Fault-tolerant cooperative control in an offshore wind farm using model-free and model-based fault detection and diagnosis approaches

Hamed Badihi, Youmin Zhang, Henry Hong

Department of Mechanical and Industrial Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada

Department of Information and Control Engineering, Xi’an University of Technology, Xi’an, Shaanxi 710048, China

1 During his Sabbatical Leave from Concordia University.

Abstract

Given the importance of reliability and availability in wind farms, this paper focuses on the development of fault diagnosis and fault-tolerant control schemes in a cooperative framework (referred to as active fault-tolerant cooperative control) at the wind farm level against the decreasing power generation caused by turbine blade erosion and debris build-up on the blades over time. In more details, the paper presents a novel integrated fault detection and diagnosis and fault-tolerant control approach oriented to the design and development of two active fault-tolerant cooperative control schemes for an offshore wind farm. Each of the schemes employs a fault detection and diagnosis system to provide accurate and timely diagnosis information to be used in an appropriate automatic signal correction algorithm for accommodation of faults in the wind farm. The effectiveness and performance of the proposed schemes are evaluated and compared using different simulations on a high-fidelity offshore wind farm benchmark model in the presence of wind turbulences, measurement noises and realistic fault scenarios.

1. Introduction

As one of the most cost-competitive forms of renewable energy, wind has remarkable potential for fulfilling the increasing demand for global energy in an environmentally responsible way. To further reduce the average cost of wind energy, large wind turbines are often installed in clusters called wind farms, particularly at offshore locations. As more and more offshore wind farms are developed further from shores, both the factors of complexity and limited accessibility and harsh climate conditions come into play, resulting in higher failure rates and maintenance challenges. This motivates the design and development of advanced fault detection and diagnosis (FDD) and fault-tolerant control (FTC) schemes in wind farms to improve their reliability and availability.

The FTC schemes can be designed in either passive or active ways. A passive FTC (PFTC) scheme employs the robustness of the closed-loop control system to accommodate faults, while an active FTC (AFTC) scheme reconfigures the closed-loop control system after fault occurrence. AFTC schemes usually require FDD information in the process of control reconfiguration.

In general, the FDD and FTC schemes can be applied at both the individual wind turbine and entire wind farm levels. Recently, research has been more focused on the application of such methods at wind turbine level (for example, see [1–5]). Most of these works try to address the FDD and FTC problems in two standard wind turbine benchmark models presented in [6,7]. A recent
review of the literature in [8] provides more references on FDD and FTC for wind turbines. In reality, some faults are more easily detected, diagnosed, and accommodated at the wind farm level. This can be performed by comparing the performance of turbines operating under similar wind conditions. The FDD and FTC at the wind farm level is a very recent field of research with only a few research works reported in the literature. Most of these works are focused only on condition monitoring and fault detection in wind farms. In [9,10], various data-mining algorithms are applied to develop models for predicting possible faults in wind farms. In [11], the relationship between the wind speed and the generated power in a wind farm is estimated using three different machine learning models. The models can detect anomalous functioning conditions of the wind farm, but they are unable to isolate and identify faults. More recently, researchers have studied the FDD and FTC problems in a standard benchmark model presented in [12] that represents a wind farm with nine turbines that are subject to different fault scenarios. For example, the authors in [13] present a fault detection and isolation approach based on a piecewise affine Takagi-Sugeno models that are identified from noise-corrupted measurements. Borcehser et al. [14] present a fault detection system relying on dynamical cumulative sum for residual evaluation, and a load distributing controller for accommodating possible faults. A passive FTC scheme is presented in [15] that integrates a fault estimation scheme with the design of a controller accommodation system. An evaluation study is also presented in [16]. Duviella et al. [17] propose an evolving classification algorithm for detection and isolation of faults due to debris build-up on the wind turbine blades. In [18], the fault diagnosis is conducted using interval non-linear parameter-varying parity equations, assuming an unknown but bounded description of the noise and modelling errors. Another work reported in [19] presents an active fault-tolerant control scheme based on a model-based FDD approach. In actuality, the above cited research works are similar in two aspects: first, they have assumed that only one fault occurs at a time in a farm, and second, they mostly rely on wind speed or its estimation which normally depends on the layout of the wind farm and direction of the wind as well. For example, the algorithms proposed in [14,17,18] are only developed for one or two specific wind directions.

