Fault diagnosis in wind turbines based on ANFIS and Takagi–Sugeno interval observers

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A B S T R A C T

Wind turbine power generation is becoming one of the most critical renewable energy sources. As wind power grows, there is a need for better monitoring and diagnostic strategies to maximize energy production and increase its security. In this paper, a fault diagnosis approach based on a data-driven technique, which represents the system behavior employing a Takagi–Sugeno (TS) model, is developed. An adaptive neuro-fuzzy inference system (ANFIS) method is used to obtain a set of polytopic-based linear representations and a set of membership functions to interpolate the linear models of the convex TS model. Then, considering the TS model, a fault diagnosis strategy based on convex state observers generate residuals to detect and isolate sensor faults. Unlike other methods, this proposal only needs to be trained with fault-free data. The proposed methodology is tested under different fault scenarios on a well-known wind turbine benchmark built upon fatigue, aerodynamics, structures, and turbulence (FAST). The results demonstrate the method’s effectiveness in detecting and isolating different sensor faults.

1. Introduction

With the growing demand for energy and concern about environmental problems, sustainable solutions have attracted enormous attention, among which wind energy has demonstrated outstanding characteristics such as availability and low-cost (Arshad & O’Kelly, 2019). Wind turbines have complex and nonlinear dynamics and operate under stochastic wind disturbances, centrifugal, gravitational, and gyroscopic loads (Rommel et al., 2020). Relying on various rotating and non-rotating components and sensors, as well as working in harsh environments, makes them prone to severe faults and breakdowns, leading to poor reliability. To avoid unforeseen faults, maintenance schedules are planned, which not only increase cost but also reduce power generation due to the required downtime (Ntalampiras, 2021). These challenges have motivated numerous investigations in wind turbines, from nominal control to fault diagnosis, and fault-tolerant control.

Several fault diagnosis (FD) schemes have been proposed to increase safety, reliability and reduce maintenance costs. In general, architectures for FD employ sensor data for detecting, isolating, and identifying faults in components that can be used to implement fault-tolerant control and condition-based maintenance (Yu et al., 2021). Due to the lack of available data, many articles are based on synthetic data from a benchmark described in Odgaard et al. (2013). This benchmark represents a 5 MW wind turbine, which is commonly used to validate different FD approaches such as a model-based Kalman filter (Honarbari et al., 2021), an observer-based approach (Chouiref et al., 2017), a support vector machine method (Noshirvani et al., 2018), a multi-integral proportional observer (Fadali et al., 2019), adaptive observers (Li et al., 2020), a reduced-order sliding mode observer (Sedigh Ziyabari et al., 2021), among others. Most of well-established FD approaches are based on accurate mathematical models that can be affected by uncertainty and disturbances. However, obtaining an accurate wind turbine model is a difficult task in practice, which still limits the application of model-based approaches (Li et al., 2021). Recently, data-driven methods are currently receiving considerable attention (Simani et al., 2021). Unlike model-based approaches that require dynamic equations, data-driven methods rely on data from measured process variables.

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Robust FD strategies can also be grounded in data-driven solutions. For example, in Rezamand et al. (2019), principal component analysis (PCA) was used to detect gearbox faults. Diagnosis and classification schemes based on artificial neural networks (ANN) have also been implemented (Dybkowski & Klimkowski, 2019; Zare & Ayati, 2021). In Márquez-Vera et al. (2021), fault detection schemes based on fuzzy logic were proposed, a hybrid scheme for FD was reported in Wen and Xu (2021), where a ReliefF-PCA and deep neural networks (DNN) were combined. However, these methods require data under different fault conditions and sufficient data for training. Nevertheless, in practice, not all possible faults types are known or are not available; thus, it is difficult to access all the fault characteristics in a large and complex wind turbine system. For this reason, appropriate methods for the available measurement data in the systems are required.

