

Dynamic state estimation and prediction for real-time control and operation

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Dynamic state estimation and prediction for real-time control and operation

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Abstract—Real-time control and operation are crucial to deal with increasing complexity of modern power systems. To effectively enable those functions, it is required a Dynamic State Estimation (DSE) function to provide accurate network state variables at the right moment and predict their trends ahead. This paper addresses the important role of DSE over the conventional static State Estimation in such new context of smart grids. DSE approaches normally based on Extended Kalman Filter (EKF) need to collect recursively time-historic data, to update covariance vectors, and to treat heavy computation matrices. Computation burden mitigates the state-of-the-art utilizations of DSE in real large-scale networks although DSE was introduced several decades ago. In this paper, an improvement of DSE by using Unscented Kalman Filter (UKF) to alleviate computation burden will be discussed. The UKF-based approach avoids using linearization procedure thus outperforms the EKF-based approach to cope with non-linear models. Performance of the method is investigated with a simulation on a 18-bus test network. Preliminary results have been gained through a case study that motivate further research on this approach.

Index Terms-- State Estimation, Dynamic State Estimation, Extended Kalman Filter, Unscented Kalman Filter, Renewable Energy Sources.

I. INTRODUCTION

CONSIDERING massive integration of the variable and unpredictable Renewable Energy Source (RES) and new types of load consumptions, e.g. heat pumps, electric vehicles, the electric power grid is becoming much more complex and dynamic. Real-time control and operation are playing an important role to reduce consequences of intermittency and uncertainty in such new context of smart grids. These functions require advanced techniques to not only estimate system state variables but also predict their trends steps ahead [1]. By improving the monitoring capability of the grid, control action will be trigger in real-time thus improve system reliability and stability.

Static State Estimation (SSE) provides a snapshot of power system operating point reflected by state variables, e.g. bus voltage magnitudes and phase angles, based on a set of measurements, e.g. voltage magnitudes, power flows, and

power injections. SSE was first introduced by Schweppe and Wildes based on Weighted Least Square (WLS) in 1970 [2]. In an effort to reduce computation burden, several hierarchical estimation methods were then proposed and summarized in [3]. Distributed approaches for SSE have gained also significant interest to comply state variables from different network areas on different voltage levels [4]. According to the way of defining network areas, different distributed algorithms for SSE were proposed. In [5], Ebrahimian and Baldick introduced a robust algorithm based on linear augmented Lagrangians for overlapping bus boundaries. Conejo et. al. presented a straight forward and effective algorithm for overlapping tie-line boundaries in [6]. By using Multi-Agent System technology, Nordman and Lehtonen proposed a new approach for distributed SSE in [7]. In our previous research work, this idea was extended with completely decentralized SSE method in [8]. Further information about static state estimation can be referred from [9].

SSE has been utilized widely in the past due to its reliable capability and reasonable accuracy for quasi static situation. For online and real-time applications, SSE has to be repeated in a small enough Δt time step (sampling time), which leads to undesirable property [10]. Actually, this kind of succession static estimators, so-called tracking estimator algorithms, can provide only information about static steady-state variables. Nowadays with highly dynamic nature of smart grids, this traditional approach might be an obstacle for advanced real-time control functions desired for the complex and uncertain electric power system.

Dynamic State Estimation (DSE) was also introduced early in 1970 by Debs and Larson with a relative simplified model for tracking state vectors in [10]. Leite da Silva et. al. extended the approach with a focus on forecasting and filtering the state vectors by using exponential smoothing and least-square estimation [11]. Since then, DSE has been known as an alternative state estimation approach that is able to predict state vectors one time step ahead based on the priori knowledge and be corrected with next measurement sets. Depending on the techniques, estimated variables of DSE can be either static state variable, e.g. bus voltage magnitudes and phase angles, or dynamic state variables, e.g. speed variables of generators.

In general, the DSE model is based on the Extended Kalman Filtering (EKF) theory including three main steps of parameter identification, state forecasting/prediction, and state filtering/correction. However, EKF needs to collect recursively time-historic data, to update covariance vectors

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and to treat heavy computation matrices. These steps mitigate the application of EKF in real large-scale power systems.

