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A radically data-driven method for fault detection and diagnosis in wind turbines

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ABSTRACT

In order to improve the reliability of wind turbines, avoid serious accidents and reduce operation and maintenance (O&M) costs, it is important to effectively detect faults of wind turbines operating in harsh environment. This paper proposes a radically data-driven fault detection and diagnosis (FDD) method for wind turbines, which implements deep belief network (DBN). The DBN requires no knowledge of physical model, instead, it employs historical data without any pre-selection. The method has been evaluated in a wind turbine benchmark simulink model, in comparison with four model-based algorithms and four data-driven methods, and the results have shown that the proposed method achieves the highest accuracy. Moreover, extensive evaluation has been taken to analyse the robustness of proposed method, and the simulation results indicate the stable performance of proposed method in faults diagnosis of wind turbine.

1. Introduction

Nowadays, the growing interest in wind energy has led to the wide installation of wind turbines, which covers a large part of total electricity generation all over the world. In order to achieve the optimal power production, wind farms are usually located in areas where wind resources are rich, which are usually far away from the load. As a result, it increases the cost of operation and maintenance (O&M). Besides, harsh operating environment also increases the risk of various faults in wind turbines. Since wind turbines of megawatt size are complex and expensive, the maintenance costs are much higher than conventional power sources. Therefore, there is an urging requirement to use advanced fault diagnosis schemes to maximize the operating time of wind turbines, and consequently to reduce the O&M cost.

Since a wind turbine is a large and complex system, it is difficult for researchers working in the filed of fault detection and diagnosis (FDD) to test and compare different methods applied to real wind turbines. To solve this problem, research [1] proposed a three-blade pitch-controlled variable-speed wind turbine benchmark model with a nominal power of 4.8 MW. This known benchmark model was described in more detail in research [2,3] and updated together with evaluation of some FDD solutions in research [4]. Moreover, several FDD methods based on this benchmark model were tested and compared with each other in [5–8]. The scheme of fault diagnosis is mainly classified into two groups, model based and data driven.

Model-based methods are designed based on the knowledge about the model of a specified wind turbine. In research [9], an algorithm named wind speed based normalized current trajectory was proposed and used to accurately detect the faults of PMSG wind turbine power converters. A FDD scheme based on adaptive filters obtained via the non-linear geometric approach was proposed in research [10], allowing to obtain an interesting decoupling property with respect to uncertainty affecting the wind turbine system. Research [11] proposed and compared three fault diagnosis schemes, a cascade of two Kalman filters, a bank of dedicated observers, and a secondary H_∞ filtering mechanism. Besides, a FDD method based on sliding mode observers was reported in research [12] and a multi-physics graphical model-based FDD method was developed in research [13]. All these methods have good performance in most of fault cases, but it is hard to avoid model-reality mismatch and the construction process are always complex.

Data-driven methods employ implicit relationships between input and output, which is learnt from historical, to detect faults. Research [14–18] applied supervisory control and data acquisition (SCADA) data and unsented Kalman filter to detect the faults of gearboxes and drivetrains, and achieve significant diagnostic performance. In research [19], Gibbs sampling was used to detect change point to reveal the evidence of fault, and Fuzzy/Bayesian network was employed to calculate the probability of the occurrence of each fault. This method could only detect some simple faults such as sensor faults while missed the others. In [20], a robust data-driven fault diagnosis scheme based on parity-space method was proposed, in which robust residual generators are constructed directly from available process measurements.

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Research [21] proposed a multiwavelet denoising method with data-driven block threshold for the FDD of wind turbines. However, methods in [20,21] had low detection rate. A FDD method based on Takagi-Sugeno fuzzy models that are identified from input-output measurements was proposed in research [22,23], but it had limited performance in certain fault scenarios such as system fault scenario.

In short, the present FDD methods either have complex design process or poor diagnostic performance. To solve these problems, this paper proposes a radically data-driven method for FDD of wind turbines applying DBN. DBN was initially proposed in [24–26], which was motivated by the establishment and simulation of the neural network of the human brain. It imitates the mechanism of the human brain to interpret data, such as images, sound and texts. Compared with traditional machine learning algorithms, such as SVM [27,28], artificial neural networks [29,30] (ANNs), DBN has better performance in transfer learning. Hence, it has been continuously improved and applied to various fields in recent years [31–35]. To validate the proposed method, the data obtained from a wind turbine benchmark model in different fault scenarios is employed to test the performance of FDD. The fault diagnosis results are compared with those obtained from four traditional model-based methods, estimation-based solution (EB), up-down counter solution (UDC), combined observer and Kalman filter solution (COK), general fault model solution (GFM), and four data-driven methods, including naive Bayes classifier based solution (NB), K-nearest neighbor classifier based solution (KNN), random forest classifier based solution (RF), decision tree classifier based solution (DT). The simulation results demonstrate the effectiveness and superiority of the proposed method compared with other methods.

The main contributions of this paper include: (I) to propose a superior data-driven FDD for the wind turbine system; (II) to provide FDD of system faults which are hard to detect with good performance; (III) to validate the strong robustness, wide practicability and high reliability of the proposed method.