This paper proposes an adaptive neuro-fuzzy inference system (ANFIS) to identify a set of analytical redundancy relations (ARRs) for the wind turbine obtained from structural analysis. As a result of a set of convex Takagi–Sugeno (TS) models (López-Estrada et al., 2019) are obtained for the different ARRs. The modeling uncertainty of each TS model is also obtained and represented in parametric form. The training data are obtained from the measurable variables in a complete fault-free scenario. Using the TS model of each ARR, a set of convex interval observers is designed to detect and isolate faults. Different fault scenarios on a wind turbine benchmark are considered to illustrate the effectiveness of the method. Therefore, the main contributions of this paper are

- A hybrid strategy of ANFIS and convex TS interval observers for the fault diagnosis in wind turbines.
- The proposed ANFIS-TS hybrid scheme identifies a set of ARRs for the wind turbine obtained from the structural analysis. A set of convex TS models for the ARRs is obtained.
- Modeling uncertainty of each convex TS model is included and is represented parametrically. The training data is obtained from the available variables in fault-free conditions.
- Convex interval observers are designed using the convex TS model for each ARR for fault diagnosis using an LMI approach.
- To illustrate the method’s effectiveness, different fault scenarios are considered in a wind turbine benchmark.

The remaining of this document is organized as follows: Section 2 presents the structural analysis for the considered wind turbine system that is used for deriving a set of ARRs. Section 3 describes the convex Takagi–Sugeno model obtained from each ARR using non-faulty data and ANFIS. Section 4 presents the fault diagnosis scheme based on interval observers. Finally, Section 5 presents the conclusions.

2. Structural analysis for wind turbine model

This work considers the wind turbine benchmark proposed in Odgaard et al. (2013). The benchmark replicates a three-bladed horizontal axis wind turbine that considers turbulent wind speed as the system input. Each subsystem is coupled through inputs and outputs that interact to structure a complex and realistic electromechanical system. The benchmark is based on an offshore horizontal variable speed wind turbine with a full converter coupling and a rated power of 5 MW built up upon fatigue, aerodynamics, structures, and turbulence (FAST) aeroelastic simulator. This simulator was developed by the National Renewable Energy Laboratory (NREL) and was certified by Germanischer Lloyd in 2005, as announced by the NREL, which means that it can be used worldwide for turbine certification. Various FD schemes have been proposed for this wind turbine benchmark, being this reason why it is the most used to simulate and validate different schemes (Fadali et al., 2019).

The FD scheme of this work uses structural analysis, which describes the interactions between the signals and the wind turbine components.

### Table 1

<table>
<thead>
<tr>
<th>ARR</th>
<th>Related variables</th>
<th>Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( P_1 = \omega_1 t_1 )</td>
<td>Generator/Converter</td>
</tr>
<tr>
<td>2</td>
<td>( \dot{\omega}_r = \omega_1 + \beta_1 )</td>
<td>Generator/Converter</td>
</tr>
<tr>
<td>3</td>
<td>( \beta_1 = \beta_1 + \beta_2 )</td>
<td>Pitch system</td>
</tr>
<tr>
<td>4</td>
<td>( \beta_2 = \beta_1 + \beta_3 )</td>
<td>Pitch system</td>
</tr>
<tr>
<td>5</td>
<td>( \beta_3 = \beta_3 + \beta_4 )</td>
<td>Pitch system</td>
</tr>
<tr>
<td>6</td>
<td>( (\omega_1, \omega_1, \tau_1) = 0 )</td>
<td>Drivetrain</td>
</tr>
<tr>
<td>7</td>
<td>( (\omega_1, \omega_1, \tau_1) = 0 )</td>
<td>Drivetrain</td>
</tr>
<tr>
<td>8</td>
<td>( \omega_m = \phi_e )</td>
<td>Drivetrain</td>
</tr>
<tr>
<td>9</td>
<td>( (\hat{\omega}_g, \omega_1) = 0 )</td>
<td>Yaw system</td>
</tr>
<tr>
<td>10</td>
<td>( M_{31} = x_1 )</td>
<td>Tower</td>
</tr>
<tr>
<td>11</td>
<td>( M_{32} = x_1 )</td>
<td>Tower</td>
</tr>
<tr>
<td>12</td>
<td>( M_{33} = x_1 )</td>
<td>Tower</td>
</tr>
</tbody>
</table>

The dynamic model is interpreted as a set of constraints and a set of variables, which leads to a bipartite graph representing the system’s structure. The structural analysis proposes a description of the nominal behavior of the system (fault-free) utilizing a description of each component and the connection they have among the known variables (measurements). Using this concept, it is possible to diagnose whether a violation of the nominal behavior has occurred.

