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Data-driven design of robust fault detection system for wind turbines

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A B S T R A C T

In this paper, a robust data-driven fault detection approach is proposed with application to a wind turbine benchmark. The main challenges of the wind turbine fault detection lie in its nonlinearity, unknown disturbances as well as significant measurement noise. To overcome these difficulties, a data-driven fault detection scheme is proposed with robust residual generators directly constructed from available process data. A performance index and an optimization criterion are proposed to achieve the robustness of the residual signals related to the disturbances. For the residual evaluation, a proper evaluation approach as well as a suitable decision logic is given to make a correct final decision. The effectiveness of the proposed approach is finally illustrated by simulations on the wind turbine benchmark model.

1. Introduction

During the past decade, the use of wind energy as a clean and renewable resource has attracted global interest. A wind turbine is an aeroelastic mechanical system which converts kinetic wind energy to electrical power. On the other hand, wind turbines still suffer from potential problems, such as vibration, corrosion and temperature changes, e.g. in the motors, sensors, blades and gearbox, which could affect the production capability and may cause remarkable downtime of the entire system. The maintenance of faulty wind turbines is costly and even dangerous since many wind turbines are installed offshore. In order to detect abnormalities in the systems as early as possible to avoid potential irreversible damage, automatic detection of the faults is highly desirable from the application point of view, which motivates us to design a fault detection system for wind turbines.

In recent years, several fault detection systems have been successfully developed for wind turbines. Most of the proposed approaches rely on the physical model of wind turbines [1–4,6,5,7,8] and based on which, the well established model-based fault diagnosis techniques [9–15] can be directly applied. However, modeling of a wind turbine is a difficult task in practice [16,17], which still limits the application of model-based approaches. Parallel to the research of model-based fault detection techniques, the data-driven methods are currently receiving considerable attention. Different from model-based approaches which require the mathematical model of system known as a priori, data-driven methods only depend on the measured process data. Several basic data-driven methods, such as principle component analysis (PCA), dynamic principle component analysis (DPCA), independent component analysis (ICA), partial least squares (PLS) and subspace aided approach (SAP), have been well developed [22,23]. SAP is mainly based on identifying the primary form of residual generators directly from the measured data. Residual generator is an important concept in the model-based fault detection framework. The basic idea of a residual generator is to generate a residual between the actual output and the estimated output. If noise is not considered, the generated residual should be zero when there is no fault and nonzero when a fault appears. However, in real applications, the generated residual should be further evaluated, including threshold computation and decision making, to make a correct final decision. Two popular subspace-based fault detection approaches can be found in [24,25].

In order to promote the fault detection and other related technologies for wind turbines, Odgaard et al. developed a wind turbine simulator in [18] as a research competition for all the participants. In this framework, many effective designs have been proposed based on the benchmark physical model [19–21]. Recently, to improve the level of the wind turbine benchmark close to the actual statue, Odgaard et al. renewed the benchmark by added new challenges. Compared to the previous one, the latest benchmark is modified in many different ways. First of all, the wind turbine model is more sophisticated and realistic, which may help to achieve better simulation abilities and make the problem more realistic. Another difference is that various wind inputs are introduced into this model. An IEC [37] von Karman turbulence model

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is used to generate three types of wind input files, of which the mean wind speeds at the 90-m hub height are 11 m/s, 14 m/s, and 17 m/s [26]. These turbulent wind input files can be directly applied in the latest benchmark. Moreover, extra relevant details are implanted into the fault scenarios. As a result, more sophisticated advanced fault detection techniques are required from both academic and practical aspects.

Since it is quite difficult to obtain a precise mathematical model of the wind turbine, the data-driven approaches seem more convenient for the application point of view. On the other hand, seen from a control theory perspective, a major problem in the wind turbine control system is that the wind turbine is driven by a disturbance, the wind. The wind speed is, however, measured with a large measurement noise added, as well as a large risk of an offset [26]. As the wind speed can be treated as a disturbance input, robust residual generators should be constructed directly from the available process measurements and most importantly, these residual generators shall be sensitive to output faults and insensitive to input disturbance.

For this purpose, a robust data-driven fault detection scheme is proposed for wind turbines. The schematic of the fault detection scheme is shown in Fig. 1, which contains two steps, i.e. (a) residual generation, and (b) residual evaluation including threshold computation and decision making. In the first step, a robust residual vector instead of a single residual signal is generated under a given performance index and an optimization criterion. In the second step, a proper evaluation approach as well as a suitable decision logic is given to make a correct final decision.

The rest of the paper is organized as follows. Section 2 introduces the new wind turbine benchmark and the fault scenarios. Section 3 develops a robust fault detection scheme based on constructing robust residual generators directly from available process data. The proposed robust fault detection scheme is applied to the benchmark in Section 4. Finally, the paper ends with conclusion in Section 5.