Recent applications of Unscented Transformation techniques improve significantly the performance of Kalman Filter based estimation for DSE. Valverde and Terzija have shown the advantage of the Unscented Kalman filter (UKF) over EKF and WLS methods [12]. In [13], the capability of UKF for addressing dynamic variables, e.g. speed variables, internal voltage value, etc. was presented a simplified simulation including a small number of generators. Another research focusing on the generator variables was introduced in [14]. In all research works, UKF showed its advantage in terms of robustness, speed of converge, and bad data identification compared with the classical EKF-based method.

In this paper, a detailed model for DSE will be presented including three main steps of parameter identification, state prediction, and state correction. The paper will focus on advanced utilization of UKF and adapt this advanced technique in three mentioned steps. Combination of UKF with neural network models will be discussed to improve the performance of DSE in estimating and predicting system state.

II. DYNAMIC STATE ESTIMATION

A dynamic model that provides a more complete way of monitoring system operating conditions than the static one, can be represented by a process equation (1) and a measurement equation (2) as follows:

$$\mathbf{x}_{k+1} = \mathbf{f}(k, \mathbf{x}_k) + \mathbf{q}_k \quad (1)$$

$$\mathbf{z}_k = \mathbf{h}(k, \mathbf{x}_k) + \mathbf{r}_k \quad (2)$$

where k is the time sample; \mathbf{x}_k is the state vector; \mathbf{q}_k represents modeling uncertainties, corresponding to a white Gaussian noise with zero mean and covariance matrix \mathbf{Q}_k ; \mathbf{z}_k is the measurement vector; \mathbf{h} is a set of nonlinear load-flow functions for the current network configuration; \mathbf{r}_k is a Gaussian error vector, with zero mean and diagonal covariance matrix \mathbf{R}_k .

In this state-space model, equation (1) can be interpreted as the memory of the system state time evolution and equation (2) is considered as its refreshment. Such memory will be responsible for the forecasting capability of the model. Depending on availability of measurements, the model can be adequacy or parsimony.

The basic idea of state estimation function is to determine the most likely system state vector \mathbf{x} , including either static steady-state variables or dynamic state variables:

$$\mathbf{x} = [\boldsymbol{\theta}_i, \mathbf{V}_i, \mathbf{P}_{inject}, \boldsymbol{\omega}_i, \boldsymbol{\delta}_i]^T,$$

based on the quantities, that are measured and acquired by remote terminal units (RTU), are presented as:

$$\mathbf{z} = [\mathbf{V}, \mathbf{P}_{flow}, \mathbf{Q}_{flow}, \mathbf{P}_{inject}, \mathbf{Q}_{inject}]^T.$$

While SSE based on WLS provides only a snapshot of the current state vector, i.e. \mathbf{x}_k at a certain time k , DSE aims to provide not only time-varying solutions but also predict the future operating points of the system. The idea of one step ahead prediction recently mentioned by Venayagamoorthy et. al in [1] is crucial to enable real-time operation and control functions. It is an overview about several previous works

using neural network models for dynamic state estimation of generators, with a special focus on wind turbine. This paper adopts and extends the idea to get early predictions for having time to allocate optimally distributed resources.

A. EKF-based DSE

As the most popular approach to handle complexity of the above model, the EKF-based method is to simplify equation (1), with the assumption of the quasi steady-state behavior of the system, as follows:

$$\mathbf{x}_{k+1} = \mathbf{F}_k \mathbf{x}_k + \mathbf{g}_k + \mathbf{q}_k \quad (3)$$

where matrix \mathbf{F}_k represents how fast the transition between states are; vector \mathbf{g}_k is associated with the trend behavior of the state trajectory.

DSE depends heavily on the forecasting technique adopted [15]. Different forecasting techniques can be applied for the estimation of \mathbf{F}_k , \mathbf{g}_k , and \mathbf{Q}_k . Kalman filter in [16], exponential smoothing in [11], and artificial neural networks (ANN) in [17]–[18], have been successfully utilized under this context. In general, DSE is achieved by implementing three steps, i.e. parameter identification, state prediction (forecasting), and state correction (filtering). The DSE process can be illustrated in Fig. 1.

