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Sensor fault detection and isolation in doubly-fed induction generators accounting for parameter variations

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ABSTRACT

A fault detection and isolation (FDI) system for monitoring rotor current sensors in a doubly-fed induction generator (DFIG) for wind turbine applications is presented. The FDI system is designed so that the effect of parameter variations (resistances and inductances) is minimized. The residual generation is based on the generalized observer scheme (GOS) including parameter estimation. A decision system made of a combination of vector CUSUM (Cumulative sum) algorithms is used to process the residual vector and to achieve detection and isolation of incipient (small magnitude) faults. The approach is validated using signals obtained from a simulated vector-controlled DFIG.

1. Introduction

Wind energy conversion systems (WECS) present an increasing penetration in modern power system and a growing amount of installed capacity. According to modern grid codes, wind farms are intended to have an active role in the power systems operation, with both grid support and fault-ride through capabilities [1]. Because WECS work under extreme conditions and are complex systems, they can be subject to diverse kinds of faults, some of which can turn into failures and cause large downtimes [2,3]. Therefore, improving the reliability of wind turbines becomes an important issue for both research and industry.

The doubly-fed induction generator (DFIG), a class of induction machine, is one of the most widely used electrical machines in the megawatt-class wind turbines [1]. In a DFIG-based wind turbine, as depicted in Fig. 1, the stator is connected to the grid while the rotor is connected to a back-to-back converter via slip-rings [4]. The converter rating is only a fraction of the total power of the system (around ±30%), reducing the size and cost of the converter, while allowing a certain range of rotor speed variation (−40% to +30%) around the synchronous speed [5]. These generators, can be subject to diverse fault scenarios as described in Ref. [6], among which sensor faults. Hence, fault detection and isolation (FDI) of sensor faults is necessary since control systems rely on the information provided by measured signals.

Any model-based FDI system consists of two parts: the residual generator and the decision system [7]. A model of the process to be diagnosed, both in healthy and faulty modes, is used along with measurements and actuator commands to generate symptoms in the form of residuals. The decision system processes the residuals in order to detect a change in their statistics, which characterizes the fault occurrence. Many references focus on model-based sensor FDI for controlled induction machines [8–12], and some of them specifically for DFIG in wind turbine applications [13,14]. Only Refs. [11,12] use a multiple observer approach for residual generation. All these works consider the total loss of a sensor as faulty condition, except for Refs. [8,10], that also consider an offset (additive fault) and a gain drop (multiplicative fault) among the possible faults. Another common characteristic of the reported works is that the decision process is made of deterministic rules. One major problem in model-based FDI is that the uncertainties in the model of the induction machine, notably parameter variations, may reduce the performance of the FDI systems described in the above mentioned references. Only Refs. [10], that will be recalled further in this paper, proposes the estimation of some electrical parameters by means of an observer. The estimated parameters are used for adapting both the control law and the FDI system.

In order to alleviate this problem, a signal-based approach has been proposed in Ref. [15], where a model of the balanced three-phase signals (currents/voltages) is used to perform sensor FDI. The approach was successfully applied for both stator current and stator voltage sensor FDI in a DFIG-based wind turbine [16]. However, when trying to use the method for rotor current sensor FDI, it was concluded that the effect of the faults was partially hidden due to

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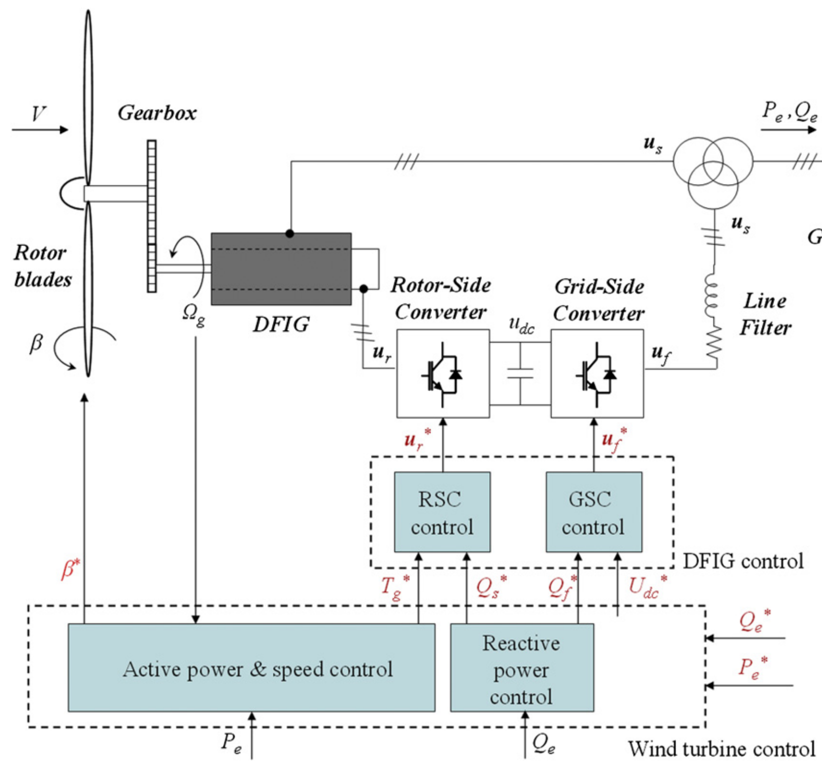