In the case of a wind turbine, it is enough to know the relationships between variables and components. Fig. 1, shows the interaction between components and system variables; for each of these variables, there is an associated sensor. The components and measured variables are associated as follows. The wind speed \( \omega_r \) is the kinetic energy that drives the system. The rotor blades move due to the wind impulse and the pitch system regulates the angle of the blades \( \beta_i \). The drivetrain connects a low-speed shaft to the rotor \( \omega_r \); the gears increase the rotation speed to the high-speed shaft \( \omega_1 \) and decrease the torque \( \tau_1 \) that drives the generator, coupled to a converter, to produce electrical power \( P_e \). The tower contains the nacelle, which is deflected by loads and flexibility, causing the nacelle movement characterized by the acceleration in \( X \) and \( Y \) directions \( \left[ \ddot{x}_X \quad \ddot{x}_Y \right]^T \). Additionally, there are complementary sensors in the system, an azimuth angle sensor \( \phi_m \) is available for the low-speed shaft that connects the rotor to the drivetrain. A sensor for each of the three-blade root moment \( M_{31} \) and a sensor to measure the yaw error \( \hat{\omega}_g \). The controlled inputs of the system are the generator reference torque \( \tau_{g,ref} \), the reference angle of the blades \( \beta_i \), and yaw reference angular velocity \( \omega_{ref} \). The aerodynamic torque of the rotor \( \tau_1 \) is estimated from the wind speed \( \omega_r \).

Consequently, there are enough sensors to measure the variables linking the components. Fig. 2 shows the structure graph of the components and measured variables. From the information in this graph, the ARRs can be generated. ARRs are available when matching components and measured variables (Blanke et al., 2006). Table 1 contains the components of the wind turbine and the ARRs that are generated from the relationships with the measured variables.

The purpose of the ARRs is to generate residuals for fault diagnosis. These residuals are used to check if the behavior of the system is within the nominal operating limits. Violation of the allowed limits is considered a fault. Residuals are computed as the difference between the measured and predicted behavior. The ARRs can be static, such as ARR1, ARR8 and ARR9 in Table 1, while the nine remaining ARRs are dynamic. The residual computation of the static ARRs is simple since they are derived from mathematical expressions. The dynamic ARRs are generated by comparing measured and observer-based estimation signals. The expression of each dynamic ARR model is calibrated in regressive form, as shown in Table 2.

ARRs in regressive form have the purpose of incorporating the dynamic behavior of the system. Each dynamic expression of ARR in regressive form from Table 2 is converted into an ANFIS model to structure a convex TS system and design the respective TS observer.
3. Fault diagnosis based on ANFIS and convex Takagi–Sugeno interval observers

This section presents the proposed method for fault diagnosis based on ANFIS and convex TS interval observers. The scheme flow chart is presented in Fig. 3. The general idea is to obtain uncertain convex TS models for each of the dynamic ARRs using ANFIS. Subsequently, use the obtained convex TS models to design a bank of convex TS interval observers. Finally, use the observers designed for fault isolation using a fault (incidence) matrix. These three stages are described next. The section ends with the considered fault scenarios.

### 3.1. Convex Takagi–Sugeno system from ANFIS

An ANFIS is considered to learn a particular structure from input–output data and approximate nonlinear systems behaviors (Alcala et al., 2020). In this work, an ANFIS is used to approximate each wind turbine subsystem’s nonlinear behavior employing a set of fuzzy if-then rules and convex Takagi–Sugeno models. The objective is to obtain an approximated model for fault diagnosis, although the data sets for the learning stage are comprised of fault-free sensor data. The input data for the ANFIS are composed of each regressive expression of Table 2, which represents the wind turbine in nominal operating conditions. The training provides a set of consequent parameters and a set of premise parameters that define the membership functions (MF) of the convex TS models, producing nonlinear relationships between the different linear parameters that define the membership functions (MF) of the convex TS representation for the ARR.

