Sustainable Energy, Grids and Networks 1 (2015) 45–52

Contents lists available at ScienceDirect

Sustainable Energy, Grids and Networks

journal homepage: www.elsevier.com/locate/segan

Wind turbine simulator fault diagnosis via fuzzy modelling and identification techniques

Silvio Simani [a,*], Saverio Farsoni [a], Paolo Castaldi [b]

[a] Department of Engineering, University of Ferrara, Ferrara, FE. 44122, Italy
[b] Electric and Informatics Department, University of Bologna, Bologna, Italy

ARTICLE INFO

Article history:
Received 21 September 2014
Received in revised form
18 December 2014
Accepted 23 December 2014
Available online 9 January 2015

Keywords:
Fuzzy modelling and identification
Fault detection and isolation
Residual generators
Sustainability and availability
Wind turbine benchmark

ABSTRACT

For improving the safety and the reliability of wind turbine installations, the earliest and fastest fault detection and isolation are highly required, since it could be used also for accommodation purpose. Modern wind turbines consist of several important subsystems, which can be affected by malfunctions regarding actuators, sensors, and components. From the turbine control point-of-view they are extremely important since provide the actuation signals, the main functions, as well as the measurements. In this paper, a fault diagnosis scheme based on the identification of fuzzy models is described, in order to detect and isolate these faults in the most efficient way, in order also to improve the energy cost, the production rate, and reduce the operation and maintenance operations. Fuzzy systems are proposed here since the model under investigation is nonlinear, whilst the wind speed measurement is uncertain since it depends on the rotor plane wind turbulence effects. These fuzzy models are described as Takagi–Sugeno prototypes, whose parameters are estimated from the wind turbine measurements. The fault diagnosis methodology is thus developed using these fuzzy models, which are exploited as residual generators. The wind turbine simulator is finally employed for the validation of the obtained performances.

1. Introduction

Modern industrial processes and controlled plants can exploit many technical resources comprising for example information sciences, real-time solutions, advanced diagnosis and control, and computational intelligence. This paper aims at reporting recent developments in the emerging areas of technology that find applications to factory advanced control and diagnosis, such as wind turbine installations.

The control tools normally used for improving the complete behaviour of power plants can exploit both advanced control schemes and complicated hardware solutions (for example, smart sensors, virtual actuators and processing units). This high complexity degree can increase the failure rate, thus motivating the requirement of an automatic scheme employed to quickly diagnose any abnormal working situations. These remarks raised a great interest in the issues of Fault Detection and Isolation (FDI) for dynamic systems, and many model-based strategies were suggested, as described for example in [1–4]. These methods rely on the mathematical description of the process under diagnosis. However, the diagnosis principle can be based on a limited number of approaches, *i.e.*: the parity space method, the state or output estimation, the Unknown Input Observer (UIO) principle, the Kalman Filters (KF) tool, the Unknown Input Kalman Filters (UIKF) strategy, and the parameter identification approach. Moreover, techniques relying on the artificial intelligence tools were also proposed [5]. Even if several linear and nonlinear methodologies were proposed, robust and reliable (in one word, "sustainable") FDI requires future researches.

It is worth noting that the accurate detection and isolation of faults can require a precise mathematical description of the plant under diagnosis, which can be expressed as state-space or input–output formulation. In this way, after the generation of the residual signals, their evaluation should guarantee the accurate fault detection, while avoiding the indication of false alarms generated by disturbance, measurement errors, and the model-reality mismatch. However, in actual conditions, the direct design and application of these FDI approaches can be difficult, motivated by the complexity of the mathematical description involved. This unavoidable complexity cannot allow the direct use of most of the linear FDI schemes, thus requiring a viable strategy for the direct application of the diagnosis schemes to practical examples [3,6].

* Corresponding author.
E-mail address: silvio.simani@unife.it (S. Simani).
URL: http://www.silviosimani.it (S. Simani).

http://dx.doi.org/10.1016/j.segan.2014.12.001
2352-4677/

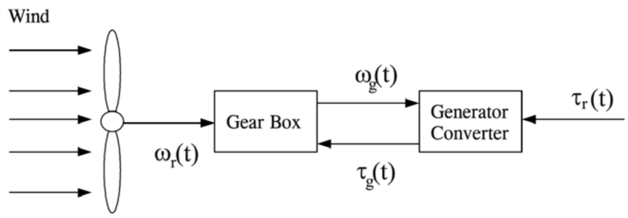

Fig. 1. Wind turbine schematic diagram.

With reference to wind turbines, as considered in this work, many papers considered the model-based FDI problem [7,8]. They showed that the more accurate the representation is at modelling the plant dynamics, the better its behaviour will be in diagnosing abnormal working situations.

This paper proposes the use of the fuzzy modelling and identification tool with application to a wind turbine benchmark for determining a straightforward solution of the FDI task. Two key issues of the proposed study are remarked. First, the model complexity does not imply the need of a complex mathematical description. In fact, as described here, the fuzzy modelling and identification tool can be exploited, thus avoiding purely nonlinear equations. Moreover, the mathematical description of the residual generators is derived via an identification approach. On the other hand, fuzzy prototypes as residual generators are designed, rather than purely nonlinear filters. This aspect is quite important when the designed diagnosis tool is proposed for real-time solutions. Moreover, the diagnosis scheme proposed in this study paper will be analysed in comparison with different approaches relying *e.g.* on banks of UIO/KF, as described in [1,3].

