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Optimal parameterization of Kalman filter based three-phase dynamic state estimator for active distribution networks

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ABSTRACT

This paper presents a new method for the assessment of the process noise covariance matrix for three-phase dynamic state estimation in unbalanced active distribution networks which operate under normal conditions. The assessment is done in order to minimize the estimation error. The proposed assessment method, based on minimization of a particular cost function, enables the a priori assessment of covariance matrix by extracting information from previously observed measurements, without the need to simulate the true state of the system. The method was applied on two commonly used Kalman filter based estimation algorithms in nonlinear systems: Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). A comparative analysis was performed between two different cost functions based on average root mean square of innovations and maximum likelihood technique. Also, the importance of determining initial state vector and its error covariance matrix needed for the initialization of dynamic state estimation was examined, as well as the ability of UKF and EKF to handle measurement nonlinearities. The analysis was carried out and the proposed method was verified on modified IEEE 13- and 37-bus distribution test systems.

1. Introduction

The rise of distributed generation induces the increase in requirements for monitoring and control of distribution networks (DNs), giving the estimation in DNs more importance. One of the problems in power system dynamic state estimation (DSE) is non-linearity of both the process model and the measurement model. Different filtering methods are proposed to handle this problem. Most widely used methods are first order Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), which present extensions to the classical Kalman filter.

The DSE has been particularly explored at power generation and the transmission network level [1–4]. However, the DSE solutions applicable at this level cannot be applied to DN due to its high level of imbalance and high R/X ratio. Regardless of this fact, the DSE of DNs has not yet been investigated extensively.

Parameter identification for process model and measurement model is responsible for proper behavior of state estimators based on Kalman filtering. Adaptive filter tuning encompasses the estimation of initial state vector, its error covariance matrix, process and measurement noise covariance matrix, as well as other unknown model parameters [5]. The influence of initialization scenario (initial state vector and its error covariance matrix) on estimation accuracy has been poorly elaborated in literature. More attention has been paid to the assessment of noise covariance matrices. Although measurement noise is relatively easy to assess, the assessment of process noise level is a much more challenging task.

There are four standard approaches for assessment of Kalman filter parameters: Bayesian, maximum likelihood (ML), covariance matching and correlation techniques [6]. Methods developed based on these approaches commonly rely on assumptions that arise from characteristics of the analyzed system. Results that can be achieved using a particular method depend on how well these assumptions are met. The ML approach combined with EKF/UKF is used in various research fields for parameter identification of the chaotic model [7], parameterized process noise covariance matrix [8] and process modeled with stochastic differential equation [9]. Recently, Kalman filtering has been combined with ML estimators in order to simultaneously obtain system state and parameter estimates [10].

Numerous methods for the assessment of process noise covariance matrix can be found in power system literature. In [11], three different methods for covariance matrix calibration are proposed and tested in quasi-steady-state conditions. One of the methods assumes perfect a priori knowledge of bus injections, while other two are more realistic and based on a posteriori knowledge of state estimates and its error covariance matrix. However, they are not capable of tracking sudden system changes as soon as they occur, hence prediction-error

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covariance estimation method was proposed in [2] to overcome this drawback. The methods mentioned above rely on the assumptions that the system dynamics can be modeled as a random walk process and that the measurement model is linear, known and time-invariant. Random walk is suitable when state estimation is driven by measurements with high refresh rate, such as phasor measurement units (PMUs). Also, if a state vector is given in rectangular coordinates, the use of PMUs can lead to a linear measurement model, but only if conventional measurements of branch/bus power flows/injections are excluded. A more realistic approach is made in [12], where measurements of active/reactive bus power injections are added in a simulated DN.

The implementation of PMUs is quite uncommon in today's DNs [13]. The first operational system that provides low-latency real-time state estimation by using PMU measurements of a real active DN is presented in [14]. The cost should be significantly lower to enable practical utilization of multiple PMUs in real DNs [15]. Therefore, in this paper only conventional measurements (active/reactive branch power flows, active/reactive bus power injections and bus voltage magnitudes) are included in the state estimation process aimed to carry out the analyzes concerning actual conditions in which the DN currently operates.

A new method for the assessment of process noise covariance matrix applicable in normal operating conditions in real DNs is presented here. The proposed method starts from a simple parametric representation of the covariance matrix. The aim is to find a covariance matrix parameter that minimizes the difference between the observed and predicted measurements, in order to achieve optimal filter accuracy. For that purpose we used three-phase dynamic state estimators based on EKF and UKF. Cost functions based on the average root mean square error and ML technique were examined and compared for purposes of innovation analysis. In addition, we studied how different initialization scenarios affect the estimation accuracy. The method was tested on modified IEEE 13- and 37-bus unbalanced distribution test systems with connected distributed generators (DGs).

The paper is organized in the following order: In Section 2 system dynamics and measurements are modeled, Section 3 describes EKF and UKF estimation algorithms and the applied performance indices, while Section 4 explains the proposed method for the assessment of process noise covariance matrix in detail. Finally, the results are given in Section 5 and major conclusions are drawn in Section 6.

