Hybrid Model–Based Fault Detection of Wind Turbine Sensors

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Abstract: In order to improve reliability of wind turbines, it is important to detect faults in their very early occurrence, and to handle them in an optimal way. This paper focuses on the pitch sensors of the turbine blade system, as they are mainly used for wind turbine control, in order to maximise the power production, and the efficiency of the whole process. On the other hand, as the input–output behaviour of the system under diagnosis is nonlinear, this work suggests a modelling scheme relying on piecewise affine models, whose parameters are identified through the acquired input–output measurements affected by measurement uncertainty. Therefore, these hybrid prototypes are exploited for generating suitable residual signals, which allow the detection and the isolation of the considered sensor faults. This noise rejection scheme is used since the wind turbine measurements are not very reliable, due to the uncertainty of wind speed acting on the wind turbine, and to the turbulence around the rotor plane. A detailed benchmark model simulating the wind turbine where realistic fault conditions can be considered shows the effectiveness of both the identification and fault diagnosis techniques.

1. INTRODUCTION

The key step towards system supervision, monitoring, diagnosis, and control design is to find a suitable mathematical description of the process under investigation. In some cases system modelling based on insight on the physical laws, which govern the real process behaviour might be cumbersome and practically infeasible. On the other hand, input–output process measurements can be successfully used to infer analytical descriptions of the system in the framework of a parametric structure, which possess approximation properties with respect to the complex, nonlinear, unknown analytical functions that are amenable as candidate to describe the real behaviour of the observed process (Juditsky et al. [1995]). So, the choice of the parametric structure become an important and difficult step towards the system identification, especially when the behaviour of the target process is nonlinear, as it is common by far in real world applications (Billings and Voon [1983]).

The mathematical treatment of nonlinear models follows different approaches and cover topics ranging from approximation theory, estimation theory, non–parametric regression to the most modern techniques based on use of neural networks, wavelets, and fuzzy models (Sjöberg et al. [1995]). The modelling approach suggested in this work refers to a nonlinear process, namely a wind turbine, which operates at different regimes, in which distinct models can be associated to each admissible operating condition. A switching function governs the transition among different models or interpolations of models. Such mathematical descriptions are referred in current literature as hybrid models. This paper suggests a fault diagnosis strategy based on dynamic, discrete–time, time–invariant, affine models describing locally the behaviour of the monitored wind turbine in its different operating regimes. This type of models have been formerly proposed by Simani, et al., and used in stochastic environment for time series model identification (Fantuzzi et al. [2002]).

Concerning the fault diagnosis issue, symptoms are signals representing inconsistencies between the model and the actual system being monitored. Any inconsistency will indicate a fault in the system. Residual must, therefore, be different from zero when a fault occurs and zero otherwise. However, the deviation between the model and the plant is influenced not only by the presence of the fault but also the modelling error. Several techniques had been proposed for Fault Detection and Isolation (FDI) in dynamic systems (Chen and Patton [1999]). In particular, in this work, the hybrid modelling scheme is combined with the model–based method to formulate a FDI technique exploiting the identified piecewise affine prototype (Fantuzzi et al. [2002]) for residual generation. Under such a scheme, a number of local affine models are designed and the estimate of outputs is given by a fusion of local outputs. The diagnostic signal (symptom or residual) is the difference between the estimated and actual system output. In this paper, the different operating points are self–selected with a clustering method presented in (Babuska [1998]). On the basis of knowledge of the operating point regions, the identification of the structure, and the parameters of each local affine dynamic model has

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been performed (Fantuzzi et al. [2002]). This modelling scheme is used here since the wind turbine measurements are not very reliable, due to the uncertainty of wind speed acting on the wind turbine, and to the turbulence around the rotor plane. A detailed benchmark model simulating the wind turbine where realistic fault conditions can be considered shows the effectiveness of both the proposed identification and fault diagnosis techniques.

The remainder of this paper is organised as follows. Section 2 recalls the structure of the exploited multiple model. Section 3 shows the design of the diagnostic scheme for the FDI of dynamic systems. The application of the FDI approach to the wind turbine is described in Section 4. The example demonstrates the effectiveness of the technique proposed. Finally, some concluding remarks are included in Section 5.

