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FDI and FTC of wind turbines using the interval observer approach and virtual actuators/sensors

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ABSTRACT

In this work, the problem of Fault Detection and Isolation (FDI) and Fault Tolerant Control (FTC) of wind turbines is addressed. Fault detection is based on the use of interval observers and unknown but bounded description of the noise and modeling errors. Fault isolation is based on analyzing the observed fault signatures on-line and matching them with the theoretical ones obtained using structural analysis and a row-reasoning scheme. Fault tolerant control is based on the use of virtual sensors/actuators to deal with sensor and actuator faults, respectively. More precisely, these FTC schemes, that have been proposed previously in state space form, are reformulated in input/output form. Since an active FTC strategy is used, the FTC module uses the information from the FDI module to replace the real faulty sensor/actuator by activating the corresponding virtual sensor/actuator. Virtual actuators/sensors require additionally a fault estimation module to compensate the fault. In this work, a fault estimation approach based on batch least squares is used. The performance of the proposed FDI and FTC schemes is assessed using the proposed fault scenarios considered in the wind turbine benchmark introduced in IFAC SAFEPROCESS 2009. Satisfactory results have been obtained in both FDI and FTC.

1. Introduction

Wind turbines stand for a growing part of power production. The future of wind energy passes through the installation of offshore wind farms. In such locations a non-planned maintenance is very costly. Reducing the cost of wind energy is a key factor in driving successful growth of the wind energy sector. One way of reducing this cost is to use more refined control systems to balance load reduction and power production in an optimal way (Bossanyi, 2003; Simani & Castaldi, in press). Hence, the detailed modeling of wind turbines has been a hot topic of research in the last years (van der Veen, van Wingerden, Fleming, Scholbrock, & Verhaegen, 2013). Another way of reducing the costs is developing wind turbines that require less scheduled and especially non-scheduled service and have less downtime due to failure (Tabatabaeipour, Odgaard, Bak, & Stoustrup, 2012). Therefore, a Fault Tolerant Control (FTC) system that is able to maintain the wind turbine connected after the occurrence of certain faults can avoid major economic losses (Sloth, Esbensen, & Stoustrup, 2010). An important part of an active FTC system is the implementation of a Fault Detection and Isolation (FDI) system that is able to detect, isolate and, if possible, estimate the faults (Isermann, 2006). Model-based FDI is often necessary to obtain a good diagnosis of faults.

The problem of model-based fault diagnosis in wind turbines has recently been addressed (Odgaard & Stoustrup 2012), the main motivation being the importance gained in many countries by this technology for electricity generation. So far, revising the literature, methods ranging from Kalman filters (Wei, Verhaegen, & van den Engelen, 2008), observers (Odgaard, Stoustrup, Nielsen, & Damgaard, 2009), parity equations (Dobrila & Stefansen, 2007), dynamic weighting ensembles (Razavi-Far & Kinnaert, 2013) and fuzzy modeling and identification methods (Badihi, Zhang, & Hong, in press) have already been suggested as possible model-based techniques for fault diagnosis of wind turbines.

The problem of model-based fault tolerant control in wind turbines has been addressed even more recently. In Sloth et al. (2010) and Sloth, Esbensen, and Stoustrup (2011), active and passive fault tolerant control designs for wind turbines are presented. The Linear Parameter Varying (LPV) control design method is applied, which leads to Linear Matrix Inequalities (LMI) based optimization in case of active fault tolerant and Bilinear Matrix Inequalities (BMIs) in case of passive fault tolerant problems. It is shown through simulations that both active and passive controllers have better performance than classical Proportional Integral (PI) controller and that active fault-tolerant controller is better than passive FTC in faulty condition. However, the authors conclude that the choice between active and passive FTC should also

