Application of Kalman Filter for Parameter Estimation of Doubly-Fed Induction Generators in Wind Turbine Systems

Morteza Hadipour¹, M. R. Alizadeh Pahlavani², Hassan Meyar Naimi ³

1- Department of Electrical Engineering, Hamedan Branch, Islamic Azad University, Hamedan, Iran
   Email: Hadipour.morteza1365@gmail.com (Corresponding author)
2- Department of Electrical Engineering, Malek Ashtar University of Technology, Tehran, Iran
   Email: mr_alizadehp@iust.ac.ir
3- Department of Electrical Engineering, Hamedan Branch, Islamic Azad University, Hamedan, Iran
   Email: h_meyarnaimi@yahoo.com

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ABSTRACT:
In this paper presents a method for state estimation in doubly fed induction generators (DFIGs) using an Extended Kalman Filter and Unscented Kalman Filter. In this work, the conventional nonlinear state space model of a DFIG is augmented with different modes of estimates by using two methods (EKF and UKF) in order to estimate generator parameters such as rotor angle deviation, rotor speed, rotor position and etc. The effectiveness of this method is tested using MATLAB/Simulink.

KEYWORDS: Doubly-fed induction generator, Estimation, Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF)

1. INTRODUCTION
In a Fixed Speed Wind Turbine, the stator is connected to the grid directly and in a variable speed turbine the turbine control is done through a power electronic converter. Benefits using a variable speed turbine include better efficiency in energy, control of active and reactive power, lesser mechanical loads, pitch control, noise reduction. The DFIG is one of the machines which employ the principle of variable speed. The DFIG delivers power to the grid through both stator and rotor terminals. The stator is directly connected to the grid while the rotor is connected to the grid via power electronic converters. The stator winding is connected directly to the grid while rotor is fed via the AC/DC/AC converter at a variable frequency.

2. DOUBLY-FED INDUCTION GENERATOR (DFIG)

schematic of the doubly-fed induction generator with a back-to-back converter can be seen in Fig(1). The back-to-back converter consists of, machine-side converter (MSC) and grid-side converter (GSC), that are connected. Between the two converters a dc-link capacitor is placed, as energy storage, in order to keep the voltage variations in the dc-link voltage small.

The equivalent circuit of the doubly-fed induction generator, with inclusion of the magnetizing losses, can be seen in Fig (2). This equivalent circuit is valid for one equivalent Y phase and for steady-state calculations.
The equivalent circuit for the DFIG becomes the ordinary equivalent circuit for a cage-bar induction machine.

\[
V_s = R_s I_s + j \omega_1 L_{s\omega} I_s + j \omega_1 L_m (I_s + I_r + I_{Rm})
\]

\[
\frac{V_r}{S} = \frac{R_r}{S} I_r + j \omega_1 L_{r\omega} I_r + j \omega_1 L_m (I_s + I_r + I_{Rm})
\]

\[
0 = R_m I_{Rm} + j \omega_1 L_m (I_s + I_r + I_{Rm})
\]

Where the following notation is used.

- \(V_s\) stator voltage
- \(R_s\) stator resistance
- \(V_r\) rotor voltage
- \(R_r\) rotor resistance
- \(I_s\) stator current
- \(R_m\) magnetizing resistance
- \(I_{Rm}\) rotor current
- \(L_{s\omega}\) stator leakage inductance
- \(L_{r\omega}\) rotor leakage inductance
- \(s\) slip

The slip, \(s\), equals

\[
s = \frac{\omega_1 - \omega_2}{\omega_1}
\]

Where \(\omega_2\) is the rotor speed and \(\omega_2\) is the slip frequency. Moreover, if the air-gap flux, stator flux and rotor flux are defined as

\[
\Psi_m = L_m (I_s + I_r + I_{Rm})
\]

\[
\Psi_s = L_{s\omega} I_s + L_m (I_s + I_r + I_{Rm}) = L_{s\omega} I_s + \Psi_m
\]

\[
\Psi_r = L_{r\omega} I_r + L_m (I_s + I_r + I_{Rm}) = L_{r\omega} I_r + \Psi_m
\]

The equations describing the equivalent circuit, i.e.,

\[
V_s = R_s I_s + j \omega_1 \Psi_s
\]

\[
\frac{V_r}{S} = \frac{R_r}{S} I_r + j \omega_1 \Psi_r
\]

\[
0 = R_m I_{Rm} + j \omega_1 \Psi_m
\]

The resistive losses of the induction generator are

\[
P_{\text{loss}} = 3(R_s |I_s|^2 + R_r |I_r|^2 + R_m |I_{Rm}|^2)
\]

And it is possible to express the electro-mechanical torque, \(T_e\), as

\[
T_e = 3n_p \text{Im}[\Psi_m I_r^*] = 3n_p \text{Im}[\Psi_m I_r^*]
\]

Where \(n_p\) is the number of pole pairs.
2.2. Phase-Locked Loop (PLL)-Type Estimator [1]
A PLL-type estimator can be used for estimation of the angle and frequency of a signal, e.g., the synchronous frequency, \( \omega_1 \), and its corresponding angle, \( \theta_1 \). The PLL-type estimator used in this thesis is described by

\[
\frac{d\hat{\theta}_1}{dt} = \gamma_1 \epsilon
\]

\[
\frac{d\hat{\omega}_1}{dt} = \gamma_2 \epsilon
\]

(13)

(14)

Where \( \epsilon = \sin(\theta_1 - \hat{\theta}_1) \) and \( \theta_1 - \hat{\theta}_1 \) is the error in the estimated angle. In the above equations \( \gamma_1 \) and \( \gamma_2 \) are gain parameters. The notation "hat" indicates an estimated variable or parameter. If the true frequency and position are given by \( d\omega_1/dt = 0 \) and \( d\theta_1/dt = \omega_1 \), then it is shown estimation error equations for \( \omega_1 \)