2. Benchmark system and faults description

2.1. Benchmark model

The wind turbine benchmark proposed by Odgaard and Johnson in [26] is described at the system level. It mainly consists of five subsystems: blade and pitch system, drive train system, generator and converter system, controller system and sensors. The benchmark simulates a three-bladed horizontal axis, and variable speed wind turbine containing a pitch, torque controller and a yaw controller. It is disturbed by unknown wind disturbances and controlled in closed-loop with PI controllers. Combined with an IEC von Karman turbulence wind model and deliberately designed faults, the benchmark is complex and realistic. It is suitable for testing different detection and isolation schemes on the wind turbine.

Most components of the benchmark are implemented within the Simulink environment, in which fifteen sensors are available for measuring the input and output variables. All of these sensors are modeled by adding a band-limited white noise. The detailed descriptions of sensors and noise power are summarized in Table 1.

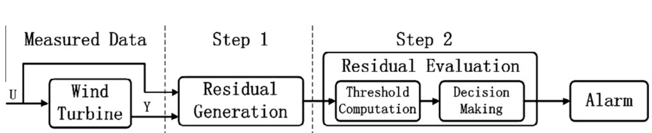

Fig. 1. Block diagram of standard residual generation and decision logic structure.

2.2. Fault scenarios

In the benchmark model, ten sensor and actuator faults are considered along the time span of 630 s. Faults 1–6 are sensor faults, including measurements that are stuck, scaled or offset from the true values. Faults 7–10 are actuator faults, including Faults 7 and 8 in pitch actuators, Fault 9 in generator torque and Fault 10 in yaw actuator. Faults 7 and 8 are modeled by changing the parameters in the relevant pitch actuator model. Fault 9 is modeled by adding an offset on the generated generator torque and Fault 10 is modeled by setting the yaw angular velocity to 0 rad/s. Detailed descriptions of these faults and their durations are summarized in Table 2.

3. Robust data-driven fault detection design

The robust fault detection scheme will be presented in this section. Based on the method proposed by Ding et al. [24], we first identify the parity space directly from the measured data. Then, we select the optimal parity vectors under a given performance index as well as an optimization criterion. It follows the construction of robust residual generators using the observer-based residual generation technique. At last, the robust fault detection scheme is summarized into an algorithm.

3.1. Identify parity space directly from measured data

A Linear Time-Invariant (LTI) system is usually modeled in the following discrete-time state-space form.

$$x(k+1) = Ax(k) + Bu(k) + w(k) \quad (1)$$

$$y(k) = Cx(k) + Du(k) + v(k) \quad (2)$$

where $x(k) \in \mathbf{R}^n$ is the vector of the state variables, $u(k) \in \mathbf{R}^l$ are the input signals and $y(k) \in \mathbf{R}^m$ are the measured output signals. $w(k) \in \mathbf{R}^n$ and $v(k) \in \mathbf{R}^m$ are process noise and measurement noise, respectively. As standard assumptions, $w(k)$ and $v(k)$ are zero-mean and normal distributed white noise, and they are independent of the input vector $u(k)$ and the initial state vector $x(0)$. We define the following block Hankel matrices for outputs:

$$Y_p = \begin{bmatrix} y(k-s) & y(k-s+1) & \dots & y(k-s+N-1) \\ y(k-s+1) & y(k-s+2) & \dots & y(k-s+N) \\ \vdots & \vdots & \vdots & \vdots \\ y(k) & y(k+1) & \dots & y(k+N-1) \end{bmatrix}$$

$$Y_f = \begin{bmatrix} y(k+1) & y(k+2) & \dots & y(k+N) \\ y(k+2) & y(k+3) & \dots & y(k+N+1) \\ \vdots & \vdots & \vdots & \vdots \\ y(k+s+1) & y(k+s+2) & \dots & y(k+s+N) \end{bmatrix}$$

Table 1
Available sensors and the added noise power [26].

Sensor type	Symbol	Unit	Noise power
Wind speed at hub height	$v_{h,m}$	m/s	0.0071
Rotor speed	$w_{r,m}$	rad/s	10^{-4}
Generator speed	$w_{g,m}$	rad/s	2×10^{-4}
Generator torque	$\tau_{g,m}$	Nm	0.9
Generated electrical power	$p_{g,m}$	W	10
Pith angle of ith Blade	$\beta_{i,m}$	deg	1.5×10^{-4}
Azimuth angle low speed side	ϕ_m	rad	10^{-4}
Blade root moment of ith blade	$M_{i,m}$	Nm	10^3
Tower top acceleration in x direction	$\ddot{x}_m$	m/s^2	5×10^{-4}
Tower top acceleration in y direction	$\ddot{y}_m$	m/s^2	5×10^{-4}
Yaw error	Ξ_m	deg	5×10^{-2}