This work proposes the use of the fuzzy logic theory, since it seems to be a simple tool able to manage complicated and unknown situations [9]. In particular, the residual generators applied to the wind turbine benchmark are derived as Takagi–Sugeno (TS) fuzzy descriptions [10], whose parameters are estimated via a system identification strategy. The efficacy of the suggested approaches are verified on the wind turbine benchmark measurements. Real-time simulations comprising realistic fault and working situations are used to assess the efficacy of the suggested methodologies.

It is worth noting that, with respect to the previous work by one of the same authors [11], this paper extends the results and improves the efficacy of the proposed solution. On the other hand, the identification approach, which is extended to the fuzzy framework and applied to the wind turbine data in this study, was developed by one of the same authors in [12]. Moreover, the design of the fuzzy estimators, which in this paper is exploited for the fault isolation task, was described in a paper by the same author [13], but applied to a diesel engine system.

Finally, the paper has the structure as detailed below. Section 2 addresses the wind turbine model exploited in the work. Section 3 describes the fuzzy modelling and identification tool used for FDI strategy development. The suggested FDI scheme is considered in Section 4. The obtained results reported in Section 5 serve to highlight the efficacy of the fuzzy tool, which is compared also with respect to a different FDI scheme. Section 6 concludes the work by summarising the main points of the paper and suggesting some future research issues.

2. Wind turbine simulated model

The paper considers a realistic wind turbine with horizontal axis and three blades that move the rotor shaft due to the incoming wind flow. A gear-box is used for up-scaling the rotational speed of the power generator. More details of this benchmark wind turbine are available in [7]. Fig. 1 provides the diagram of this power plant.

The converter torque $\tau_g(t)$ and the turbine blade pitch angle $\beta_r(t)$ are the two control inputs used to regulate the rotational speed $\omega_r(t)$ and the generated power $P_g(t)$. On the other hand, $\omega_g(t)$ represents the generator speed, whilst $\tau_g(t)$ is generator torque depending on the converter torque reference, $\tau_r(t)$. $\tau_{aero}(t)$ is the aerodynamic torque, whose estimate is computed from the wind speed, $v(t)$. However, this measurement is very uncertain, as shown *e.g.* in [7].

The aerodynamic description is provided by Eq. (1):

$$\tau_{aero}(t) = \frac{\rho\, A\, C_p\, (\beta_r(t),\ \lambda(t))\ v^3(t)}{2\,\omega_r(t)} \tag{1}$$

with the air density ρ, the turbine blade area A, the reference pitch angle $\beta_r(t)$, and the tip–speed ratio $\lambda(t)$, described by Eq. (2):

$$\lambda(t) = \frac{\omega_r(t)\, R}{v(t)} \tag{2}$$

where the rotor radius is R. With reference to Eq. (1), the term C_p describes the power coefficient that is usually represented by a two-dimensional map. Since the wind speed measurement $v(t)$ is uncertain, it is assumed that $\tau_{aero}(t)$ is affected by an error, which justifies the proposed approach of Section 3. The proposed scheme is also able to manage the nonlinearity described by the expressions of Eqs. (1) and (2).

The drive-train is described as a one-body model and the complete hydraulic pitch system is modelled as a second order transfer function [7]. Under these hypotheses, the overall continuous-time state-space model of the wind turbine process is described by Eq. (3):

$$\begin{cases} \dot{x}_c(t) = f_c\,(x_c(t), u(t)) \\ y(t) = x_c(t) \end{cases} \tag{3}$$

where the available control inputs are represented by the vector $u(t) = \left[\beta_{1\,m_i}(t),\ \beta_{2\,m_i}(t),\ \beta_{3\,m_i}(t),\ \tau_g(t)\right]^T$ and the output measurements are described by the vector $y(t) = x_c(t) = \left[P_g(t),\ \omega_{g\,m_i}(t),\ \omega_{r\,m_i}(t)\right]^T$, respectively. These measurements are provided by two redundant sensor signals, with $i = 1, 2$. The static function $f_c\,(\cdot)$ describes the nonlinear relation between inputs and outputs. As described in Section 3, this nonlinear system will be approximated using the fuzzy models estimated from N data sequences $u(k)$ and $y(k)$, where $k = 1, 2, \ldots, N$, are the sampling intervals.

With reference to the available redundant measurements from the benchmark, $\omega_{g\,m_i}$ and $\omega_{r\,m_i}$ represent the generator and rotor speed signals, respectively. $\beta_{j\,m_i}(t)$ refers to the ith measurement of the jth blade pitch. The look-up table $C_p\,(\beta,\ \lambda)$ is selected for describing a high-fidelity wind turbine, which is the test-rig for the validation of the proposed approach.

Finally, the measurement errors are described as Gaussian processes with statistics that represent realistic wind turbine measurement sensors.

2.1. Fault mode and effect analysis

The benchmark system considered in this paper simulates a number of realistic faults, described in Table 1, which represent typical malfunctions of wind turbine installations. More details are available in [7].

In order to simplify the approach to the FDI task, the links between the fault situations reported above and the considered wind turbine measurements were considered and analysed.