\( \hat{\omega}_1 \) and \( \hat{\theta}_1 \) are asymptotically stable if \( \{\gamma_1, \gamma_2\} > 0 \). This implies that \( \hat{\omega}_1 \) and \( \hat{\theta}_1 \) will converge to \( \omega_1 \) and \( \theta_1 \) respectively, asymptotically. If the difference \( \theta_1 - \hat{\theta}_1 \) is small, it is possible to approximate

\[
\sin(\theta_1 - \hat{\theta}_1) \approx \theta_1 - \hat{\theta}_1 \quad \text{and the following characteristic polynomial of the system described by)} \quad p^2 + \gamma_2 p + \gamma_1
\]

(15)

Where \( p = d/dt \). If the parameters are chosen as

\[
\gamma_1 = p^2 \quad \gamma_2 = 2p
\]

(16)

then \( \rho \) can be adjusted to the desired bandwidth of the PLL-type estimator.

2.3. Kalman filter

Since the late 1960s, the Kalman filter has received huge attention from various fields in industry and academia and played a key role in many engineering disciplines for trajectory planning, state and parameter estimation, signal processing, etc [2], [3]. In [4] the behavior of two estimation techniques based on the Kalman filter is analyzed.

Kalman filter (KF) is a digital optimal linear data processor used to estimate the states of a system subject to process noise and to measurement noise [5]. The states can be constant (parameters) or dynamic (time varying) states when using Kalman Filter and are modeled as random variables with mean \( \bar{x} \) and a covariance \( P \). What the filter needs to know is:

1. System and measurements descriptive equations
2. Process and measurements noise variances Q and R
3. Initial values of states with their initial covariances \( x_0 \) and \( P_0 \)

Kalman filtering process in the discrete model at a time step starts with a prediction of the states and their probability moments (variance and mean) in the next time step using the recursive system, followed by a correction of the predicted moments using measured observations [5].

The methods utilize an Extended Kalman Filter (EKF) and an Unscented Kalman Filter (UKF) for parameter estimation of DFIGs in wind turbine systems[3]. However, the observability of the (linearized) DFIG model is not addressed and the two Kalman filters are not tested under parameter variations. Moreover, the two filters were not optimally tuned (parameter estimation converges after 6 s) and the used nonlinear state space model depends on state, input and output (which is not admissible from a theoretical point of view) [3]. In this paper, an Extended Kalman filter (EKF) is proposed for parameter estimation of all electrical parameters of DFIGs in wind turbine systems. The estimated parameters are the stator and rotor resistances, the leakage inductances of stator and rotor, and the mutual inductance [5].

The EKF is a nonlinear extension of the Kalman filter for linear systems. Its design is based on a discrete nonlinear system model [6]. When the state space system is non-linear then KF can still be used after getting modified to become either Extended Kalman Filter (EKF) or Unscented Kalman Filter (UKF) [5]. EKF linearizes the states and observations equations in order to deal with non-linearity issues [7] whereas UKF calculates the probability moments, of both a number of projected states samples and their projected observations, in order to address the non-linearity anomalies [8].

2.4. Existing Research Using EKF and UKF in Machines Parameters Estimation
EKF and UKF have been used instead of the simple Kalman Filter when the system model equations are non-linear. An example of the such non-linearity is the power flow equation between the synchronous machine and a bus at the output of the machine [5]:

\[ p = \frac{EV \sin(\delta - \theta)}{X_d} \]  

(17)

Where \( P \) is active power, \( E \) and \( \delta \) are the internal voltage source and the angle of the machine, \( V \) and \( \theta \) are the voltage and angle of the bus; \( \delta \) is a state variable in this case. Both Filters (UKF and EKF) have been used to estimate parameters of synchronous and induction machines. Azad et al [9] estimated stator and rotor resistances and inductances (in addition to other electromagnetic states) of doubly fed induction generator (DFIG) used in wind turbine using rotor and stator \( d \) and \( q \) axis voltages and currents with UKF or EKF. UKF is used by Valverde et al [10] to estimate the \( d \) and \( q \) magnetizing reactances \( x_{md} \), \( x_{mq} \), and the field resistance \( r_f \) (with various electromagnetic states). Additional mechanical measurements not provided by PMUs or DFRs, i.e. rotor speed \( \omega \) and rotor angle \( \delta \), are required in [10] and [9]. high lights the difficulties in obtaining \( x_{mq} \) and \( \delta \) simultaneously because of a relation between them, hence [10] uses either a sensor to measure \( \delta \) or a fixed ration between \( x_{mq} \) and \( x_{md} \). The simultaneous estimation of \( \delta \) and \( x_q \) is similarly challenging because of the relation between \( x_q \) and \( x_{mq} \), 

\[ x_q = x_{ls} + x_{mq} \]

\( x_{ls} \) being the leakage reactance [11]. The Results of the proposed method is shown in Fig. 5-7.

3. CONCLUSION
This paper proposed a method for estimating electrical
parameters of doubly-fed induction generators (DFIG) in wind turbine systems (WTS) using an method utilizes an (UKF and EKF) Kalman filter. For implementation of EKF, the nonlinear state space model of DFIG is derived to estimate electrical parameters of DFIG( rotor speed deviation, estimation of position, rotor angle deviation). Simulation results show that the estimator (UKF and EKF) has a relatively good tracking performance. Also, rotor speed and rotor angle deviation estimations are acceptable with a negligible percentage errors.

REFERENCES