Fig. 4 depicts the construction of the convex TS model $\hat{\omega}_j$ for approximating subsystem $\omega_j$. The input dataset is comprised of the variables in the regression form of $\omega_j$, presented in Table 2; namely, $\tau_r(k)$, $\tau_g(k)$, and its delays $\omega_j(k-1)$ and $\omega_j(k-2)$. The ANFIS adjusts the premise and consequent parameters during the learning stage. Once the learning has finished, it proceeds to construct the convex TS representation for the $\hat{\omega}_j$ ARR.

The inputs to the ANFIS are weighted by means of the membership functions during the learning process until the neuro-fuzzy parameters are optimized. The ANFIS uses backpropagation and recursive least squares methods to adjust the consequent parameters during the learning stage. Once the learning has finished and the premise and
where \( \varphi \) respectively;

\[ P \] subsystem consequent parameters for each ANFIS have been calculated, it proceeds to construct the convex TS representation for each wind turbine subsystem. Therefore, for the polynomial representation, the case of the subsystem \( \hat{\omega}_y \) will be used; it is formulated as:

\[ P_i = p_i \omega_y(k) + p_{i1} \omega_y(k-1) + p_{i2} \omega_y(k-2) + p_{i3} \tau_y(k) + p_{i4} \tau_r(k) + p_{i5}, \]

\[ \forall i = 1, \ldots, N_c, \]

where \( P_i \) is a linear polynomial representation of a subsystem, \( p_i, \forall i = 1, \ldots, N_c \) are the system parameters obtained from ANFIS; \( N_c \) represents the number of premise parameters as displayed in Fig. 4; and \( N_p \) represents the number of vertices. Terms in (1) can be rearranged as:

\[
P_i = \begin{bmatrix}
p_{i1} & p_{i2} & p_{i3} & p_{i4} & p_{i5} 
p_{i1} & p_{i2} & p_{i3} & p_{i4} & p_{i5} 
p_{i1} & p_{i2} & p_{i3} & p_{i4} & p_{i5} \end{bmatrix} x + \begin{bmatrix}
p_{i6} & p_{i7} & p_{i8} & p_{i9} & p_{i10} 
p_{i6} & p_{i7} & p_{i8} & p_{i9} & p_{i10} 
p_{i6} & p_{i7} & p_{i8} & p_{i9} & p_{i10} \end{bmatrix} u,
\]

(2)

where \( x = [\omega_y(k-1), \omega_y(k-2), \tau_y(k)]^T \) is the state vector and \( u = [\tau_y, \tau_r]^T \) is the input vector. The polynomial structure is transformed to a discrete-time state-space representation as:

\[
x(k+1) = A_i x(k) + B_i u(k) + h_i, \quad \forall i = 1, \ldots, N_c,
\]

(3)

where \( A_i, B_i, h_i \) are constant matrices structured from the consequent parameters of the polynomial structure. The membership function is constructed by considering the GB function, which is defined by three neuro-fuzzy parameters as follows:

\[
\mu_i(Z) = \frac{1}{1 + \frac{Z-Z_m}{2s_m}}, \quad \forall m = 1, \ldots, N_MF, \quad \forall Z = 1, \ldots, N_c,
\]

(4)

where \( a, b, c \) determines the width, slope, and center of the GB function, respectively; \( Z \) represents the vector of ANFIS input variables (from now on, it will be referred to as premise parameter); \( N_MF \) represents the number of MF per premise parameter. For a common case where \( N_MF = 2 \), the normalized weights \( (N_i) \) are calculated as follows:

\[
\mu_i(Z) = \prod_{j=1}^{N_c} \frac{\mu_i(Z)}{\sum_{j=1}^{N_c} \mu_j(Z)}, \quad \forall i = 1, \ldots, N_c.
\]

(5)

where \( \mu_i(Z) \) corresponds to any of the weighting functions that depend on each \( i \)th rule, such as the normalized weights are obtained as:

\[
\mu_i(Z) = \frac{\mu_i(Z)}{\sum_{j=1}^{N_c} \mu_j(Z)}, \quad \forall i = 1, \ldots, N_c.
\]

(6)