2. HYBRID MODELLING AND IDENTIFICATION

The main idea underlying the mathematical description of nonlinear dynamic systems is based on the interpretation of single input–single output, nonlinear, time–invariant regression models such as:

\[ y(t+n) = F(y(t+n-1), \ldots, y(t), u(t+n-1), \ldots, u(t)) \tag{1} \]

with \( t = 0, 1, \ldots \), \( y(\cdot) \) and \( u(\cdot) \) belong to the bounded input \( U \) and output \( Y \) sets, respectively. \( n \) is the finite system memory (i.e. the model order), and \( F(\cdot) \) is a continuous nonlinear function defining a hypersurface from an \( A_n \) to \( Y \), being \( A_n \) the Cartesian product \( U^n \times Y^n \). The identification of the nonlinear system can be translated to the approximation of its mathematical model given by (1) using a parametric structure that exhibits arbitrary accuracy interpolation properties. A piecewise model defined through the composition of simple models having local validity is the natural candidate to perform this task, as it combines function interpolation properties with mathematical tractability.

2.1 Piecewise Affine Structure

The piecewise model consists of a collection of parametric submodels of the type:

\[ y(t+n) = \sum_{j=0}^{n-1} a_{ij} y(t+j) + \sum_{j=0}^{n-1} b_{ij} u(t+j) + \beta^{(i)}(t), \quad t = 0, 1, \ldots \tag{2} \]

in which the system operating point is described by the input and output samples \( y(t+n-1), \ldots, y(t) \) and \( u(t+n-1), \ldots, u(t) \), that can be collected with a vector \( x_n(t) = [y(t), \ldots, y(t+n-1), u(t), \ldots, u(t+n-1)]^T \). The switching function \( \chi_i(x_n(t)) \), \( i = 1, \ldots, M \) is

\[ \chi_i(x_n(t)) = \begin{cases} 1 & \text{if } x_n(t) \in A_n^{(i)} \\ 0 & \text{otherwise} \end{cases} \tag{3} \]

where \( \{A_n^{(1)}, \ldots, A_n^{(M)}\} \) is a partition of \( A_n \), whose structure will be characterised in the following. Thus, the output \( y(t+n) \) of the nonlinear dynamic system described by (1) can be approximated by the piecewise affine model \( f(\cdot) \) in the form:

\[ y(t+n) = f(x_n(t)) = \sum_{i=1}^{M} \chi_i(x_n(t)) [x_n(t), 1]^T a_i^{(i)} \tag{4} \]

where the model parameters are collected in the vector \( a_i^{(i)} \). It is worthwhile noting that the model is affine in each \( A_n^{(i)} \) being the affine submodel parameters.

2.2 Local Model Identification

It is assumed that the input–output data \( u(t) \) and \( y(t) \), \( t = 0, 1, \ldots, L \) generated by a system of the type of (2) are available. Restricting the investigation also to find order \( n \) and parameters \( a_i^{(i)} \) for local model in the form of (2) in region \( A_n^{(i)} \), the following matrix should be defined:

\[
\Sigma_k^{(i)} = \begin{bmatrix}
    y(k) & x_k^T(0) & 1 \\
    y(k+1) & x_k^T(1) & 1 \\
    \vdots & \vdots & \vdots \\
    y(k+N_i-1) & x_k^T(N_i-1) & 1
\end{bmatrix}
\tag{5}
\]

with \( k + N_i - 1 \leq L \) and \( N_i \) is chosen so that \( k + N_i - 1 \) is large enough to avoid unwanted linear dependence relationships due to limitations in the dimension of the vector spaces involved. To determine the model order \( n \) in region \( A_n^{(i)} \), it is possible to consider the sequence of increasing–dimension positive definite or positive semidefinite \( (2k+2) \times (2k+2) \) symmetric matrices

\[
\Sigma_2^{(i)}, \Sigma_4^{(i)}, \ldots, \Sigma_k^{(i)}, \ldots
\tag{6}
\]

testing their singularity as \( k \) increases. As soon as a singular matrix \( \Sigma_k^{(i)} \) is found then \( n = k \), and the parameters \( a_i^{(i)} \) describe the dependence relationship of the first vector of \( x_n^{(i)} \) on the remaining ones as

\[
\Sigma_n^{(i)} [a_i^{(i)}] = 0
\tag{7}
\]

It is worth noting that the vectors \( x_n(0), x_n(1), \ldots, x_n(N_i-1) \) in (5) must belong to the region \( A_n^{(i)} \) according to the partition defined in (3).