Fig. 1. Scheme of DFIG-based wind turbine.

the use of the rotor currents in the control law. Therefore a model-based approach is needed for FDI of rotor current sensors. Besides, either a robust or an adaptive approach is needed to handle the model uncertainties and the parametric changes due to temperature, notably.

The aim of this paper is to address the issue of FDI of incipient (small magnitude) faults like sensor offset or drift in a DFIG for a 2 MW wind turbine. To this end, an FDI system for rotor current sensors based on the machine model and including parameter adaptation is considered. This model is used for residual generation by means of a multi-observer strategy relying on the Generalized Observer Scheme (GOS). Another important difference with respect to previous works is the use of a statistical approach for the decision system, based on the multiple CUSUM algorithm developed in Ref. [17]. In this approach, the whole residual vector is evaluated at once, and the decision system consists of a combination of n_f (the number of faults) vector CUSUM algorithms, allowing both fault detection and fault isolation. The proposed design methodology is systematic and can be applied in a straightforward way to generating units of different rated power.

2. Problem statement

The model of a DFIG and the considered control law are first presented, as they are prerequisites for the precise problem statement.

2.1. DFIG model

The reader can refer to Ref. [18] for a detailed explanation of the material recalled below. In this work we use a dq rotating reference frame aligned with the stator voltage vector. Specifically, we consider that the q axis is leading by 90° the d axis, and that the stator voltage vector is aligned with the negative direction of the q axis. Therefore, the DFIG dynamics in dq coordinates are expressed in a generator convention (currents flowing out of the machine) as follows:

$$\frac{\mathrm{d}\mathbf{i}_s}{\mathrm{d}t} = -\left[\alpha R_s \mathbf{I} + \left(\omega_s + \mu n_p \Omega_g\right)\mathbf{J}\right]\mathbf{i}_s + \left[\kappa R_r \mathbf{I} - \epsilon n_p \Omega_g \mathbf{J}\right]\mathbf{i}_r + \kappa \mathbf{u}_r - \alpha \mathbf{u}_s \tag{1}$$

$$\frac{\mathrm{d}\mathbf{i}_r}{\mathrm{d}t} = \left[\kappa R_s \mathbf{I} + \xi n_p \Omega_g \mathbf{J}\right]\mathbf{i}_s - \left[\beta R_r \mathbf{I} + \left(\omega_s - \nu n_p \Omega_g\right)\mathbf{J}\right]\mathbf{i}_\mathrm{r} - \beta \mathbf{u}_r + \kappa \mathbf{u}_s \tag{2}$$

In the previous equations, $\mathbf{m} = [m_d, m_q]^T$ represents a 2-dimensional vector, where subindices d and q refer to a component aligned or in quadrature with the reference frame, respectively. $\mathbf{i}$ and $\mathbf{u}$ represent the current and voltage, respectively. R and L represent resistance and inductance, respectively, and ω denotes electrical frequency. Subindices s, r and m mean stator, rotor and magnetizing (or mutual), respectively. $L_s = L_{ls} + L_m$ and $L_r = L_{lr} + L_m$, where L_{ls} and L_{lr} are the stator and rotor leakage inductances, respectively, and $\sigma = 1 - L_m^2/(L_s L_r)$ is the leakage coefficient. $\alpha = 1/(\sigma L_s), \beta = 1//(\sigma L_r)$, $\epsilon = L_m/(\sigma L_s), \xi = L_m/(\sigma L_r), \kappa = L_m/(\sigma L_s L_r), \mu = (1-\sigma)/\sigma$, and $\nu = 1/\sigma$. Matrices **I**, **J** and **Z** (used further in the text) are defined as

$$\mathbf{I} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad \mathbf{J} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

A vector **m** is related to its respective three-phase signal vector $\mathbf{m}_{abc} = [m_a, m_b, m_c]^T$, considered to be balanced, through

$$\mathbf{m} = \mathbf{P}_t(\theta)\mathbf{m}_{abc} \tag{3}$$

where $\mathbf{P}_t(\theta)$ is the matrix of the *Park* 's transformation (see the appendix section). It depends nonlinearly on θ, the angle of the