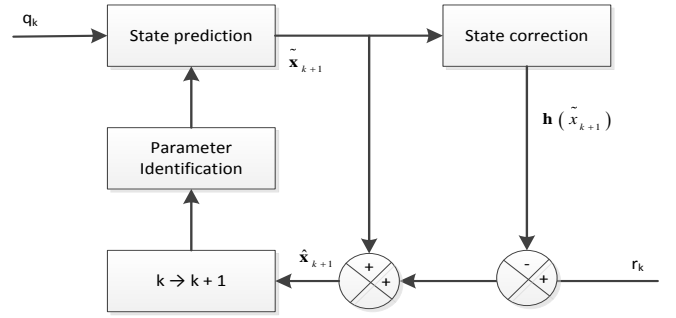


Fig. 1. Dynamic state estimation process.

1) Step 1 – Parameter identification

Parameter identification aims to estimate values of \mathbf{F}_k , \mathbf{g}_k , and \mathbf{Q}_k that are used for the state prediction step. Considering an application of Holt's linear exponential smoothing technique, values of \mathbf{F}_k and \mathbf{g}_k can be obtained as follows:

$$\mathbf{F}_k = \alpha_k (1 + \beta_k) \mathbf{I} \quad (4)$$

$$\mathbf{g}_k = (1 + \beta_k) (1 - \alpha_k) \mathbf{x}_k^- - \beta_k \mathbf{a}_{k-1} + (1 - \beta_k) \mathbf{b}_{k-1} \quad (5)$$

where \mathbf{I} is the identity matrix, and all associated parameters can be calculated based on priori knowledge, see more details in [11]. This technique can give a prediction at a very short-term (few minutes ahead) step although the implementation is rather simple. However, this linearization step that aims for the quasi steady-state model might not be suitable for significant dynamic situations.

2) Step 2 - State prediction (forecasting)

At this stage, state vector $\tilde{\mathbf{x}}_{k+1}$ is predicted with its covariance matrix $\mathbf{P}_{\tilde{\mathbf{x}}_{k+1}}$ by following equations:

$$\tilde{\mathbf{x}}_{k+1} = \mathbf{F}_k \hat{\mathbf{x}}_k + \mathbf{g}_k \quad (6)$$

$$\mathbf{P}_{\tilde{\mathbf{x}}_{k+1}} = \mathbf{F}_k \mathbf{P}_{\hat{\mathbf{x}}_k} \mathbf{F}_k^T + \mathbf{Q}_k. \quad (7)$$

while $\mathbf{P}_{\tilde{\mathbf{x}}_k}$ is the covariance matrix to estimate $\hat{\mathbf{x}}_k$ at time k .

State prediction is an interesting area that the computational intelligence (CI) can be exploited. ANN as a typical application of CI has been extensively studied in [17]-[18]. The prediction model can be improved by integrating load forecasting, that has been proposed as a concept of forecasting-aided state estimation (FASE) in [15].

3) Step 3 - State correction (filtering)

By updating a new set of measurements \mathbf{z}_{k+1} , the predicted state vector $\tilde{\mathbf{x}}_{k+1}$ can be corrected (filtered) leading to a new state vector $\hat{\mathbf{x}}_{k+1}$ with its error covariance $\mathbf{P}_{\hat{\mathbf{x}}_{k+1}}$. An objective function for correcting process, at time $k+1$, is presented as follows:

$$\mathbf{J}(x) = [z - \mathbf{h}(x)]^T \mathbf{R}^{-1} [z - \mathbf{h}(x)] + [x - \tilde{x}]^T \mathbf{P}_{\tilde{x}}^{-1} [x - \tilde{x}] \quad (8)$$

where the time index $k+1$ has been omitted for simplification; and \mathbf{R} is variance vector of the measurement errors.