Given the importance of FDD and FTC at a wind farm level, this paper presents a novel integrated FDD and FTC approach in a cooperative framework referred as the active fault-tolerant cooperative control (AFTCC) by recognizing the differences in controlling a wind farm from a single wind turbine. Here, the term “active” is due to the integrated design of both FDD and FTC [20], while the term “cooperative” is due to the cooperative design for multiple wind turbines (wind farm) which is beyond a design for a single wind turbine and will be demonstrated in the later parts of this paper for both FDD and FTC strategies. The proposed approach is oriented to the design and development of two AFTCC schemes for an offshore wind farm against decreased power generation faults that is caused by turbine blade erosion and debris build-up on the blades over time. The first scheme is based on a model-free FDD system that incorporates a rule-based threshold testing technique for residual evaluation. Conversely, the second scheme is based on a model-based FDD system that incorporates data-driven models developed using a fuzzy modelling and identification (FMI) technique. Both schemes are relying on an appropriate automatic signal correction (ASC) algorithm that employs the provided accurate and timely FDD information for accommodating the possible faults in a wind farm.

The proposed AFTCC schemes not only provide necessary FDD information for condition monitoring purposes, but also provide the effective possibility of the accommodation of faults in a wind farm. To further highlight the contribution of this paper compared to the other relevant works in the existing literature, it is worth mentioning that the proposed schemes in this paper are designed and developed in a way to be valid for any layout of a wind farm with any direction of the wind, while the considered fault may occur simultaneously in more than one turbine in the farm. This is actually a more general case that may happen in a real wind farm in operation, and has never been studied in the available literature so far.

The effectiveness and performance of the proposed AFTCC schemes are evaluated and compared using different simulations on a high-fidelity offshore wind farm benchmark model in the presence of wind turbulences, measurement noises and realistic fault scenarios. Moreover, extensive Monte Carlo simulations are performed to evaluate the robustness of the proposed schemes with respect to modelling errors, disturbances and measurement uncertainties.

The remainder of the paper is organized as follows: In Section 2, the wind farm benchmark model used in this paper is briefly described. The considered fault is described and analysed in Section 3. Section 4 presents the AFTCC based on integrated FDD and FTC approach against the fault discussed in Section 3. The details of the FDD at wind farm level are presented in Section 5. Section 6 presents the simulation results with some comments and discussions. Finally, conclusions are drawn in Section 7.

2. Overview of the wind farm benchmark model

This paper considers an advanced wind farm simulation toolbox called SimWindFarm that is developed as a part of the EU-FP7 project, AEOLUS [21]. The toolbox provides a realistic wind farm simulation benchmark model that allows control designers to...
develop, implement, and investigate farm level control and diagnosis algorithms under different operating conditions for an optional quantity and layout of turbines installed in a wind farm. In the benchmark model, sensor models are updated to represent noise-contaminated, uncertain measurement systems. The recommended rate and magnitude limiters are also applied on any reference signal to the actuator models. In addition, to facilitate the assessment of the robustness features of any control solution under external disturbances, different wind fields with arbitrary mean wind speeds and turbulence intensities can be generated and applied in the benchmark model. Fig. 1 shows the default layout for the considered wind farm with ten turbines. The overall structure of the simulation benchmark model under consideration is illustrated in Fig. 2.

As it is shown in Fig. 2, the wind farm simulation benchmark model is composed of four major components in the top level that operate in a closed loop:

**Network Operator:** The network operator is responsible for determining the total active power demand $P_D$ (also called operator’s total demanded power) required for a reliable connection of the wind farm to the electrical grid. This can be performed in different modes, such as absolute, delta, and frequency regulation modes. This paper employs the frequency regulation mode, in which the measured grid frequency $f_m$ is used as a feedback signal to set up active power control in real-time. The objective is to maintain the necessary balance between power generation and load, which in turn regulates the grid frequency to its reference value $f_r$, despite having a changing grid load. The baseline model for the network operator in the frequency regulation mode includes a dead-band proportional gain control which employs frequency error $f_e(k)$ in (1) to determine the total demanded power $P_D(k)$ at the time-step $k$ in (2). Such a simple control scheme regulates the grid frequency to any specified reference value, for example, 50 Hz in large areas of the world.

$$f_e(k) = f_m(k) - f_r$$

Fig. 3. The $q$th wind turbine in the farm ($q = 1, 2, \ldots, N$). Note that in addition to the generated power $P_{d,q}$, the model provides many other measured variables such as coefficient of thrust $C_{r,q}$ and so on.