Each premise parameter \( Z_{i_o} \) is estimable and varies in a defined interval \( Z_{i_o} \subseteq [Z_{i_o}^L, Z_{i_o}^U] \in \mathbb{R} \). The polytopic TS model for each subsystem is obtained as:

\[
x(k+1) = \sum_{i=1}^{N_c} \mu_i(Z_{i_o}) \left( A_i x(k) + B_i u(k) + h_i \right),
\]

(7)

where \( N_i \) is obtained by \( N_i = (N_MF)^{N_c} = 32 \). It is important to mention that uncertainties are part of the model due to noise, model mismatches, and the method itself. Taking into account these issues, which are denoted by the \( \Delta A \) matrices, system (7) is rewritten as:

\[
x(k+1) = \sum_{i=1}^{N_c} \mu_i(Z_{i_o}) \left( (A_i + \Delta A_i) x(k) + B_i u(k) + h_i \right),
\]

(8)

The values of the uncertain matrices are proportional to the values of the parameters, which are adjusted by the minimum deviation to
Under the assumption that:

\[ r_i = y_i - \hat{y}_i, \]

where the characteristic function \( f_{\beta_i} \) is defined as:

\[ f_{\beta_i}(a) = a + z\phi + z^T\varphi = \{a_i + \varphi_i z + \varphi_i z^T\}_{i \in \{1, m\}}, \]

with \( a = a^T \in \mathbb{R}^{m \times m} \) and \( \varphi \in \mathbb{R}^{m \times d} \), if there exist a diagonal matrix \( P \in \mathbb{R}^{d \times d} \), a symmetric matrix \( Q = Q^T \in \mathbb{R}^{d \times d} \), block diagonal matrices \( W_i \in \mathbb{R}^{d \times d}, i = 1, \ldots, N \), with the following structure:

\[
W_i = \begin{pmatrix}
W_i \in \mathbb{R}^{d \times d} & 0 \\
0 & W_i \in \mathbb{R}^{d \times d}
\end{pmatrix}
\]

and constants \( \epsilon_1 > 0, \epsilon_2 > 0, \gamma > 0 \) such that:

\[ P > 0 \]

\[ Q > 0 \]

and, for \( i = 1, \ldots, N \):

\[
\begin{pmatrix}
(PD_i - W_i)^T & P - Q - \gamma I_{2n} - \epsilon P \\
0 & \gamma I_{2n}
\end{pmatrix} \geq 0
\]

\[ P \begin{pmatrix} A_i & 0 \\ 0 & A_i \end{pmatrix} - W_i \geq 0 \tag{21}
\]

\[
\begin{pmatrix}
a_{i,1}P + \varphi_{i,1} \left( \begin{pmatrix} A_i^T & 0 \\ 0 & A_i^T \end{pmatrix} - W_i \right) \\
+ \varphi_{i,1} \begin{pmatrix} A_i & 0 \\ 0 & A_i \end{pmatrix} - W_i \end{pmatrix} \geq 0
\]

with:

\[ D_i = \begin{pmatrix} A_i + \Delta A_i^+ & 0 \\ 0 & A_i + \Delta A_i^- \end{pmatrix} \tag{23}
\]

\[ \gamma = \begin{pmatrix} C & 0 \\ 0 & C \end{pmatrix} \tag{24}
\]

\[ \eta = 2 \max_{i=1}^{N} \left( \|\Delta A_i^+ - \Delta A_i^-\|_2 + \|\Delta A_i^-\|_2 + \|\Delta A_i^-\|_2 \right) \tag{25}
\]

\[ \epsilon = 1 + \epsilon_1 + (1 + \epsilon_1)^{-1} \tag{26}
\]

then, the TS interval observer (11) with gains calculated as:

\[ \bar{L} = P^{-1}W \tag{27}
\]

\[ \bar{L} = P^{-1}W \tag{28}
\]

ensure the estimation of the interval \( x(k) \) given by (10), provided that (11) and (14) are fulfilled.

The overall system of LMIs (18),(19),(20),(21) and (22) can be solved efficiently using available solvers, as YALMIP toolbox. The proof of the theorem can be consulted in Rotondo et al. (2016).