2. Description of DSE model

2.1. Quasi-static process model

First step in DSE is to identify the adequate mathematical model to describe time behavior of the system. Considering that the system state changes steadily but slowly during normal operating conditions, state vector transition can be satisfactorily described by a process model consisting in the linear stochastic discrete-time equation [1]:

$$\boldsymbol{x}_{k+1} = \boldsymbol{F}_k\boldsymbol{x}_k + \boldsymbol{g}_k + \boldsymbol{w}_k, \tag{1}$$

where $\boldsymbol{x}$ is $n\times 1$ dimensional state vector consisting of bus voltage magnitudes and phase angles, k is time sample, $\boldsymbol{F}$ is $n\times n$ dimensional state transition matrix, $\boldsymbol{g}$ is $n\times 1$ dimensional vector associated with the trend behavior of the state trajectory, $\boldsymbol{w}$ is $n\times 1$ dimensional vector for modeling process noise (it is commonly assumed for process noise to be white and distributed according to a Gaussian distribution with zero mean and covariance matrix $\boldsymbol{Q}$), and n is number of state variables for which $n_{\max} = 3\cdot 2\cdot N$ applies, where N represents the total number of buses in DN (excluding slack bus). The number of state variables is usually lower than $n_{\max}$, given that the presence of single- and two-phase laterals, as well as single- and two-phase loads is typical for DNs [16].

The most commonly used technique for online update of matrix $\boldsymbol{F}$ and vector $\boldsymbol{g}$ is Holt's linear exponential smoothing method [1,17] which involves a parametric representation of matrix $\boldsymbol{F}$ and vector $\boldsymbol{g}$ presented by the following equations:

$$\boldsymbol{F}_k = \alpha(1+\beta)\boldsymbol{I}_n, \tag{2}$$

$$\boldsymbol{g}_k = (1+\beta)(1-\alpha)\boldsymbol{x}_k^- - \beta\boldsymbol{a}_{k-1} + (1-\beta)\boldsymbol{b}_{k-1}, \tag{3}$$

$$\boldsymbol{a}_k = \alpha\boldsymbol{x}_k^+ + (1-\alpha)\boldsymbol{x}_k^-, \tag{4}$$

$$\boldsymbol{b}_k = \beta(\boldsymbol{a}_k - \boldsymbol{a}_{k-1}) + (1-\beta)\boldsymbol{b}_{k-1}, \tag{5}$$

where α and β are smoothing parameters with values between 0 and 1, $\boldsymbol{I}_n$ is $n\times n$ dimensional identity matrix, $\boldsymbol{x}^-$ and $\boldsymbol{x}^+$ are the predicted and estimated state vector, respectively, $\boldsymbol{a}$ and $\boldsymbol{b}$ are $n\times 1$ dimensional level and slope vector, respectively.

Generally, smoothing parameters could be updated at every time step. If we want to increase/decrease the influence of the system state at a current time step k on a state prediction for the next time step $k+1$, then parameter α should be set to a value as close as possible to 1/0. The same applies to parameter β if the aim is to make the prediction more/less affected by the trend of change of system state between two consecutive time steps $k-1$ and k.

In order to determine parameters $\boldsymbol{a}$ and $\boldsymbol{b}$, it is necessary to have information about the behavior of the system at points earlier in time, which can be achieved by system monitoring.

2.2. Measurement model

The relationship between measurements and system state variables is expressed by the non-linear stochastic equation:

$$\boldsymbol{z}_k = \boldsymbol{h}(\boldsymbol{x}_k) + \boldsymbol{e}_k, \tag{6}$$

where $\boldsymbol{z}$ is $m\times 1$ dimensional vector of measurements, $\boldsymbol{h}$ is $m\times 1$ dimensional non-linear vector function with at least n independent equations in order to achieve the network observability, $\boldsymbol{e}$ is $m\times 1$ dimensional white Gaussian measurement noise vector with zero mean and covariance matrix $\boldsymbol{R}$ and m is the total number of measurements in DN so that $m \geqslant n$.

In a real DN, available telemetered devices provide real-time measurements of active/reactive power flows and injections, current flow and injection magnitudes, as well as voltage magnitudes [16,18,19]. One of the major problems for distribution state estimation is a lack of telemetered devices [18]. Thus, fictitious virtual and pseudo measurements are required to improve redundancy and provide observability. Zero power/current injection measurements in nodes with no load/DG connected are treated as high accurate virtual measurements. Pseudo measurements can be obtained from historical daily load profiles, historical DG database or weather forecast and therefore they are characterized by limited accuracy.

The measurement noise depends on the accuracy of measurement devices, which are known for all real-time measurements. Given that pseudo measurements are fictitious, their accuracies should be adopted appropriately.

Standard deviation can be estimated from measurement true value and measurement accuracy through following expression [16,20]:

$$\sigma = z^{true}\cdot(Accuracy/300). \tag{7}$$

This approach for standard deviation calculation is only applicable to real-time and pseudo measurements, and not to virtual measurements ($z^{true} = 0$). It is for this reason that virtual measurements were modeled with very small standard deviation (typical values are within the range 10^{-4}–10^{-6} [20,21]).

This information makes the measurement noise covariance matrix $\boldsymbol{R}$ much easier to define then the process noise covariance matrix $\boldsymbol{Q}$. If measurements errors are mutually independent for one snapshot of measurements, then $\boldsymbol{R}_k$ is the diagonal matrix given with:

$$\boldsymbol{R}_k = diag\{\sigma_{k,1}^2, \sigma_{k,2}^2, \ldots, \sigma_{k,l}^2, \ldots, \sigma_{k,m}^2\}, \tag{8}$$