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Dynamic state estimation in power systems: Modeling, and challenges

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ABSTRACT

This paper proposes Extended Kalman Filter (EKF) based dynamic state estimator for power systems using phasor measurement unit (PMU) data. Dynamic state estimation in power systems provides synchronized wide area system history of the dynamic events which is key in the analysis and understanding of the system performance, behavior, and the types of control decisions to be made for large scale power system contingencies. In this paper, 2-axis-fourth-order state space modeling and validation of the synchronous machine is explained in detail. The model is then used for dynamic state estimation using EKF in IEEE 3-Generator-9-Bus Test System. The simulation results show that the model and estimation approach are capable to provide accurate information about the states of the machine and eliminate the noise effects on the measurement signal. The main challenges of dynamic estimation in large power systems are also addressed in this paper.

1. Introduction

Extended Kalman Filter (EKF) has been among the most referred estimation approaches for dynamic state estimation in power systems [1,2]. The advent of Phasor Measurement Units (PMUs) [3] has facilitated online state estimation in large scale power systems which was previously impossible using low rate and non-synchronous data provided by Supervisory Control and Data Acquisition (SCADA) systems. As the number of installed PMUs are gradually increasing worldwide, real time estimation in large interconnected power grids is becoming more realistic [2]. PMU is a recently developed power system measurement device that samples input three phase voltage and current waveforms, using a common synchronizing signal received by Global Positioning System (GPS), and calculates the phasors (magnitudes and angles) of the bus by deploying Discrete Fourier Transform [3]. Different estimation approaches and case studies have been used to investigate dynamic state estimation in power systems. Feasibility studies of applying Extended Kalman Filter (EKF) to IEEE 3-Generator-9-Bus Test System using classical model of the synchronous generator are investigated in [1]. EKF with unknown input is the estimation approach for Single-Machine-Infinite-Bus (SMIB) in [2]. Another form of nonlinear Kalman Filter, Unscented Kalman Filter (UKF), is used to design an observer for different power system case studies using the PMU installed on the main bus of the generator [4–6]. In [7], a divide-by-difference-filter based algorithm is proposed for dynamic estimation of the generator rotor angle in a large power system. The results of state estimation in a SMIB using extended particle filter are also presented in [8]. Simulations are performed on 2-axis-fourth-order state space model of the synchronous machine in [2,6] using either EKF or UKF to design dynamic state estimator for various power systems.

The paper is organized as follows. In Section 2, mathematical description of the synchronous generator is explained and the 2-axis-fourth-order state space model of the machine is derived. EKF principles and equations are presented in Section 3. Section 4 presents simulation results for IEEE 3-Generator-9-Bus Test System. Section 5 presents an application and the major challenges of dynamic state estimation in power systems. Section 6 concludes the paper.

2. Single-machine-infinite-bus state space model

Fig. 1 shows a simplified equivalent model of a general power system which is a single generator connected through a transformer and parallel transmission lines to infinite bus. The classical dynamic model of the synchronous machine is as follows [9]:

$$\frac{d\delta}{dt} = \omega_0 \Delta\omega \tag{1}$$

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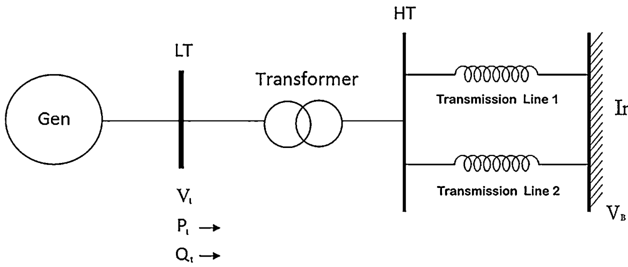

Fig. 1. Single-Machine-Infinite-Bus (SMIB) diagram [2].

$$\frac{d\Delta\omega}{dt} = \frac{1}{2H}(P_m - P_e - D\Delta\omega) \tag{2}$$

In this model, D and H are damping factor and inertia constant, $\Delta\omega$ is the per unit rotor speed deviation, δ is the rotor angle, and P_m and P_e are the power provided by the prime mover and the electrical output power of the generator both in per unit. The next step is to develop the 2-axis-fourth-order model of the synchronous generator which includes e'_q and e'_d, the q and d axis components of the generator internal voltage. Based on the phasor diagram of the synchronous machine, equations describing the q and d axis components of the generator internal voltage and their first order differential equations are given in Eqs. (3)–(6) [9].

$$e'_q = e_q + R_a i_q + x'_d i_d \tag{3}$$

$$e'_d = e_d + R_a i_d + x'_q i_q \tag{4}$$

$$\frac{de'_q}{dt} = \frac{1}{T'_{do}}(E_{fd} - e'_q - (x_d - x'_d)i_d) \tag{5}$$

$$\frac{de'_d}{dt} = \frac{1}{T'_{qo}}(-e'_d + (x_q - x'_q)i_q) \tag{6}$$

x_d and x_q are direct and quadratic axis reactances, and x'_d and x'_q are direct and quadratic axis transient reactances, all in per unit. Also, T'_{do} and T'_{qo} are direct and quadratic axis transient open circuit time constants in second. δ is defined as the angle such that e'_q, the q axis component of the voltage behind the transient reactance x'_d, leads the terminal bus E_t or V_t, and E_{fd} is the field voltage of the machine. Considering the phasor diagram of the synchronous machine, the d-axis and q-axis voltages (e_d, e_q) can be expressed as [2,10]

$$\begin{cases} e_d = V_t \sin(\delta) \\ e_q = V_t \cos(\delta) \end{cases} \rightarrow E_t = V_t = \sqrt{e_d^2 + e_q^2} \tag{7}$$