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take into account the tolerance to errors in the fault diagnosis system. In Sami and Patton (2012), a robust FTC strategy that optimizes the wind energy captured by a wind turbine operating at low wind speeds (5 MW), using an adaptive gain Sliding Mode Control (SMC) is presented. The proposed method involves a robust descriptor observer design that can provide simultaneously a robust estimation of the states and the "unknown outputs" (sensor faults and noise) in order to guarantee the robustness of the sliding surface against unknown output effects. In Odgaard and Stoustrup (2012), an FTC scheme based on estimates of the generator speed using a bank of unknown input observers, and considering faults in the rotor and generator speed sensors, is proposed. One observer is designed for each of the sets of non-faulty rotor and generator speed sensors. The unknown input observers are used to detect and isolate these faults too. In Kamal, Aitouche, Ghorbani, and Bayart (2012), a multiobserver switching control strategy for robust active fault tolerant fuzzy control of variable-speed wind energy conversion systems in the presence of wide wind variation, wind disturbance, parametric uncertainties and sensor faults was proposed. In Badihi et al. (in press), fault tolerance is achieved using a gain-scheduled PI control system based on Fuzzy Gain Scheduling. A projection-based approach is used by Jain, Yamé, and Sauter (2013) in order to obtain an active FTC system that neither uses a priori information about the model of the wind turbine in real-time nor an explicit fault diagnosis scheme. An active FTC scheme based on adaptive filters obtained via the non-linear geometric approach is proposed in Simani and Castaldi (in press), allowing to obtain an interesting decoupling property with respect to uncertainty affecting the wind turbine system.

The use of on-line fault estimation is essential for all active fault compensation approaches. A number of suitable estimation methods, essentially observer-based or Kalman filter-based fault estimation, are proposed in the literature (Edwards, Spurgeon, & Patton, 2000; Patton & Klinkhieo, 2009; Wang & Daley, 1996). In Montes de Oca, Rotondo, Nejjari, and Puig (2011), a recursive least square method is applied for actuator fault estimation in LPV systems.

In Odgaard, Stoustrup, and Kinnaert (2013), a benchmark model for fault detection and isolation, as well as fault tolerant control of wind turbines, has been proposed. The benchmark model describes a realistic generic three blade horizontal variable speed wind turbine with a full scale converter coupling and a rated power of 4.8 MW. Solutions to FDI and FTC for this benchmark model have been published recently: (Blesa, Puig, Romera, & Saludes, 2011; Chen et al., 2011; Rotondo, Nejjari, Puig, & Blesa, 2012; Tabatabaeipour et al., 2012), among others, and compared in Odgaard et al. (2013).

In this paper, the problem of fault diagnosis in wind turbines is addressed applying the interval observer based approach proposed in Puig et al. (2006). The proposed model based fault detection methodology relies on the use of interval observers and assumes an unknown but bounded description of the noise and the modeling errors. Fault isolation is based on analyzing the observed fault signatures on-line and matching them with the theoretical ones obtained using structural analysis and a row-reasoning scheme. On the other hand, the fault tolerant control approach considered in this work uses the idea of virtual sensors/actuators. The paper suggests the reformulation of these FTC schemes, previously proposed in state space form by Lunze, Rowe-serrano, and Steffen (2003), in an input/output form. A fault estimation scheme based on batch least squares approach is also suggested. The performance of the proposed FTC schemes is assessed using the fault scenarios considered in the FTC benchmark presented in Odgaard et al. (2013).

In Section 2, the proposed fault detection and isolation technique based on interval observers is presented. In Section 3, the proposed fault tolerant control approach based on virtual sensors and actuators is introduced. In Section 4, the wind turbine used in the FDI/FTC competition is briefly introduced and the set of residuals is generated using structural analysis. Results of the application of the proposed FDI/FTC approaches to the wind turbine benchmark are presented in Section 5. Finally, some conclusions are drawn in Section 6.

