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Adaptive state estimator with intersection of confidence intervals based preprocessing

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A B S T R A C T

The paper presents an effective solution for improving power system state estimation performance by applying the intersection of confidence intervals (ICI) algorithm, a state-of-the-art adaptive signal processing technique used in signal denoising. Since many power utilities worldwide still run state estimators based on the weighed least squares (WLS) algorithm using supervisory control and data acquisition (SCADA) measurements, the ICI algorithm is added to pre-process SCADA measurements without changing the structure of the WLS algorithm. Due to its adaptive window size and high sensitivity to noise in the input measurement series, the proposed ICI-based solution results in an enhancement of the state estimator output and overall performance when compared to the original algorithm. As test beds, the IEEE systems with 30 and 118 buses were used, while as an example of the real power system, the complete mathematical model of the Croatian transmission power system was simulated. Several case studies indicate that the ICI-based state estimator reduces the input measurements mean squared error by up to 30.8%, the mean absolute error by up to 20.8%, and the maximum estimation error by up to 22.6%. Furthermore, this also led to an enhanced final output of the state estimator for all tested systems in view of the state estimation accuracy and convergence.

A R T I C L E I N F O

Keywords:
Power system state estimation
Adaptive filtering
Intersection of confidence intervals (ICI) algorithm

1. Introduction

Nowadays, power systems operators face numerous challenges due to the integration of modern technical solutions for generating and storing of electrical energy, as well as undergoing electrification of the transport system, all of which will have substantial impact on future smart grid [1–3]. To help them cope with the challenges, the area of power system state estimation has been recognized as one of the main fields for possible advancements, since the state estimator (SE) plays an important role in the power system control centre [4], as its outputs are used in the calculations such as power flows and security analysis. As inputs in the SE, the conventional supervisory control and data acquisition (SCADA) measurements are used, which can be combined with synchronized phasor measurements, collected by phasor measurement units (PMUs) [5–9].

Therefore, hybrid models are often proposed in literature [10–16] and a number of authors have studied the topic of the optimal placement of the PMUs [17–20]. Although there are utilities populating their power systems with the PMUs, linear SEs using the synchronized phasor measurements only are still not a realistic solution for larger power systems [21]. On the other hand, there are utilities still using only SCADA measurements as inputs for their weighted least squares (WLS) based SEs, and therefore, solutions are needed to optimally use the existing set of measurements in order to improve the SE performance [22–24], while the inclusion of the synchronized phasor measurements will additionally improve SE performance. Therefore, the challenge tackled in this paper was how to apply a state-of-the-art adaptive signal processing technique used in signal denoising, the intersection of confidence intervals (ICI) algorithm, in the state estimation area in order to improve the final output of the SE. Without modifying the structure of the WLS algorithm, which is quite convenient for power utilities, the adaptive ICI filter was added as a pre-processor for noisy measurements. The proposed adaptive SE was shown to efficiently reduce noise from noisy measurement series by adequately varying the estimator size. Moreover, the ICI algorithm applied to the SE was shown to significantly enhance final output estimation quality when compared to

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the original method. In order to test the performances of the proposed approach, three power system models of various sizes, as well as configuration and number of measurements, were used. From the IEEE test systems, the IEEE test systems with 30 and 118 buses were used, while the Croatian transmission power system model was utilized as a real-life power system example. Various performance indices were calculated and the simulation results were compared to those obtained using the classical WLS-based SE.

The paper is organized as follows. The theoretical background and the mathematical model of the proposed SE are given in Section 2. Case studies, the achieved results and their elaboration are presented in Section 3. The paper Conclusion is given in Section 4.

2. Theoretical background

2.1. Theory of power system state estimation

Although the classical power system theory based on the WLS method was developed several decades ago, it is still used in the control rooms worldwide. Here, we provide a brief description of the background theory for the purpose of paper completeness.

The SCADA measurements are used as inputs in the classical SE, and the measurements vector $\mathbf{z}$ usually comprises voltage magnitudes, active and reactive power flows and injections,

$$\mathbf{z} = [\mathbf{V},\mathbf{P_{flow}},\mathbf{Q_{flow}},\mathbf{P_{inj}},\mathbf{P_{inj}}]^T, \tag{1}$$

while the state vector $\mathbf{x}$ groups voltage angles and magnitudes (i.e. voltage phasors) on all buses in the power system,

$$\mathbf{x} = [\theta,\mathbf{V}]^T. \tag{2}$$

Since the power flows and injections are nonlinearly related to the state vector elements, the set of nonlinear equations $\mathbf{h}(\mathbf{x})$ gives the relation between the measurements and the state vector

$$\mathbf{z} = \mathbf{h}(\mathbf{x}) + \mathbf{e}, \tag{3}$$

where $\mathbf{e}$ is the error vector of uncorrelated measurement errors. The weight of each measurement is determined by standard deviations σ that populate the measurement error covariance matrix $\mathbf{R} = \mathrm{diag}\{\sigma_1^2,\cdots,\sigma_m^2\}$, where m is the number of measurements. Standard uncertainty is calculated from the maximum uncertainty Δu_i [25,26], with the assumption of a uniform probability distribution over the range of uncertainty,

$$\sigma_i = \frac{\Delta u_i}{\sqrt{3}}. \tag{4}$$

The goal of the SE is to minimize the objective function $J(\mathbf{x})$

$$J(\mathbf{x}) = \frac{1}{2}[\mathbf{z}-\mathbf{h}(\mathbf{x})]^T\mathbf{R}^{-1}[\mathbf{z}-\mathbf{h}(\mathbf{x})]. \tag{5}$$

