$\frac{\partial Q_{ij}}{\partial |V_i|} = -V_j (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) - 2(b_{ij} + b_{si}) V_i \quad (50)$$

$$\frac{\partial Q_{ij}}{\partial |V_j|} = -V_i (g_{ij} \sin\theta_{ij} - b_{ij} \cos\theta_{ij}) \quad (51)$$

Current phasors of branches:

$$\bar{I}_{ij} = |I_{ij}| \angle \theta_{I_{ij}} = \overline{V}_i (g_{si} + j b_{si}) + (\overline{V}_i - \overline{V}_j)(g_{ij} + j b_{ij}) = C + jD \quad (52)$$

Then:

$$C = V_i \cos\theta_i (g_{si} + g_{ij}) - V_i \sin\theta_i (b_{si} + b_{ij}) + b_{ij} V_j \sin\theta_j - g_{ij} V_j \cos\theta_j \quad (53)$$

$$D = V_i \cos\theta_i (b_{si} + b_{ij}) + V_i \sin\theta_i (g_{si} + g_{ij}) - b_{ij} V_j \cos\theta_j - g_{ij} V_j \sin\theta_j \quad (54)$$

$$\frac{\partial \theta_{I_{ij}}}{\partial \theta_i} = [V_i^2 (b_{si} + b_{ij})^2 + V_i^2 (g_{si} + g_{ij})^2 + V_i V_j \sin\theta_{ij} (g_{ij} b_{si} - b_{ij} g_{si}) - V_i V_j \cos\theta_{ij} (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})] / (C^2 + D^2) \quad (55)$$

$$\frac{\partial \theta_{I_{ij}}}{\partial \theta_j} = [V_j^2 (b_{ij}^2 + g_{ij}^2) + V_i V_j \sin\theta_{ij} (g_{ij} b_{si} - b_{ij} g_{si}) - V_i V_j \cos\theta_{ij} (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})] / (C^2 + D^2) \quad (56)$$

$$\frac{\partial \theta_{I_{ij}}}{\partial |V_i|} = [V_j \cos\theta_{ij} (b_{ij} g_{si} - g_{ij} b_{si}) - V_j \sin\theta_{ij} (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})] / (C^2 + D^2) \quad (57)$$

$$\frac{\partial \theta_{I_{ij}}}{\partial |V_j|} = [V_i \cos\theta_{ij} \; (g_{ij} b_{si} - b_{ij} g_{si}) + V_i \sin\theta_{ij} \; (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})]/(C^2 + D^2) \quad (58)$$

$$\frac{\partial |I_{ij}|}{\partial \theta_i} = [V_i V_j \cos\theta_{ij} \; (g_{ij} b_{si} - b_{ij} g_{si}) + V_i V_j \sin\theta_{ij} \; (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})]/(\sqrt{C^2 + D^2}) \quad (59)$$

$$\frac{\partial |I_{ij}|}{\partial \theta_j} = [V_i V_j \cos\theta_{ij} \; (b_{ij} g_{si} - g_{ij} b_{si}) - V_i V_j \sin\theta_{ij} \; (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})]/(\sqrt{C^2 + D^2}) \quad (60)$$

$$\frac{\partial |I_{ij}|}{\partial |V_i|} = [V_i (g_{si} + g_{ij})^2 + V_i (b_{si} + b_{ij})^2 + V_j \sin\theta_{ij} \; (g_{ij} b_{si} - b_{ij} g_{si}) - V_j \cos\theta_{ij} \; (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})]/(\sqrt{C^2 + D^2}) \quad (61)$$

$$\frac{\partial |I_{ij}|}{\partial |V_j|} = [V_j (g_{ij}^2 + b_{ij}^2) + V_i \sin\theta_{ij} \; (g_{ij} b_{si} - b_{ij} g_{si}) - V_i \cos\theta_{ij} \; (b_{ij}^2 + g_{ij}^2 + b_{ij} b_{si} + g_{ij} g_{si})]/(\sqrt{C^2 + D^2}) \quad (62)$$

نشریه هوش مصنوعی و داده کاوی

تخمین حالت مقاوم در سیستم‌های قدرت به کمک پیش فیلتر اطلاعات اندازه‌گیرها

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چکیده:

تخمین حالت پایه و اساس هرگونه عملیات کنترلی و تصمیم‌گیری در شبکه‌های قدرت است. اولین نیازِ یک شبکه امن، داشتن یک تخمین‌گر حالت ایمن و دقیق جهت تصمیم‌گیری بر اساس دانش دقیق از وضعیت شبکه می‌باشد. این مقاله تخمین‌گری ارائه می‌کند که بر خلاف روش های رایج با محاسبات کم و سریع و بدون نیاز به فرآیند تکرار و محاسبه خطای تخمین، قادر است داده نامتعارف را تشخیص دهد. این تخمین‌گر مجهز به یک پیش‌فیلتر می‌باشد که بر اساس آنالیز اجزای اصلی (PCA) داده‌های اندازه‌گیرها در زمان‌های متفاوت شکل گرفته است. علاوه بر این، الگوریتم پیشنهادی با بهره‌مندی از روابط دینامیکی سیستم و ویژگی پیش‌بینی در فیلتر کالمن توسعه یافته (EKF)، حالات شبکه را سریع و دقیق تخمین می‌زند، لذا قادر به به مانیتورینگ زمان-واقعی شبکه قدرت می‌باشد. همچنین مدل دینامیکی پیشنهادی باعث گردیده تخمین‌گر توانایی تخمینِ آنلاینِ حالات یک شبکه وسیع قدرت را نیز داشته باشد. نتایج شبیه‌سازی الگوریتم ارائه شده بر روی سیستم ۹ باسه IEEE نشان می‌دهند که تخمین‌گر حتی با حضور داده نامتعارف به خوبی و با دقت حالات سیستم را تخمین می‌زند و با سرعت مناسبی آن را رصد می‌کند.

کلمات کلیدی: داده نامتعارف، فیلتر توسعه یافته کالمن، داده پرت، PCA، واحد اندازه‌گیری فازور، تخمین حالت مقاوم.