Note also that in the presence of noise the above procedure described to determine order and model parameters would obviously be useless since matrices \( \Sigma_k \) would always be non–singular (positive definite).

In order to solve the problem in a mathematical framework, it is necessary to characterise the noise affecting the input–output data. Following common assumptions (Kulman [1982], Beghelli et al. [1990]), the noises \( \tilde{u}(t) \) and \( \tilde{y}(t) \) are assumed additive on input–output data \( u^*(t) \) and \( y^*(t) \) and region independent, so that:

\[
\begin{cases}
    u(t) = u^*(t) + \tilde{u}(t) \\
    y(t) = y^*(t) + \tilde{y}(t)
\end{cases}
\tag{8}
\]

Obviously, only \( u(t) \) and \( y(t) \) are available for the identification procedure, and moreover every noise term \( \tilde{u}(t) \) and \( \tilde{y}(t) \) is modelled with a zero–mean white process and is supposed to be independent of every other term. These structures are also commonly known as “Error-Variables” models. Under these assumptions, \( \tilde{\sigma}_u \) and \( \tilde{\sigma}_y \) being the input and output noise variances respectively,
the generic positive definite matrix $\Sigma_k^{(i)}$ associated with the input-output noise-corrupted sequences can always be expressed as the sum of two terms $\Sigma_k^{(i)} = \Sigma_k + \tilde{\Sigma}_k$ where

$$\tilde{\Sigma}_k = \text{diag}[\tilde{\sigma}_y I_{k+1}, \tilde{\sigma}_y I_k, 0] \geq 0. \quad (9)$$

Thus, it is again possible to determine the order and parameters of the model in region $A_n^{(i)}$ from the analysis of the sequence of increasing dimension ($(2k + 2) \times (2k + 2)$) symmetric positive definite matrices:

$$\Sigma_2^{(i)}, \Sigma_3^{(i)}, \ldots \Sigma_k^{(i)}, \ldots \quad (10)$$

The solution of the above identification problem requires the computation of the unknown noise covariances $\tilde{\sigma}_u$ and $\tilde{\sigma}_y$, that can be achieved solving the following relation:

$$\Sigma_k^{(i)} = \Sigma_k^{(i)} - \tilde{\Sigma}_k \geq 0. \quad (11)$$

in the variables $\tilde{\sigma}_u, \tilde{\sigma}_y$, where $\tilde{\Sigma}_k = \text{diag}[\tilde{\sigma}_y I_{k+1}, \tilde{\sigma}_y I_k, 0]$. It is worthy to note that to set the value of variables $\tilde{\sigma}_u, \tilde{\sigma}_y$ which make matrix $\Sigma_k^{(i)}$ positive semidefinite forms a curve.

If the noise characteristics are common to all the regions $A_n^{(i)}$, since the physical nature of the process generating the noise is independent of the model structure and of the partition of $A_n$, and all assumptions regarding the Frisch scheme are fulfilled, a common point $(\tilde{\sigma}_u, \tilde{\sigma}_y)$ in the noise plane exists for the singularity curves.

In real applications, we are forced to relax these assumptions, thus no common point can be determined among curves $\Gamma_n^{(i)} = 0$ in the noise plane and a unique solution to the identification problem can be obtained only by introducing a criterion to select a different noisy point for each region as best approximation of the ideal case (Fantuzzi et al. [2002]).