3.3. Fault diagnosis based on residual generation

By considering the estimated outputs (12–13), the following residuals can be obtained as:

\[ \epsilon_i(k) = \hat{y}(k) - \bar{y}(k) \tag{29}
\]

\[ \tilde{r}(k) = y(k) - \hat{y}(k) \tag{30}
\]

where \( r(k) \in \mathbb{R}^N \) is the residual. In the ideal case, \( r(k) \approx 0 \) if there are no faults present. However, it may be non-zero in a fault-free scenario due to measurement noise, modeling errors, among others.
A robust passive approach based on an adaptive threshold can be used (Puig et al., 2008). Thus, using this passive approach, the impact of the parameter uncertainties on the residual $r(k)$ associated with each output of the system $y(k)$ is bounded by an interval that will include the zero value in the absence of faults. Therefore, a fault detection test can be formulated as:

$$y(k) \in \left[\hat{y}(k), \overline{y}(k)\right]$$

where $y(k)$ is the sensor output, and $\hat{y}(k)$ and $\overline{y}(k)$ are the limits of the predicted output given by (12) and (T5).

The residuals are derived from the ARRs described in Section 2, the respective observers will be designed for the dynamic residuals:

$$r_1(k) = P_k^r(k) - \hat{P}_k^r(k)(\omega_k(k), r_1(k)),$$

$$r_2(k) = r_2(k) - F_1^r(k),$$

$$r_{1+2}(k) = \beta_1^r(k) - \hat{\beta}_1^r(k),$$

$$r_3(k) = \alpha_3(k) - \hat{\alpha}_3(k),$$

$$r_4(k) = \phi_4^r(k) - \phi_4^r(k)\theta_4^r(k),$$

$$r_5(k) = \xi_5^r(k) - \hat{\xi}_5^r(k),$$

$$r_{9+10}(k) = M_{R_1}(k) - \hat{M}_{R_1}(k),$$

The equations mentioned above search to generate residuals sensitive only to one fault. However, from the obtained ARRs, it is clear that some faults cannot be isolated because the same fault activates different residuals. In this scenario, the method only guarantees the detection but not the isolation.

In a fault scenario, the residuals are activated when exceeding the limits of the interval. If the interval limits are well-defined, then all false alarms can be avoided because the ARR guarantee the separability of the effect of each fault on the residuals. These residuals are stored in a fault incidence matrix, whose elements are constructed by considering the following logic:

$$\psi_{j,i}(k) = \begin{cases} 0 & \text{if } r_i(k) \in \left[\hat{r}_j(k), \overline{r}_j(k)\right], \forall j \in [1, N_f], \\ 1 & \text{if } r_i(k) \notin \left[\hat{r}_j(k), \overline{r}_j(k)\right], \forall j \in [1, N_f], \end{cases}$$

where $N_f$ is the number of faults. Fault isolation is done by evaluating the incidence matrix and the knowledge of the binary relationship between the residuals.

3.4. Fault scenarios

The FAST wind turbine benchmark covers different types of possible faults, as listed in Table 3. These faults have different degrees of severity; some are very serious and should result in a quick and safe shutdown; other faults are less severe and can cause a performance degradation. Different numerical simulations are carried out for the diagnostic scheme based on Table 3. Each fault scenario is related to different types of faults that can occur in a real environment (sensors, actuators or components). The results obtained are described in the next section.

4. Results

This section presents the results of the fault diagnosis obtained from numerical simulations carried out in the benchmark described in Olggaard et al. (2013). The wind speed used for the simulations was $17 \text{ m/s}$ on average with the profile shown in Fig. 5. The simulations were carried out for a time interval of $630 \text{ s}$ with a sampling frequency of $80 \text{ Hz}$, counting $50,401$ samples per variable in the data vectors.