Similar to WLS estimation for SSE, minimization of $\mathbf{J}(x)$ leads to an iterative solution, i.e. iterated extended Kalman filter, as follows:

$$\hat{\mathbf{x}}_{k+1} = \tilde{\mathbf{x}}_{k+1} + \mathbf{K}_{k+1} [\mathbf{z}_{k+1} - \mathbf{h}(\tilde{\mathbf{x}}_{k+1})]. \quad (9)$$

The gain matrix \mathbf{K}_{k+1} is computed by following equation:

$$\mathbf{K}_{k+1} = [\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H} + \mathbf{P}_{\tilde{\mathbf{x}}}^{-1}]^{-1} \mathbf{H}^T \mathbf{R}^{-1} \quad (10)$$

where, $\mathbf{H}_{k+1} = \frac{\partial \mathbf{h}(x)}{\partial x}$: Jacobian matrix.

Respectively to $\hat{\mathbf{x}}_{k+1}$, its error covariance matrix $\mathbf{P}_{\hat{\mathbf{x}}_{k+1}}$ is computed as follows:

$$\mathbf{P}_{\hat{\mathbf{x}}_{k+1}} = [\mathbf{H}^T \mathbf{R}^{-1} \mathbf{H} + \mathbf{P}_{\tilde{\mathbf{x}}}^{-1}]^{-1}. \quad (11)$$

B. UKF-based DSE

Basically, EKF is an extension of Kalman filtering through a linearization procedure to solve nonlinear models. Though this approach has been considered feasibly, it provides only an approximation to optimal nonlinear estimation. It causes to biased estimates and erroneous covariance [1]. Furthermore, calculation of the Jacobian matrix \mathbf{H}_{k+1} for each time step could also slow down the process of DSE.

UKF-based DSE is an improvement to cope with non-linear nature of DSE. Based on the unscented transformation (UT) theory, the approach propagates statistical distribution of the state via non-linear equations to provide better results. Above three main steps of DSEs will be adjusted according to UT technique as follows:

1) Step 1 - Parameter identification (including sigma points calculation)

Besides identifying \mathbf{F}_k and \mathbf{g}_k , this stage includes also sigma point calculation. From the current state vector $\hat{\mathbf{x}}_k$ and its

covariance $\mathbf{P}_{\hat{\mathbf{x}}_k}$, UT propagate statistical distribution to form a matrix \mathbf{X}_k of $2N+1$ sigma vectors as follows:

$$\mathbf{X}_k = \begin{bmatrix} \hat{\mathbf{x}}_k & \hat{\mathbf{x}}_k \sqrt{(N+\lambda)\mathbf{P}_{\hat{\mathbf{x}}_k}} & -\hat{\mathbf{x}}_k \sqrt{(N+\lambda)\mathbf{P}_{\hat{\mathbf{x}}_k}} \end{bmatrix} \quad (12)$$

where $\lambda = \alpha^2(N+\kappa) - n$ is a scaling parameter with the spreading constant α ($10^{-4} \leq \alpha \leq 1$) and the secondary scaling κ (usually, $\kappa = 3 - n$).

2) Step 2 - State prediction (forecasting)

From the sets of sigma points in (11), the prediction step in (5) is adjusted as follows:

$$\tilde{\mathbf{X}}_{k+1}^i = \mathbf{F}_k \mathbf{X}_k^i + \mathbf{g}_k \quad (13)$$

$$\tilde{\mathbf{x}}_{k+1} = \sum_{i=0}^{2N} W_i^m \tilde{\mathbf{X}}_{k+1}^i \quad (14)$$

$$\mathbf{P}_{\tilde{\mathbf{x}}_{k+1}} = \sum_{i=0}^{2N} W_i^c (\tilde{\mathbf{X}}_{k+1}^i - \tilde{\mathbf{x}}_{k+1}) (\tilde{\mathbf{X}}_{k+1}^i - \tilde{\mathbf{x}}_{k+1})^T + \mathbf{Q}_k. \quad (15)$$

with weighting factors given by

$$W_0^m = \frac{\lambda}{N+\lambda};$$

$$W_0^c = \frac{\lambda}{N+\lambda} + 1 - \alpha^2 + \beta;$$

$$W_k^m = W_k^c = \frac{1}{2(N+\lambda)}.$$

3) Step 3 - State correction (filtering)

