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Identification of synchronous generator model with frequency control using unscented Kalman filter

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ABSTRACT

In this paper, phasor measurement unit (PMU) data-based synchronous generator model identification is carried out using unscented Kalman filter (UKF). The identification not only gives the model of a synchronous generator's swing dynamics, but also gives its turbine-governor model along with the primary and secondary frequency control block models. PMU measurements of active power and voltage magnitude, are treated as the inputs to the system while the measurements of voltage phasor angle, reactive power and frequency are treated as the outputs. UKF-based estimation is carried out to estimate the dynamic states and the parameters of the model. The estimated model is then built and excited with the injection of the inputs from the PMU measurements. The outputs of the estimation model and the outputs from the PMU measurements are compared. Case studies based on PMU measurements collected from a simulation model and real-world PMU data demonstrate the effectiveness of the proposed estimation scheme.

1. Introduction

Supervisory control and data acquisition (SCADA) systems use nonsynchronous data with low density sampling rate to monitor power systems. The measurements collected from SCADA cannot capture the system dynamics. Phasor measurement units (PMUs) equipped with GPS antenna provide voltage and current phasors as well as frequency with a high density sampling rate up to 60 Hz. PMU data can capture the system electromechanical dynamics. In this paper, PMU data will be used for synchronous generator parameter estimation.

Synchronous generator parameter estimation has been investigated in the literature. Based on the scope of estimation, some only investigated electrical state estimation (*e.g.* rotor angle and rotor speed) [1,2], while others estimated both system states and generator parameters [3–6]. Based on estimation methods, there are at least two major systematic methods for parameter estimation: least squares estimation (LSE) [7–9] and Kalman filter-based estimation [10–14]. To use LSE for dynamic system parameter estimation, a window of data is required. On the other hand, Kalman filter-based estimation can carry out estimation procedures at each time step. Thus Kalman filter-based estimation can be used for online estimation. This is also one of the reasons why PMU data-based system identification opts for Kalman filter-based estimation [10–14].

Kalman filter was originally proposed for the linear systems. For nonlinear systems, there are two approaches to handle nonlinearity: extended Kalman filter (EKF) and unscented Kalman filter (UKF). In EKF, nonlinear systems are approximated by linear systems using linearization techniques. EKF was first applied by PNNL researchers in dynamic model identification using PMU data [5,6,10]. Huang et al. [5] focuses on parameter calibration for a simple generator dynamic model. Kalsi et al. [6] present parameter calibration for a multi-machine power system under varying fault locations, parameter errors and measurement noises. In [10], parameter calibration for a more complicated generator model which includes electromechanical dynamics, electromagnetic dynamics, exciter dynamics, voltage control blocks and power system stabilizer (PSS), was presented. EKF-based simple generator model estimation was also carried out in [12,11]. Limitations of EKF method have also been investigated in [11].

In UKF, a nonlinear system model will not be linearized. The stochastic characteristic of a random variable is approximated by a set of sigma points. This technique is essentially Monte-Carlo simulation technique. Dynamic process of these sigma points will be computed based on the nonlinear estimation model. Statistic characteristics of the dynamic process will then be evaluated. UKF can overcome the limitation of the linearization process required by the

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EKF method. However, more computing effort is required due to the introduction of sigma points. In [13], UKF is applied for state estimation. Accuracy and convergence for both EKF and UKF are compared in [13]. This paper focuses on state estimation only. Parameter estimation was not discussed. In [14], UKF is applied to estimate the following parameters E_q, x'_d and H along with states. A comparison of various Kalman filter methods is documented in [15].

The synchronous generator model identified in the aforementioned papers focuses on the generator electromechanical, electromagnetic and excitation system only. For example, a 4th order transient generator estimation model is assumed in [15]; a subtransient generator estimation model is adopted in [10]. None has addressed frequency control system identification. The goal of this paper is to apply UKF for parameter and state estimation for a synchronous generator model consisting of electromechanical dynamics and frequency control. Contributions of this paper are summarized in the following paragraphs.

- Not only electromechanical dynamics related states and parameters, but also turbine-governor dynamics, primary and secondary frequency control parameters will be estimated. Estimation related to frequency control based on PMU data has not been seen in the literature.
  Particularly, we will estimate the following parameters and states: inertia constant H, damping factor D, internal voltage E_q, transient reactance x'_d, mechanical power input P_m, Droop regulation R, turbine-governor time constant T_r, and secondary frequency control integrator gain K_i.
  Some parameters are difficult to estimate due to nonlinearity. Parameters conversion is adopted in this paper in order to make estimation easier.
- Event playback method [10] is used in this paper to validate the identified low-order model. For validation, estimated parameters will be used to create a dynamic simulation model. Then event playback will be used to inject the same inputs to the dynamic simulation model. The output signals from the simulation will be compared with the PMU measurements.
- Lastly, real-world PMU data-based identification will be used to demonstrate the effectiveness of the proposed estimation model.