With reference to the identification of the system order $n$ in the $i$-th region $A_n^{(i)}$, it must be noted that the $r_n^{(i)} + 1 = 0$ curve has a single point in common with the $\Gamma_n^{(i)} = 0$ curve in ideal conditions, which corresponds to a double singularity of the matrix $\Sigma_n^{(i)}$. In real cases, the order $n$ can be computed finding the point $(\tilde{\sigma}_u, \tilde{\sigma}_y) \in \Gamma_n^{(i)} = 0$ that makes $\Sigma_n^{(i)}$ closer to the double singular condition (i.e. minimal eigenvalue equal to zero and the second minimum eigenvalue near to zero). As $n$ is unknown, increasing system orders $k$ must be tested, and the value of $k$ associated to the minimum of the second eigenvalue of the matrix $\Sigma_n^{(i)}$ corresponds to the order $n$. This criterion is consistent as it leads to the common point of the curves when the assumptions of the Frisch scheme are not violated.

Note that since the order $n$ of the piecewise model described by (4) is region independent, it can be determined by choosing $k$ that fulfil the following inequality:

$$\max_{i = 1, \ldots, M_k} \lambda_k^{(i)} < \epsilon \quad (12)$$

when $\epsilon$ is an arbitrary positive constant and $\lambda_k^{(i)}$ is the minimal eigenvalue different from zero of matrix $\Sigma_n^{(i)}$. This result led to derive an algorithm for the selection of the model order (Fantuzzi et al. [2002]).

Once the model order $n$ is selected, the parameters $a_{n_i}^{(i)}, i = 1, \ldots, M$ can be computed considering for each region a different noise $(\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)})$. The values $(\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)})$ can be computed by solving an optimisation problem which minimises both the distances between $(\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)})$ and $(\tilde{\sigma}_u^{(i)}, \tilde{\sigma}_y^{(i)})$ with $i \neq j$ and the continuity constraints (Fantuzzi et al. [2002]):

$$J((\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)}), \ldots, (\bar{\sigma}_u^{(M)}, \bar{\sigma}_y^{(M)})) =$$
$$= d \left( (\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)}), \ldots, (\bar{\sigma}_u^{(M)}, \bar{\sigma}_y^{(M)}) \right) +$$
$$+ (C_n A_n)^T H C_n A_n \quad (13)$$

$H$ being a definite positive weighting matrix, and $d(\cdot)$ a distance defined as:

$$d \left( (\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)}), \ldots, (\bar{\sigma}_u^{(M)}, \bar{\sigma}_y^{(M)}) \right) =$$
$$= \sum_{i=1}^{M} \sum_{j=1}^{M} \sqrt{\bar{\sigma}_u^{(i)} - \bar{\sigma}_u^{(j)}}^2 + \bar{\sigma}_y^{(i)} - \bar{\sigma}_y^{(j)}^2. \quad (14)$$

It is worthwhile observing that the matrix $A_n$ collects the parameters $a_{n_i}^{(i)}$, $i = 1, \ldots, M$ which depend on $(\bar{\sigma}_u^{(i)}, \bar{\sigma}_y^{(i)})$.

3. FDI BASED ON IDENTIFIED HYBRID MODELS

The problem treated in this section regards the detection and isolation of sensor faults of the process under diagnosis on the basis of the knowledge of the measured uncertain sequences $u(t)$ and $y(t)$.

It is assumed that the monitored system, depicted in Fig. (1), is described by a model of the type of (4). The term $y(t) \in R^m$ is the system output vector, and $u(t) \in R^r$ the control input vector. The signal $\varepsilon(t)$ takes into account the modelling error, which is due to process noise, parameter variations, nonlinearities, etc. According to

\begin{align}
\text{Input Measurements} & \quad \text{Output Measurements} \\
\begin{array}{c}
u^*(t) \\
f_a(t) \\
u(t)
\end{array} & \begin{array}{c}
\text{Monitored System} \\
\text{Input Faults} \\
\text{Output Measurements} \\
y^*(t) \\
y(t) \\
f_y(t)
\end{array}
\end{align}

\begin{align}
\begin{array}{c}
f_a(t) \\
u(t)
\end{array} & \begin{array}{c}
\text{Input Faults} \\
\text{Output Faults} \\
\end{array}
\end{align}

Fig. 1. The structure of the monitored system, with sensor faults.