2. Fault detection, isolation and estimation

2.1. Problem set-up

Let us consider that the wind turbine to be monitored can be described by a MIMO linear uncertain dynamic model expressed as follows:

$$x(k+1)=A(\tilde{\theta})x(k)+B(\tilde{\theta})u(k)+F_a(\tilde{\theta})f_a(k) \tag{1}$$

$$y(k)=C(\tilde{\theta})x(k)+F_y(\tilde{\theta})f_y(k)+\tilde{v}(k) \tag{2}$$

where $u(k)\in\mathbb{R}^{n_u}$ is the system input, $y(k)\in\mathbb{R}^{n_y}$ is the system output, $x(k)\in\mathbb{R}^{n_x}$ is the state-space vector, $\tilde{v}(k)\in\mathbb{R}^{n_y}$ is the output noise that is assumed to be bounded $|\tilde{v}_i(k)|<\sigma_i$ with $i=1,\ldots,n_y$, $f_a(k)\in\mathbb{R}^{n_u}$ and $f_y(k)\in\mathbb{R}^{n_y}$ represent faults in the actuators and output sensors, respectively. $A(\tilde{\theta})$, $B(\tilde{\theta})$, $C(\tilde{\theta})$, $F_a(\tilde{\theta})$ and $F_y(\tilde{\theta})$ are matrices of appropriate dimensions where $\tilde{\theta}\in\mathbb{R}^{n_\theta}$ is the parameter vector.

The system (1) and (2) is monitored using a linear observer with Luenberger structure that uses an *interval model* of the system, i.e. a model with parameters bounded by intervals[1]:

$$\theta\in\Theta=\{\theta\in\mathbb{R}^{n_\theta}|\underline{\theta}_i\le\theta_i\le\overline{\theta}_i,\ i=1,\ldots,n_\theta\} \tag{3}$$

that represent the uncertainty about the exact knowledge of the real parameters $\tilde{\theta}$. This observer, known as an *interval observer*, is expressed as follows (Meseguer, Puig, Escobet, & Saludes, 2010):

$$\begin{aligned}\hat{x}(k+1,\theta)&=(A(\theta)-LC(\theta))\hat{x}(k,\theta)+B(\theta)u(k)+Ly(k)\\&=A_0(\theta)\hat{x}(k,\theta)+B(\theta)u(k)+Ly(k)\\\hat{y}(k,\theta)&=C(\theta)\hat{x}(k,\theta)\end{aligned} \tag{4}$$

where $\hat{x}(k,\theta)$ is the estimated system state vector, $\hat{y}(k,\theta)$ is the estimated system output vector and $A_0(\theta)=A(\theta)-LC(\theta)$ is the observer matrix.

The observer gain matrix $L\in\mathbb{R}^{n_x\times n_y}$ is designed to stabilize the matrix $A_0(\theta)$ and to guarantee a desired performance regarding fault detection for all $\theta\in\Theta$ using the LMI pole placement approach (Chilali & Gahinet, 1996).

The input/output form of the system (1) and (2) using the shift operator q^{-1} and assuming zero initial conditions is given by

$$y(k)=y_0(k,\tilde{\theta})+G_{f_a}(q^{-1},\tilde{\theta})f_a(k)+G_{f_y}(\tilde{\theta})f_y(k)+\tilde{v}(k) \tag{5}$$

where $y_0(k,\tilde{\theta})$ is the system output when the system is not affected by faults, disturbances and noises:

$$y_0(k,\tilde{\theta})=G_u(q^{-1},\tilde{\theta})u(k) \tag{6}$$

$$G_u(q^{-1},\tilde{\theta})=C(\tilde{\theta})(qI-A(\tilde{\theta}))^{-1}B(\tilde{\theta}) \tag{7}$$

$$G_{f_a}(q^{-1},\tilde{\theta})=C(\tilde{\theta})(qI-A(\tilde{\theta}))^{-1}F_a(\tilde{\theta}) \tag{8}$$

$$G_{f_y}(\tilde{\theta})=F_y(\tilde{\theta}) \tag{9}$$

[1] The intervals for uncertain parameters can be inferred from real data using set-membership parameter estimation algorithms (Milanese, Norton, Piet-Lahanier, & Walter, 1996; Ploix, Adrot, & Ragot, 1999).