With the Gain matrix $\mathbf{G}(\mathbf{x})$ and the Jacobian matrix $\mathbf{H}(\mathbf{x})$ introduced

$$\mathbf{G}(\mathbf{x}) = \mathbf{H}^T(\mathbf{x})\mathbf{R}^{-1}\mathbf{H}(\mathbf{x}), \tag{6}$$

$$\mathbf{H}(\mathbf{x}) = \partial\mathbf{h}(\mathbf{x})/\partial\mathbf{x}, \tag{7}$$

an iterative algorithm is run in order to obtain an estimate of the power system. The change of the state vector elements is calculated iteratively until the maximum change in the state vector elements $\Delta\mathbf{x}^k$ gets smaller than the predefined tolerance

$$\mathbf{G}(\mathbf{x}^k)\Delta\mathbf{x}^k = \mathbf{H}^T(\mathbf{x}^k)\mathbf{R}^{-1}[\mathbf{z}-\mathbf{h}(\mathbf{x}^k)], \tag{8}$$

$$\Delta\mathbf{x}^k = \mathbf{x}^{k+1}-\mathbf{x}^k. \tag{9}$$

The flowchart of the state estimator is given in Fig. 1.

2.2. Adaptive ICI-Based Estimator

The idea behind the proposed preprocessing preceding the SE is to

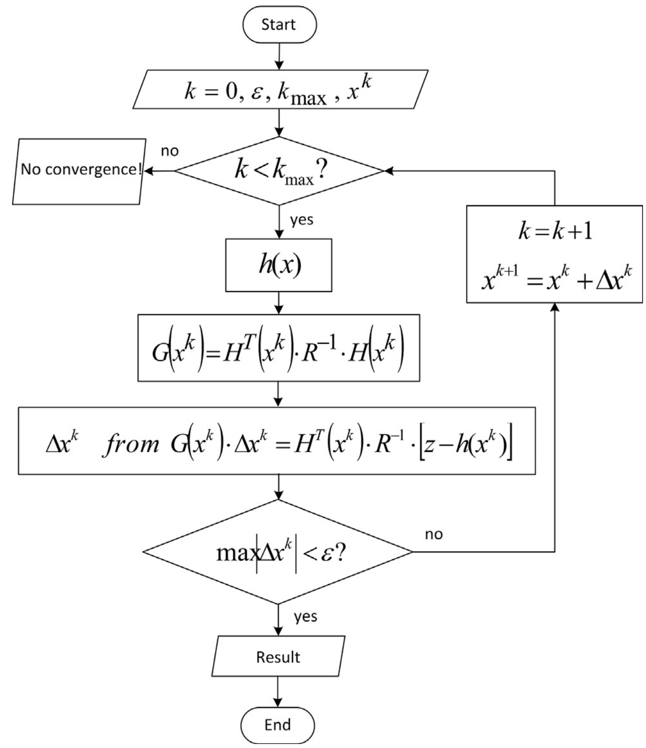

Fig. 1. State estimator flowchart.

restore, as accurately as possible, the estimate $\hat{y}(X_i)$ of the true measurements $y(X_i)$ from the set of the observed noisy measurements $z(X_i)$, such that the estimation error is minimal. The noisy measurements series, used in discussion given in sequel, can be modeled as the original measurements series corrupted by zero-mean additive white Gaussian noise, having standard deviation σ, i.e. $\zeta \sim N(0,\sigma^2)$. Hence, the noisy measurements series model is given by

$$z(X_i) = y(X_i) + \zeta(X_i). \tag{10}$$

Note that the measurements series theoretically may be both discrete and continuous. Assuming that measurements series $z(X)$ is physically continuous ($X \in \mathbb{R}$), its discrete representation (used for SE in real-life applications) is obtained by sampling the continuous domain X with a regular interval Δ. Therefore, $z(X_i)$ is extracted from $z(X)$ as $z(X_i) = z(X)|_{X=i\Delta}$, where $i \in \mathbb{Z}$.

Estimation error, namely point-wise mean squared error (MSE), as a function of the estimation error variance $\sigma^2_{\hat{y}_w(X)}$ and the sum of the squared estimation bias $b^2_{\hat{y}_w(X)}$ (both dependent on the scale parameter w value), can be calculated as [27,29–31,28,32]

$$\mathrm{MSE}_{\hat{y}_w(X)} = (b_{\hat{y}_w(X)})^2 + (\sigma_{\hat{y}_w(X)})^2. \tag{11}$$

The minimal point-wise MSE can be obtained by finding proper w value, denoted as w^*, which provides the optimal trade-off between the estimation bias and the variance [27]

$$w^* = \underset{w}{\mathrm{argmin}}\,\mathrm{MSE}_{\hat{y}_w(X)}. \tag{12}$$

As shown in [33,34], the ICI algorithm may be used as a tool to choose proper scale value w^+, as close to w^* as possible, resulting in the associated estimate $\hat{y}_{w^+}$, as close to the ideal $\hat{y}_{w^*}$ as possible.

The brief outline of the ICI algorithm is given in sequel, while for a more detailed study one should refer to [33,35–38].

The absolute estimation error at X can be calculated using [27]

$$|e(X)| = |y(X)-\hat{y}_w(X)| \leqslant |b_{\hat{y}_w(X)}| + |\zeta_{\hat{y}_w(X)}|, \tag{13}$$