to Eqs. (8), in realistic situations the variables $u^*(t)$ and $y^*(t)$ are measured by means of sensors, whose outputs are affected by noise. Neglecting sensor dynamics, faults affecting the measured input and output signals $u(t)$ and $y(t)$ are modelled as:

$$\begin{align}
\{ u(t) = u^*(t) + f_a(t) \\
y(t) = y^*(t) + f_y(t)
\end{align} \quad (15)$$

in which, the vectors $f_a(t) \in R^r$ and $f_y(t) \in R^m$ are composed of additive signals, which assume values different from zero only in the presence of faults.
There are different approaches to generate the diagnostic signals, residuals or symptoms, from which it will be possible to diagnose the considered fault cases. In this work, a model–based approach is used to estimate the outputs of the system from the input–output measurements. As depicted in Fig. (2), residuals can be generated by the comparison of the measured and the estimated outputs:

\[ r(t) = \hat{y}(t) - y(t). \]  

The symptom evaluation refers to a logic device which processes the redundant signals generated by the first block in order to estimate when a fault occurs, and to univocally identify the unreliable sensors. Faults can be detected by using a simple thresholding logic:

\[ |r(t)| \begin{cases} \leq \text{Threshold}, & \text{in fault–free conditions}, \\ > \text{Threshold}, & \text{in faulty conditions}. \end{cases} \]  

and, in more detail, according to the following relations:

\[ \begin{align*} r(t) &< \bar{r} - \nu \sigma_r, & \text{in fault–free conditions;} \\
\text{or} \quad r(t) &> \bar{r} + \nu \sigma_r, & \text{in faulty conditions.} \end{align*} \]  

where \( \bar{r} \) and \( \sigma_r \) represent the mean and the standard deviation values of the fault–free residual \( r(t) \), respectively. Due to the presence of modelling errors, \( \nu \) has to be properly selected in order to achieve the best performances in term of false alarm and missed fault rates (Patton et al. [2009]). In practice, as shown in Section 4, the value of \( \nu \) can be fixed according e.g. to the three-sigma rule.

4. WIND TURBINE MODELLING AND FDI

The three blade horizontal axis turbine considered in this paper works by the principle that the wind is acting on the blades, and thereby moving the rotor shaft. In order to upscale the rotational speed to the needed one at the generator, a gear box is introduced. A more accurate description of the benchmark model can be found in (Odgaard et al. [2009], Odgaard and Stoustrup [2009]).

The rotational speed, and consequently, the generated power can be regulated by means of two control strategies: the converter torque and the pitch angle of the turbine blades. In partial load of the wind turbine is controlled to generate as much power as possible. This is achieved by keeping a specific ratio between the tip speed of the blades and the wind speed, which in turn is regulated by controlling the rotational speed and by adjusting the converter torque. In the full power region the converter torque is kept constant and the rotational speed is adjusted by controlling the pitch angle of the blades, which changes the aerodynamic power transfer from the wind to the blades (Odgaard et al. [2009]). The wind turbine model is illustrated in Fig. 3, according to the nomenclature defined in (Odgaard et al. [2009]).

\begin{equation}
\tau_{aero}(t) = \rho A C_p(\beta(t), \lambda(t)) \frac{\dot{v}(t)}{2 \omega_r(t)} \tag{19}
\end{equation}

where \( \rho \) is the density of the air, \( A \) is the area covered by the turbine blades in its rotation, \( \beta(t) \) is the generic pitch angle of the blades, \( v(t) \) the wind speed, whilst \( \lambda(t) \) is the tip-speed ratio of the blade, defined as:

\begin{equation}
\lambda(t) = \frac{\omega_r(t) R}{\dot{v}(t)} \tag{20}
\end{equation}

with \( R \) the rotor radius, \( C_p \) represents the power coefficient, here described by means of a two-dimensional map (look–up table) (Odgaard et al. [2009]). Equation (19) is used to estimate \( \tau_{aero}(t) \) based on an assumed estimated \( v(t) \), and measured \( \beta(t) \) and \( \omega_r(t) \). Due to the uncertainty of the wind speed, the estimate of \( \tau_{aero}(t) \) is considered affected by an unknown measurement error, which can be estimated by means of the approach described in Section 4.
2. Moreover, the nonlinearity represented by the relations (19) and (20) motivates the modelling approach suggested in Section 2.