<table>
<thead>
<tr>
<th>Fault Class</th>
<th>Description</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault 1</td>
<td>Blade root bending moment sensor</td>
<td>Scaling</td>
</tr>
<tr>
<td>Fault 2</td>
<td>Accelerometer</td>
<td>Offset</td>
</tr>
<tr>
<td>Fault 3</td>
<td>Generator speed sensor</td>
<td>Scaling</td>
</tr>
<tr>
<td>Fault 4</td>
<td>Pitch angle sensor</td>
<td>Stuck</td>
</tr>
<tr>
<td>Fault 5</td>
<td>Generator power sensor</td>
<td>Scaling</td>
</tr>
<tr>
<td>Fault 6</td>
<td>Low speed shaft position encoder</td>
<td>Bit error</td>
</tr>
<tr>
<td>Fault 7</td>
<td>Pitch actuator</td>
<td>Abrupt</td>
</tr>
<tr>
<td>Fault 8</td>
<td>Pitch actuator</td>
<td>Slow</td>
</tr>
<tr>
<td>Fault 9</td>
<td>Torque offset</td>
<td>Offset</td>
</tr>
<tr>
<td>Fault 10</td>
<td>Yaw drive</td>
<td>Stuck drive</td>
</tr>
</tbody>
</table>

The mechanical and electrical parameters predefined in the benchmark were not changed, since the characteristics of the wind turbine model meet the requirements to perform FD tests in a realistic environment.

Fault-free simulations were performed to form the data sets for ANFIS training. The data sets were divided into 70% for training, 15% for validation, and 15% for testing. The number of fuzzy rules (FR) is related to the number of premise parameters of each ARR subsystem as FR = $2N$. For the case of $\alpha_3, \omega_3, \beta_3, 32$ FRs were obtained; for $\hat{\alpha}_3$ and $\hat{\omega}_3$, 16 FRs were obtained. Therefore, the number of local models was the same as FR for the TS representation. Due to the space limitation, the model is not presented here, but for $\hat{\beta}_3$, the corresponding model is:

$$x(k + 1) = \sum_{i=1}^{N_f} \mu_N(\zeta(k)) (A_i + \Delta A_i)x(k) + B_iu(k) + h_j,$$

$$y(k) = Cx(k).$$

The results obtained are described in the next section.
To obtain a perspective of the effectiveness of the proposed method, it is compared with different FD schemes. Table 5 compares the reported detection time for different methods, taking as a reference the detection time requirements reported in Odgaard et al. (2013). The detection times ($T_D$) are in terms of the sampling time ($T_s$) which is 0.0125 s in this case. The first column is related to the fault number, and the second column displays the required detection time. The rest of the columns display different detection methods, including this paper’s proposal. The results reported in the literature of four relevant methods are considered. A fusion classifier approach (CFA), reported in Pas- hazadeh et al. (2018) where a combination of three classifiers is used for fault detection: multilayer perceptron (MLP), $k$-nearest neighbor (KNN), and decision tree. Some of the faults can be detected within the time requirements, however, this method does not consider (NC) faults 1 and 7. A support vector machine and Kalman observer (SVMKO) used to isolate faults in different components proposed by Sheibat-Othman et al. (2013). This proposal marks NC three faults and only a few are within the requirements. A scheme combining support vector machine and residual (SVMR) techniques for FD of wind turbine faults proposed by Zeng et al. (2013). The results of this combined method meet the FD time requirements, but cannot detect fault 1. Interval observers based on ARRs (IOBA) presented by Sanchez et al. (2015) which is a model-based method and improves the previous FD results with respect to the number of faults that can be detected, but it strongly depends on the model and the calibration in its methodology. Finally, the approach presented in this work is shown in Table 5 as ANFIS-TS where its
effectiveness can be observed, being able to detect all faults in the required time.

With respect to the FD times, the SVRM method can detect faults 2, 3, 7 and 8 slightly faster than the method proposed in this paper. It is important to mention that although SVRM can detect these faults faster; compared to the required time for detection, the difference with ANFIS-TS is minimal. While ANFIS-TS is superior for faults 4, 6, 9 and 10, where the improvement in detection time is more significant when the required time for detection is taken into account, particularly for faults 4 and 10. In addition, ANFIS-TS can detect fault 1, which SVRM cannot. The rest of the methods are clearly slower than ANFIS-TS. Thus, it can be concluded that ANFIS-TS is effective in FD, complying with the detection times and improving most of the FD times, demonstrating that when using the data-based methods and combining them with observers, the results are improved.