Fig. 4. Timeline for the occurrence of the considered fault in a designated number of wind turbines in the farm. Note that, the total simulation time is 1000 s, and $T_q$ stands for wind turbine number $q$ with respect to the wind farm layout shown in Fig. 1.

Fig. 5. Generator power responses during fault-free and faulty operations of wind turbines: (a) $T_1$, and (b) $T_3$ in the farm.
In (2), the constants $c$ and $d$ are, respectively, the control band and the dead band defined by user ($c > d$). Moreover, the power parameters $P_1$ and $P_2$ are defined in (3) and (4), respectively. Here, $P_{\text{min}}$ and $P_{\text{max}}$ denote the prescribed minimum and maximum limits for the total power generated by the wind farm, respectively.

$$P_1 = P_{\text{max}} + P_{\text{min}}$$  \hspace{1cm} (3)  

$$P_2 = P_{\text{max}} - P_{\text{min}}$$  \hspace{1cm} (4)

### Wind Farm Controller

As it is shown in Fig. 2, the wind farm controller acts as an interface between the network operator and wind turbines. Its main functionality is to ensure the appropriate distribution of the operator’s total demanded power $P_d$ among wind turbines in the farm. It also provides an estimate of total available power $P_a$ in the wind farm to the operator (e.g., in the case of delta mode operator). The baseline wind farm controller employs the proportional distribution algorithm in (5) which provides a set of power demands $P_d(q)$ at the time-step $k$ (i.e., $P_d$ in Fig. 2) to each of $N$ individual wind turbines. Here, $P_{\text{avg}}(k)$ and $P_{\text{max}}(k)$ represent the estimated available power from turbine $q$ and the total available power from the wind farm, respectively.

$$P_{\text{avg}}(k) = P_d(k) \frac{P_{\text{max}}(k)}{P_{\text{avg}}(k)} \quad q = 1, 2, \ldots, N$$  \hspace{1cm} (5)

**Wind Field**: As shown in Fig. 2, this component is devoted to the simulation of dynamics of $N$ turbines installed in the wind farm based on their measured nacelle wind speeds $V_{\text{nac}} = [V_{\text{nac}}]$, effective wind speeds $V_{\text{rot}} = [V_{\text{rot}}]$, and power demands $P_d = [P_d]$ with $q = 1, 2, \ldots, N$. With respect to the outputs, the component generates a set of outputs including a set of measurements $\text{Mes}$ required for use by the wind farm controller, as well as a set of coefficients of thrust $C_T = [C_T]$ for turbines which are necessary to calculate the wake effects (i.e., low speed turbulent air flows behind turbine) by the wind field component. In the component of wind turbines, each turbine is simulated using a simple model of an offshore 5 MW turbine that has already been proposed by the U.S. National Renewable Energy Laboratory (NREL) (see [22]). The baseline control system used in each individual wind turbine is shown in Fig. 3. As shown in the figure, the control system acts upon the power demand $P_{\text{avg}}$ in (5). This control system is essentially composed of a blade-pitch controller and a torque controller to compute the appropriate reference blade-pitch angle $\beta_{\text{ref}}$ and reference generator torque $\tau_{\text{ref}}$, respectively. The blade-pitch controller is fundamentally a Proportional-Integral (PI) controller that tracks a constant generator speed (rated generator speed) so that the turbine operates at its rated power in the *full-load region*. The torque controller is designed to both optimize power capture in the *partial-load region*, and to improve output power quality in the full-load region by varying the generator torque. More precisely, the torque controller is set to be active for varying the torque, during both the below and above rated wind speeds. A more complete description of the wind turbine benchmark model is available in [22].

**Wind Field**: The wind field model represents the interactions between the wind turbines installed in a wind farm. This model includes models of ambient fields and wake phenomena for simulating wakes meandering behind turbines and their effects on the ambient wind field. Thus, the wind speed throughout the farm is obtained.