A simple one-body model is used to represent the drive train, in the following form (Odgaard and Stoustrup [2009]):

\[
\dot{\omega}_r(t) = \frac{1}{J} (\tau_{\text{acro}}(t) - \tau_{\text{gen}}(t))
\]

where:

\[
\tau_{\text{gen}}(t) = p_{\text{gen}} (\tau_{\text{ref}}(t) - \tau_{\text{gen}}(t))
\]

The generator torque \(\tau_{\text{gen}}(t)\) and the reference \(\tau_{\text{ref}}(t)\) are in this context transformed to the low speed side of the drive train (rotor side).

These assumptions yield the continuous-time dynamic model of the system under diagnosis in the following form:

\[
y(t) = F_c(u(t))
\]

with:

\[
u(t) = [\tau_{\text{ref}}(t), v_{\text{hub}}(t), \beta_i(t)]^T, \quad y(t) = \omega_r(t)
\]

where \(u(t)\) and \(y(t)\) are the input and the monitored output measurements, respectively. \(F_c(\cdot)\) represents the continuous-time nonlinear function representing the discrete-time unknown function \(F\) in the form (1), which will be approximated with the discrete-time hybrid prototype (4) from \(N\) sampled data \(u(t)\) and \(y(t)\), with \(t = 1, 2, \ldots, N\), and using the procedure presented in Section 2.

Finally, the model parameters and the map \(C_p(\beta, \lambda)\) are chosen such that they represent a realistic turbine, which is used as case study, as shown in (Odgaard et al. [2009]).

4.2 Wind Turbine FDI

The proposed methodology was applied to the identification and fault diagnosis of the wind turbine described in Section 4.1. The considered process is shown in Fig. 3, where the considered \(r = 3\) inputs are the reference signal \(\tau_{\text{ref}}(t)\), the wind speed \(v_{\text{hub}}(t)\), and the pitch angle \(\beta_i(t)\) measurements \((i = 1, 2, 3)\), whilst the \(m = 1\) output corresponds to the rotor angular speed \(\omega_r(t)\). The available data from the measured inputs and outputs were \(440 \times 10^3\) samples from normal operating records acquired with a sampling rate of 100 Hz. Because of the underlying physical mechanisms described in Section 4.1, and because of the switching control logic described in (Odgaard et al. [2009], Odgaard and Stoustrup [2009]), the wind turbine system has nonlinear steady state, as well as dynamic characteristics.

Two series of data were acquired from the benchmark process. The first one was used for model identification, and the second one was exploited for the validation task. According to the algorithm recalled in Section 2 for the selection of the model order, the initial value of \(k = 1\) and \(\epsilon = 10^{-7}\) have been fixed. Under these assumptions, as stated in Section 2, the triangulation of the input-output domain \(U \times Y\) into simplexes was performed. The partition of the domain was obtained by exploiting the Matlab toolbox for data clustering presented in (Babuška [1998]). The partition of the domain for the wind turbine with \(k = 1\) has been achieved by considering the Cartesian product of the intervals \(I_1^{\text{ref}}\) and \(I_2^{\text{ref}}\).

A number of \(M_1 = 5\) regions were considered for applying (5) and to perform the identification task. Five local affine models were therefore estimated. In this case, \(x_k(t) = [y(t), u^T(t)]^T\), and the data belonging to the domain \(U \times Y\) have been clustered into the considered partition \(\{A_{1}^{(1)}, A_{1}^{(2)}, A_{1}^{(3)}, A_{1}^{(4)}, A_{1}^{(5)}\} (k = 1, M_1 = 5)\), the \(\Sigma_{k}^{(i)}\) matrices \((i = 1, \ldots, 5)\) have been computed (Fantuzzi et al. [2002]), and the test of (12) performed. In such a case, \(\max_{i=1,\ldots,5} A_{k}^{(i)} = 2.4765 \times 10^{-9}\). This value is below the selected accuracy \(\epsilon\), so the model order can be estimated as \(n = 1\). The mean square errors of the output estimation \(r(t)\), under no-fault conditions, is \(0.0043\) with respect to the estimation data, and \(0.0044\) for the validation data set. The fitting capabilities of the estimated hybrid models can be expressed also in terms of the so-called Variance Accounted For (VAF) index (Babuška [1998]). In particular, the VAF value computed for the estimation data is 97.97\%, whilst 89.15\% for the validation data. Hence, the hybrid multiple description seems to approximate the process under diagnosis quite accurately. It is worth noting how the identified model represents a trade-off between simulation accuracy (also dependent on the available data in each region) and structure complexity. Using this hybrid prototype, the model-based approach presented in Section 3 for fault diagnosis is exploited, and applied to the benchmark wind turbine process.