2. Wind turbine benchmark model

In order to evaluate the performance of various FDD methods applied to wind turbines, research [1] provided an effective wind turbine benchmark model for researchers working in the filed of fault diagnosis.

2.1. Overview of the wind turbine model

The benchmark model is a three-blade horizontal-axis turbine with variable speed and pitch angle PI control, which has a rated power of 4.8 MW. There are five sub-systems in this model, which are wind model, blade and pitch system, drive train, generator and converter, controller. The overview of this model is shown in Fig. 1.

The variables in these subsystems are defined as follows: v_w represents the wind speed acting on the turbine blades; τ_w,τ_r,τ_g represent the torque of wind, rotor and generator, respectively; ω_r and ω_g are the rotational speed of the rotor and generator, respectively; β_r is the reference to the pitch position; $\tau_{g,r}$ is the torque reference to the generator; P_r is the power reference to the wind turbine; P_g is the power produced by the generator; $v_{w,m},\omega_{r,m},\omega_{g,m},\tau_{g,m}$ are the measured values of the related parameters.

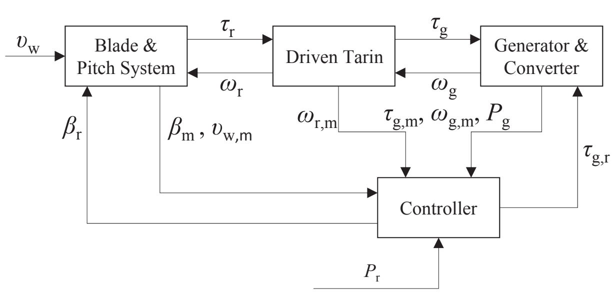

Fig. 1. An illustration of the benchmark model.

2.1.1. Blade and pitch system

This system consists of aerodynamic system and pitch system. The aerodynamic system is modelled as a torque acting on the blades, which can be expressed as:

$$\tau_r(t) = \frac{\rho\pi R^3 C_q(\lambda(t),\beta(t))v_w(t)^2}{2} \tag{1}$$

where $C_q(\lambda(t),\beta(t))$ is a mapping of the torque coefficients. Each blade is assumed to be a third of the torque given by the three blades. The hydraulic pitch system is modelled as a closed-loop transfer function:

$$\frac{\beta(s)}{\beta_r(s)} = \frac{{\omega_n}^2}{s^2 + 2\varsigma\omega_n s + \omega_n^2} \tag{2}$$

where $\beta(s),\beta_r(s)$ are the measured pitch angle and its reference; ς,ω_n represent the damping factor and natural frequency respectively.

2.1.2. Drive train

The system transfers torque from the rotor to the generator. It can be modelled by a two-mass model:

$$J_r\dot{\omega_r}(t) = \tau_r(t) - K_{dt}\theta_\Delta(t) - (B_{dt} + B_r)\omega_r(t) + \frac{B_{dt}}{N_g}\omega_g(t) \tag{3}$$

$$J_g\dot{\omega_g}(t) = \frac{\eta_{dt}K_{dt}}{N_g}\theta_\Delta(t) + \frac{\eta_{dt}B_{dt}}{N_g}\omega_r(t) - \left(\frac{\eta_{dt}B_{dt}}{N_g^2} + B_g\right)\omega_g(t) - \tau_g(t) \tag{4}$$

$$\dot{\theta}_\Delta(t) = \omega_r(t) - \frac{1}{N_g}\omega_g(t). \tag{5}$$

J_r: Moment of inertia of the low-speed shaft;
K_{dt}: Torsion stiffness of the drive train;
B_{dt}: Torsion damping coefficient of the drive train;
B_g: Viscous friction of the high-speed shaft;
N_g: Gear ratio;
J_g: Moment of inertia of the high-speed shaft;
η_{dt}: Efficiency of the drive train;
$\theta_\Delta(t)$: Torsion angle of the drive train.

2.1.3. Generator and converter

This system is modelled by a first-order transfer function:

$$\frac{\tau_g(s)}{\tau_{g,r}(s)} = \frac{a_{gc}}{s + a_{gc}} \tag{6}$$

where $a_{gc}$is the parameter of generator and converter dynamics. The power produced by the generator is given by

$$P_g(t) = \eta_g(t)\omega_g(t)\tau_g(t) \tag{7}$$

where $\eta_g$is the efficiency of the generator.

2.1.4. Controller

This benchmark model mainly focuses on the accommodation of the wind turbine, therefore the control scheme is simple. The controller consists of two modes. Mode 1 gets the optimal value through setting the pitch reference to zero ($\beta_r[n] = 0$). Mode 2 mainly uses a PI controller to keep ω_g at the nominal generator speed ω_{nom}. The control mode switches from mode 1 to mode 2 if

$$P_g[n] \geqslant P_r[n] \vee \omega_g[n] \geqslant \omega_{nom} \tag{8}$$

and the control mode switches from mode 2 to mode 1 if

$$\omega_g[n] \leqslant \omega_{nom} - \omega_\Delta \tag{9}$$

where ω_Δ is a small offset subtracted from the nominal generator speed to introduce some hysteresis in the switching scheme.