### 3. Blade erosion/debris build-up fault

In essence, decreased power generation in a wind farm may be due to several different malfunctions. However, blade erosion along with debris build-up on the blades due to dirt, ice, etc. constitutes the most probable fault which results in a lower power
generation because of changes in the aerodynamics of the wind turbine, and thereby lowering the maximum limit of obtained power. In more detail, the aerodynamic torque \( \tau_{\text{aer}} \) applied to the rotor by the wind is defined in (6), in which \( \omega_{\text{rot}} \) is the rotor angular speed, \( \rho \) is the air density, \( A \) is the swept area of the turbine rotor, and \( V_w \) is the wind speed [23].

\[
\tau_{\text{aer}}(t) = \frac{1}{2\omega_{\text{rot}}(t)} \rho AV_w^3(t)C_p(\beta(t), \dot{\lambda}(t)) \tag{6}
\]

In Eq. (6), the power coefficient \( C_p(\beta, \dot{\lambda}) \) is a three dimensional surface as a function of the tip-speed ratio \( \dot{\lambda} \) and the blade pitch angle \( \beta \) in which the latter two terms determine the operating condition of a variable speed wind turbine. For variable-speed wind turbines, the turbine is ideally operated at the peak of the \( C_p \) surface in order to capture as much power as possible. However, over time, the blade erosion and debris build-up fault shifts the turbine’s \( C_p \) surface downward, resulting in a lower energy capture through not only a decrease in the peak value of the \( C_p \) surface but also a change in the location of the peak of the \( C_p \) surface. The sensitivity of energy loss to the changes at the peak of the \( C_p \) surface caused by the aforementioned fault is considered and quantified in [24], which concludes that the fault can lead to a substantial non-optimal operation and power loss. Given the significance of the blade erosion and debris build-up fault in wind turbines, it is necessary to detect, diagnose, and accommodate such a fault in a timely and effective manner. However, it is difficult to handle this fault at a wind turbine control level, mainly due to the fact that a lower generated power may be due to either debris build-up on the blades or simply that the true wind speed is lower than the measured/estimated wind speed. Conversely, at a wind farm level, it is possible to compare the performance and operation features of the different wind turbines in a given wind farm.

The described benchmark model in Section 2, in its original form, does not include any fault. However, it is possible to fairly model a realistic scenario for the blade erosion and debris build-up fault and incorporate it into the benchmark model. In the following part of this section, the modelling of the considered fault in this paper is described.

In general, the generator power \( P_g \) can be expressed as:

\[
P_g(t) = \eta_g \eta_m P_{\text{aer}}(t) \tag{7}
\]

in which \( \eta_g \) is the generator efficiency, \( \eta_m \) is the efficiency of transmission system, and \( P_{\text{aer}} \) is the aerodynamic rotor power given by [23]:

\[
P_{\text{aer}}(t) = \tau_{\text{aer}}(t)\omega_{\text{rot}}(t) \tag{8}
\]

Now, substituting (8) into (7) and using (6) yields:

\[
P_g(t) = \frac{1}{2} (\eta_g \eta_m) \rho AV_w^3(t)C_p(\beta(t), \dot{\lambda}(t)) \tag{9}
\]

**Fig. 7.** FDD system including \( R \) modules each for conducting the monitoring of the consistency of the powers generated by any two specific turbines in a wind farm. The module output (MO) signals are analysed and respective decisions are made in the decision making (DM) process. Here, turbine \( T_i \) with \( 1 < i < N \) represents any turbine except \( T_1 \) and \( T_N \).
As mentioned previously in Section 3, the considered fault results in a lower power generation that negatively affects the total active power generated by all wind turbines in a farm as a whole. Generally speaking, when such a fault occurs in one or more turbines in a wind farm, the wind farm controller still has to follow the operator’s total demanded power $P_D$ using the proportional distribution algorithm described in (5), no matter which turbine(s) is/are faulty. Whereas, to compensate the power loss caused by the faulty turbine(s), it is necessary to avoid overloading the remaining healthy turbines, but instead to correct the reference power signal(s) to the faulty turbine(s) and thereby accommodating the fault effects. In fact, overloading the healthy wind turbines may lead to high structural loading and fatigue.