From predicted state vector $\tilde{\mathbf{x}}_{k+1}$ and its covariance \mathbf{M}_{k+1} , a new set of sigma points is generated as:

$$\hat{\mathbf{X}}_{k+1} = \begin{bmatrix} \tilde{\mathbf{x}}_{k+1} & \tilde{\mathbf{x}}_{k+1} \sqrt{(N+\lambda)\mathbf{P}_{\tilde{\mathbf{x}}_{k+1}}} & -\tilde{\mathbf{x}}_{k+1} \sqrt{(N+\lambda)\mathbf{P}_{\tilde{\mathbf{x}}_{k+1}}} \end{bmatrix} \quad (16)$$

to be propagated through the measurement-update equations:

$$\hat{\mathbf{Y}}_{k+1}^i = \mathbf{h}(\hat{\mathbf{X}}_{k+1}^i) \quad (17)$$

$$\hat{\mathbf{y}}_{k+1} = \sum_{i=0}^{2N} W_i^m \hat{\mathbf{Y}}_{k+1}^i \quad (18)$$

$$\mathbf{P}_{\hat{\mathbf{y}}_{k+1}} = \sum_{i=0}^{2N} W_i^c (\hat{\mathbf{Y}}_{k+1}^i - \hat{\mathbf{y}}_{k+1}) (\hat{\mathbf{Y}}_{k+1}^i - \hat{\mathbf{y}}_{k+1})^T + \mathbf{R}_k \quad (19)$$

$$\mathbf{P}_{\tilde{\mathbf{x}}_{k+1} \hat{\mathbf{y}}_{k+1}} = \sum_{i=0}^{2N} W_i^c (\tilde{\mathbf{X}}_{k+1}^i - \tilde{\mathbf{x}}_{k+1}) (\hat{\mathbf{Y}}_{k+1}^i - \hat{\mathbf{y}}_{k+1})^T \quad (20)$$

Then, the gain matrix \mathbf{K}_{k+1} is calculated as:

$$\mathbf{K}_{k+1} = \mathbf{P}_{\tilde{\mathbf{x}}_{k+1} \hat{\mathbf{y}}_{k+1}} \mathbf{P}_{\hat{\mathbf{y}}_{k+1}}^{-1} \quad (21)$$

Correction of the state vector and its covariance are calculated by following equations:

$$\hat{\mathbf{x}}_{k+1} = \tilde{\mathbf{x}}_{k+1} + \mathbf{K}_{k+1} (\hat{\mathbf{Y}}_{k+1}^i - \hat{\mathbf{y}}_{k+1}) \quad (22)$$

$$\mathbf{P}_{\hat{\mathbf{x}}_{k+1}} = \mathbf{P}_{\tilde{\mathbf{x}}_{k+1}} - \mathbf{K}_{k+1} \mathbf{P}_{\hat{\mathbf{y}}_{k+1}} \mathbf{K}_{k+1}^T. \quad (23)$$

III. A CASE STUDY

In this section, performance of UKF is investigated with a simulation on a 18-bus distribution grid, as shown in Fig. 2.

This test network is modified from the IEEE 34-bus test network [19] with some simplifications as follows [20]:

- Distributed loads will be approximately placed one-third at the end of the line and two-thirds at one-fourth of the way from the source end;
- Only the main three phase sections are included, the unbalance phase loads are summed up at the root;
- Constant PQ loads are represented by dynamic load models. Constant Z loads are represented by passive resistors and inductors. Constant I loads are neglected.