This paper is organized as follows. Following a description of basics of UKF algorithm in Section 2, the implementation of UKF for dynamic generator model estimation is discussed in Section 3. Section 4 presents the validation process and case studies. Finally, Section 5 presents the conclusions of this paper.

2. Basic algorithm of UKF

A continuous nonlinear dynamic system is represented by the following equations.

$$\begin{cases} \dot{x}(t) = \bar{f}[x(t), u(t), v(t)] \\ y(t) = h[x(t), u(t), v(t)] + w(t) \end{cases} \tag{1}$$

where $x(t)$ is the vector of state variables, $y(t)$ is the vector of output variables, $u(t)$ is the vector of input variables, $v(t)$ is the non-additive process noise, and $\omega(t)$ is additive measurement noise. Considering the time step of Δt, (1) can be written as (2) in the discrete time domain:

$$\begin{cases} x_k &= x_{k-1} + \bar{f}[x_{k-1}, u_{k-1}, v_{k-1}]\Delta t \\ &= f[x_{k-1}, u_{k-1}, v_{k-1}] \\ y_k &= h[x_k, u_k, v_k] + w_k \end{cases} \tag{2}$$

The state x_k is considered as a random variable vector with an estimated mean value $\hat{x}_k$ and an estimated co-variance P_{x_k}. Vector ψ_k is considered as a set of unknown model parameters. For simplification, ψ_k can also be treated as states, where $\psi_{k+1} = \psi_k$. Then, the new state vector is $X_k = \begin{bmatrix} {x_k}^T & {\psi_k}^T \end{bmatrix}^T$. The state-space model in (2) is reformulated as:

$$\begin{cases} X_k = f[X_{k-1}, u_{k-1}, v_{k-1}] \\ y_k = h[X_k, u_k, v_k] + w_k \end{cases} \tag{3}$$

Kalman filter is a recursive estimation algorithm. At each time step, given the previous step's information, such as the mean of the state $\hat{X}_{k-1}$, the covariance of the state $P_{X_{k-1}}$, Kalman filter estimation will provide the statistic information of the current step, *i.e.*, the mean of the state $\hat{X}_k$ and the covariance of the state P_{X_k}. Usually a prediction step estimates the information based on the dynamic model only, and a correction step corrects the information based on the current step's measurements. There are several references for UKF algorithm in literatures. For rest of this section, [16] is the reference for all UKF algorithm related equations.

Unscented Kalman filter (UKF) is a Monte-Carlo simulation method. A set of sigma points will be generated based on the given statistic information: mean and covariance of the states. Sigma point vectors will emulate the distribution of the random variable. The set of sigma points is denoted by χ^i and their mean value represented by $\hat{X}$ while their covariance represented by P_X. For n number of state variables, a set of $2n+1$ points are generated based on the columns of matrix $\sqrt{(n+\lambda)P_X}$. As shown below, at $k-1$ step, $2n+1$ sigma points (vectors) are generated.

$$\begin{cases} \chi^0_{k-1} = \hat{X}_{k-1} \\ \chi^i_{k-1} = \hat{X}_{k-1} + \left[\sqrt{(n+\lambda)P_{X_{k-1}}}\right]_i, & i = 1, \ldots, n \\ \chi^{i+n}_{k-1} = \hat{X}_{k-1} - \left[\sqrt{(n+\lambda)P_{X_{k-1}}}\right]_{i+n}, & i = 1, \ldots, n \end{cases} \tag{4}$$

where λ is a scaling parameter ($\lambda = \alpha^2(n+\kappa) - n$), α and κ are positive constants. In the *prediction* step, prediction of the next step state will be carried out for all these sigma points. Based on the information of the sigma points of the next step, the mean and the covariance of the states will be computed. UKF will use weights to calculate the predicted mean and covariance. The associated weights are as follows.

$$\begin{cases} W_{m_0} = \dfrac{\lambda}{(n+\lambda)} \\ W_{c_0} = \dfrac{\lambda}{(n+\lambda)} + (1 - \alpha^2 + \beta) \\ W_{m_i} = \dfrac{1}{2(n+\lambda)}, & i = 1, \ldots, 2n \\ W_{c_i} = \dfrac{1}{2(n+\lambda)}, & i = 1, \ldots, 2n \end{cases} \tag{5}$$

where β is a positive constant, W_{m_i} is used to compute the mean value, and W_{c_i} is used to compute the covariance matrix. α, κ and β are the Kalman filter parameters which can be used to tune the filter. Scaling parameter β is used to incorporate prior knowledge of the distribution of $x(k)$ and for Gaussian distribution $\beta = 2$ is optimal [18]. The scaling parameter α is a positive value used for an arbitrary small number to a minimum of higher order effects. To choose α, two laws have to be take into accounts. First, for all choices of α, the predicted covariance must be defined as a positive semidefinite. Second, The order of accuracy must be preserved for both the mean and covariance [17]. See [18,17] for more details regarding