This work followed the standard way of adding the uncertainty by using the measured data covariance. Nevertheless, a better form of adding this uncertainty could be by considering them as part of the fuzzy identification of the ANFIS. On the other hand, the selected interval limits affect the fault diagnosis observer. To improve the method, techniques based on set membership can be implemented to propagate the uncertainties through zonotopic interval observers. Finally, faults 4, 7, and 8 can be detected but not isolated because of the construction of the residuals, which are based on the ARR. However, it is possible to implement an additional residual evaluation based on an ANN that could discern between the slight differences of the residuals and thus
Table 5
Comparison of results of different FD schemes.

<table>
<thead>
<tr>
<th>Fault</th>
<th>T₀ required</th>
<th>T₀ obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ANFIS-TS</td>
<td>CFA</td>
</tr>
<tr>
<td>1</td>
<td>&lt;10 T₀</td>
<td>2 T₀</td>
</tr>
<tr>
<td>2</td>
<td>&lt;10 T₀</td>
<td>7 T₀</td>
</tr>
<tr>
<td>3</td>
<td>&lt;10 T₀</td>
<td>2 T₀</td>
</tr>
<tr>
<td>4</td>
<td>&lt;10 T₀</td>
<td>2 T₀</td>
</tr>
<tr>
<td>5</td>
<td>&lt;10 T₀</td>
<td>2 T₀</td>
</tr>
<tr>
<td>6</td>
<td>&lt;10 T₀</td>
<td>4 T₀</td>
</tr>
<tr>
<td>7</td>
<td>&lt;8 T₀</td>
<td>5 T₀</td>
</tr>
<tr>
<td>8</td>
<td>&lt;100 T₀</td>
<td>9 T₀</td>
</tr>
<tr>
<td>9</td>
<td>&lt;3 T₀</td>
<td>2 T₀</td>
</tr>
<tr>
<td>10</td>
<td>&lt;50 T₀</td>
<td>3 T₀</td>
</tr>
</tbody>
</table>

isolate the faults that are not possible with the method proposed in this article (see Puig & Blesa, 2013 where the residual order of activation is used for improving isolability).

5. Conclusions

In this work, a fault detection scheme for a wind turbine based on Takagi–Sugeno interval observers was proposed considering parametric uncertainty. Unlike other FD works, TS models are structured based on the measurements available in the system. The proposed method generates confidence intervals that represent the lack of knowledge due to modeling errors. It is verified that the fault-free measurements are within the intervals, avoiding false alarms.

Structural analysis of the wind turbine was carried out to obtain a bipartite graph that relates a set of components and a set of measured variables. Consequently, the ARRs that structured convex Takagi–Sugeno (TS) models were obtained with an approach based on neuro-fuzzy learning to identify the wind turbine dynamics. To get the convex TS representation with modeling uncertainty, the ANFIS were used, which were trained with fault-free data.

The Takagi–Sugeno observers were designed with fuzzy learning from inputs and outputs measurements. The fault diagnosis was addressed by a bank of interval TS observers with adaptable thresholds.

A convex TS system was obtained in the proposed methodology that considers the parametric uncertainty using only measurements and system data. Therefore, observers can be designed, and the LMI improved. There is an exploit framework to implement methods without using the equations of the dynamic system. When no model faithfully represents a real system, considering the uncertainty bands represents a detection advantage in faults that are not modeled.

As future work, robust fault diagnostic schemes will be implemented, where the uncertainty propagates in the parameters, adding noise at the outputs. Another avenue that will be explored is the implementation of observers based on zonotopes.

CRediT authorship contribution statement

Esven-Jesús Pérez-Pérez: Investigation, Software, Writing – original draft. Francisco-Ronay López-Estrada: Conceptualization, Methodology, Supervision, Writing – original draft, Project administration, Funding acquisition. Vicenç Puig: Conceptualization, Resources, Supervision, Writing – review & editing. Guillermo Valencia-Palomino: Formal analysis, Validation, Writing – review & editing. Ildeberto Santos-Ruiz: Validation, Data curation, Writing – review & editing.

Declaration of competing interest

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