In addition, the d-axis and q-axis currents (i_d, i_q) are [2,10]

$$\begin{cases} i_d = I_t \sin(\delta + \phi) \\ i_q = I_t \cos(\delta + \phi) \end{cases} \rightarrow I_t = \sqrt{i_d^2 + i_q^2} \tag{8}$$

Using Eqs. (3), (4) and (7) and by neglecting the stator resistance ($R_a = 0$), i_d and i_q can be written as

$$i_d = \frac{e'_q - V_t \cos(\delta)}{x'_d} \tag{9}$$

$$i_q = \frac{V_t \sin(\delta) - e'_d}{x'_q} \tag{10}$$

The air gap torque T_e of the generator in per unit is equal to the terminal power P_e or P_t (generator terminal electrical power) [2]. Therefore, it is obtained

$$T_e = P_t + R_a I_t^2 \xrightarrow{R_a=0} T_e \cong P_t = e_d i_d + e_q i_q \tag{11}$$

Eqs. (7), (9) and (10) are inserted into Eq. (11) to obtain

$$T_e \cong P_t = \frac{V_t}{x'_d} e'_q \sin(\delta) - \frac{V_t}{x'_q} e'_d \cos(\delta) + \frac{V_t^2}{2}\left(\frac{1}{x'_q} - \frac{1}{x'_d}\right)\sin(2\delta) \tag{12}$$

Using Eqs. (1), (2), (5), (6), (9) and (10), the fourth order model of a synchronous generator is derived as follows:

$$\begin{aligned} &\frac{d\delta}{dt} = \omega_0 \Delta\omega \\ &\frac{d\Delta\omega}{dt} = \frac{1}{2H}\left(P_m - \frac{V_t}{x'_d} e'_q \sin(\delta) + \frac{V_t}{x'_q} e'_d \cos(\delta) - \frac{V_t^2}{2}\left(\frac{1}{x'_q} - \frac{1}{x'_d}\right)\sin(2\delta) - D\Delta\omega\right) \\ &\frac{de'_q}{dt} = \frac{1}{T'_{do}}\left(E_{fd} - e'_q + (x_d - x'_d)\left(\frac{e'_q - V_t \sin(\delta)}{x'_d}\right)\right) \\ &\frac{de'_d}{dt} = \frac{1}{T'_{qo}}\left(-e'_d + (x_q - x'_q)\left(\frac{V_t \sin(\delta) - e'_d}{x'_q}\right)\right) \end{aligned} \tag{13}$$

Eqs. (12) and (13) are used in a recursive EKF estimation program after being discretized with the first term of the Taylor Series.

3. Extended Kalman Filter algorithm

EKF is a powerful recursive algorithm for dynamic state estimation in nonlinear systems. This optimal estimation approach minimizes the covariance of squared error between real states and estimated ones. A nonlinear discrete stochastic difference equation and measurement equation can be generally presented in the following form [11]:

$$\begin{aligned} &x_{k+1} = f_k(x_k, u_k, w_k) \\ &y_{k+1} = h_{k+1}(x_{k+1}, v_{k+1}) \\ &w_k \sim (0, Q_k) \\ &v_k \sim (0, R_k) \end{aligned} \tag{14}$$

f is the nonlinear function of the states and inputs, x_{k+1} represents state vector, u_k is the control input vector, y_{k+1} is the output vector, w_k and v_k are the process and measurement noise, Q_k and R_k are the process and measurement noise covariance, and k is the time step for each iteration. EKF recursive algorithm is performed in two stages: time update and measurement update. As a result, the following steps can be applied to nonlinear system for dynamic state estimation [11,12].

1. The filter is initialized as follows:

$$\begin{aligned} &\hat{x}_0^+ = E(x_0) \\ &P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T] \end{aligned} \tag{15}$$

For $k = 1, 2, 3, \ldots, n$ the following stages are performed.

2. Partial derivative matrices of the system equation are obtained by Eq. (16).

$$\begin{aligned} &F_k = \left.\frac{\partial f_k}{\partial X}\right|_{\hat{x}_k^+} \\ &L_k = \left.\frac{\partial f_k}{\partial w}\right|_{\hat{x}_k^+} \end{aligned} \tag{16}$$

- Time update equations of EKF are as follows:

$$\begin{aligned} &P_{k+1}^- = F_k P_k^+ F_k^T + L_k Q_k L_k^T \\ &\hat{x}_{k+1}^- = f_k(\hat{x}_k^+, u_k, 0) \end{aligned} \tag{17}$$

- Partial derivative matrices of output equation are derived by Eq. (18).