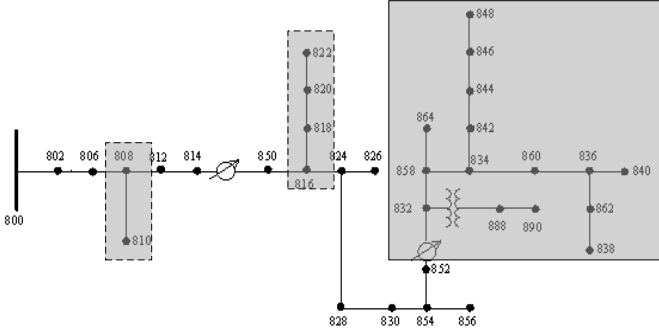


Fig. 2. Single-line diagram of the 18-bus test network modified from the IEEE 34-bus network by representing shading areas as equivalent buses. Note that placements of distributed loads will create additional buses in some line sessions.

Network model is built in a real-time simulation on the Real-Time Digital Simulation (RTDS) platform. To perform the slow dynamics of the system, 50 time-sample intervals with the time resolution of 0.08 sec. were obtained from the RTDS platform. During the simulation time, there is a voltage drop occurring at bus 800. To have realistic measurement data, values of bus voltages, power flows, and power injections from the simulation are interfered with random additive Gaussian noise: $N(0;0.1\%)$.

Fig. 3 shows the true value of voltage magnitude at bus 800 and its predicted and corrected values by using UKF. After some first time samples, the state vector is predicted quite close to the true value during steady-state operating points. Even with a significant event occurring, prediction performs relative good result and it is able to track new operating points. Fig. 3 shows also outperformance of the corrected state vector compared with the predicted state vector especially in transient periods of the system.

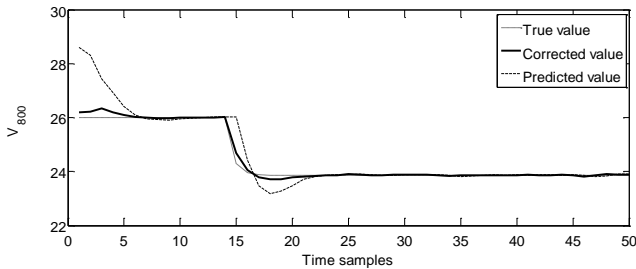


Fig. 3. Comparison of the true value with predicted and corrected values - voltage magnitude at bus 800.

To evaluate the accuracy of estimator, an overall performance index is calculated as follows:

$$J_k = \frac{\sum |\hat{\mathbf{y}}_{k+1}^i - \mathbf{y}_{k+1}^{i,true}|}{\sum |\mathbf{y}_{k+1}^i - \mathbf{y}_{k+1}^{i,true}|} \quad (23)$$

where $\mathbf{y}_{k+1}^{i,true}$ is the true vector of measurements; \mathbf{y}_{k+1}^i is the noisy measurement vector. Fig.4 presents the performance index of the method over 50 time samples.

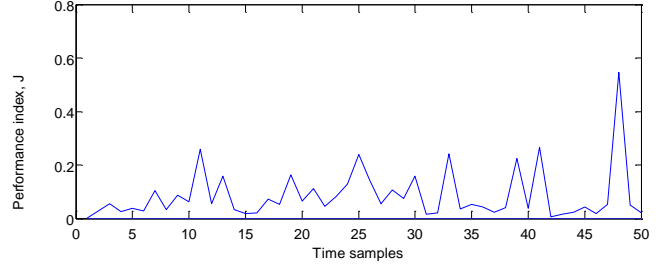


Fig. 4. Performance index over time simulation.

IV. CONCLUSION AND DISCUSSIONS

This paper addresses the important role of DSE in estimating accurate state variables at the right moment and predicting their trends steps ahead for real-time control and operation. A UKF-based DSE has been introduced to overcome difficulties when using the EKF-based approach. The proposed approach requires less computing effort while outperforms the former one in non-linear models such as DSE. Performance of the method has been verified by a simulation with a 18-bus test network. Preliminary results have shown feasibility of UKF in estimating and predicting dynamic state of the power grid.

In future work, a combination of UKF with Recurrent Neural Network (RNN) might be considered for improving DSE function. More specifically, UKF can be used to support on-line training process of RNN mentioned in [21].

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