The following simulation results were obtained by considering a fault \(f_3(t)\) affecting the \(\beta_3(t)\) sensor, whose measurement gets stuck to the constant value 5\(^\circ\) for 100 s., and commencing at the instant \(t = 2000\) s. On the other hand, a second fault case, \(f_3(t)\), corresponding to the \(\beta_3(t)\) sensor stuck at the constant value 10\(^\circ\), is considered. This fault is active for 100 s., in the period between 2600 s. and 2700 s. In general, the controller in this wind turbine simulation model, runs in two modes: power optimisation (speed controlled by converter torque), and speed control (speed controlled by pitching blades) (Odgaard et al. [2009], Odgaard and Stoustrup [2009]). A wind speed in the range from approximately 5 \(\frac{\text{m}}{\text{s}}\) to 15 \(\frac{\text{m}}{\text{s}}\) is simulated. This wind speed scenario is used to cover the relevant wind speed region of power optimisation including turbulence. As shown in Fig. 2, the considered input faults cause alteration of the signals \(u(t)\) and \(y(t)\), and therefore of the residuals \(r(t)\) given by the predictive model in the form of (4). Residuals indicate fault occurrence according to the logic (17), whether their values are lower or higher than the thresholds fixed in fault-free conditions. As an example, Fig. 4 represents the fault-free (grey continuous line) and the faulty (black dashed line) residuals \(r(t)\) related to the \(\beta_3(t)\) pitch sensor fault. The fault detection thresholds reported in the relations (17) and (18) are represented as dotted constant lines in Fig. 4. Their values were properly settled by selecting \(\nu = 6\), which leads to minimise the false alarm and missed fault rates, while maximising the correct detection and isolation rates. In these conditions, the fault is correctly detected when the corresponding residual signals exceed the thresholds by more than 50 consecutive samples, as indicated by the fault indicator function depicted in Fig. 4. The residual signal \(r(t)\) exceeds the detection threshold after about 0.001 s.
Fig. 4. $\beta_1(t)$ sensor fault residuals $r(t)$, and the fault indicator function.

On the other hand, Fig. 5 represents the fault-free (grey continuous line) and the faulty (black dashed line) residuals $r(t)$ related to the $\beta_3(t)$ pitch sensor fault.

Fig. 5. $\beta_3(t)$ sensor fault residuals $r(t)$, and the fault indicator function.

The fault detection thresholds represented as dotted constant lines in Fig. 5 were obtained with $\nu = 5.5$, leading to minimise the false alarm and missed fault rates, while maximising the correct detection and isolation rates. Also in these conditions, the fault is correctly detected when the residuals exceed the thresholds by more than 50 consecutive samples, as indicated by the fault indicator function of Fig. 5. Also in this case, the residual signal $r(t)$ exceeds the detection threshold after about 0.001 s.

Note finally that the isolation of multiple sensor faults occurring either simultaneously or sequentially in time is also possible, if a dedicated observer scheme is exploited.

5. CONCLUSION

This paper proposed a procedure for the identification and fault diagnosis of a wind turbine model using a hybrid prototypes estimated from uncertain input–output measurements. It was assumed that the process under investigation is nonlinear, and the acquired measurements are not very reliable, due to the wind speed uncertain nature. The hybrid modelling suggested here was based on a collection of several local affine models, each describing a different operating point of the process. The identification algorithm exploited data clustering technique, in order to determine the regions in which measured data can be approximated by local affine dynamic models. The proposed approach provided a model of the wind turbine, which was used to generate residuals for fault diagnosis. The effectiveness of these strategies were tested on the data acquired from the wind turbine simulated model, thus allowing the detection and isolation of the wind turbine pitch angle sensor faults. The presented diagnosis technique was not tested in case of different fault conditions.

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