The proposed AFTCC based on integrated FDD and FTC approach in this paper is shown in Fig. 6. As it is observed in this figure, the proposed approach essentially relies on an integrated FDD system and automatic signal correction (ASC) mechanism that covers the entire farm with any layouts and any wind directions. The FDD system in Fig. 6 provides the most up-to-date information about the true status of the wind farm system. As it is further discussed in Section 5, the FDD system can be developed based on either model-free or model-based monitoring of the consistency of power generation in a wind farm. Basically, the main idea behind the FDD process is to monitor the consistency of generated powers from any individual wind turbine and all other remaining turbines in the farm in real-time. Then, any inconsistencies in the generated powers should be detected, isolated and identified to generate FDD information. Finally, the FDD information is used for ASC and accommodation of the faults in faulty turbines. The ASC mechanism means that the nominal controllers at both wind turbine and wind farm levels are kept unchanged; only the output of the torque controller in any faulty turbine is corrected according to the real-time fault information from the FDD system. Here, the supervision process shown in Fig. 6 is not described explicitly, because it is very simple in the considered case. In fact, according to the provided information from the FDD system, the supervisor only identifies the faulty turbines in the farm together with their relevant estimated power losses (fault magnitudes) due to the faults. Then, to accommodate the fault effects in each faulty turbine, the estimated fault magnitude is used to correct the nominal reference generator torque control signal $T_{r,q}$ computed by the torque controller that is itself active in both partial- and full-load regions. This signal correction is defined below for the $q$th wind turbine in the farm.

![Fig. 8. Inputs and outputs of example module $M_{i,j}$.](image)

![Fig. 9. Structure of module $M_{i,j}$ designed using model-free algorithm.](image)

### Table 2

<table>
<thead>
<tr>
<th>$T_i$ and $T_j$ power consistency</th>
<th>Module output $MO_{i,j}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consistent</td>
<td>$ID_{i,j}$ $IM_{i,j}$</td>
</tr>
<tr>
<td>Inconsistent</td>
<td>$i$ $\Delta P_{i,j}$ $\overline{MP}<em>{i,j}$ $j$ $\overline{MP}</em>{j,i}$</td>
</tr>
</tbody>
</table>

Equation (9) shows that the generated power $P_g$ is a direct function of the power coefficient $C_p$ which itself can be changed due to the blade erosion and debris build-up fault. With respect to this fact, the fault can be simply modeled by scaling the generated power in a wind turbine. Therefore, a realistic scaling factor of 0.97 (3% power loss) is used. In this case, the benchmark model is modified with a generic fault scenario representing occurrence of 3% power loss in a designated number of turbines in the wind farm shown in Fig. 1. The detailed timeline for the occurrence of the considered fault scenario is shown in Fig. 4. As can be observed from the figure, during certain periods of the simulation time, the considered decreased power generation fault has occurred simultaneously in more than one turbine in the farm. For example, Fig. 5 shows the power loss effect due to occurrence of the fault in wind turbines $T_1$ and $T_3$ in the farm.

### 4. AFTCC based on integrated FDD and FTC approach

This section presents an integrated FDD and FTC approach in a cooperative framework (referred to as AFTCC) that aims at improving the reliability and availability of wind farms against the fault discussed in Section 3. Here, it is assumed that the fault(s) may occur at any time and in any turbine installed in a farm. Simultaneous faults in more than one turbine are also possible.
also applied on the corrected reference generator torque exactly zero (fault magnitude provided by the FDD system is assigned to be 0) under fault-free operation. In other words, to maintain the nominal performance of the system, there is no need to modify/compensate the nominal reference torque control signal \( \tau_{q}\) in (10) under fault-free operation. Finally, to avoid any inconsistencies in the generated powers from the turbines, but also the turbines’ reference power signals.

\[
\tau_{q,corr}(k) = \tau_{q}(k) + \frac{\hat{P}_{q}(k)}{\omega_{eq}(k)}, \quad q = 1, 2, \ldots, N \tag{10}
\]

In (10), \( \tau_{q,corr} \) is the corrected reference generator torque and \( \hat{P}_{q} \) is the estimated fault magnitude (power loss due to fault) both in the \( q \) th wind turbine in the farm. It is worth mentioning that the fault magnitude provided by the FDD system is assigned to be exactly zero (\( \hat{P}_{q} = 0 \)) under fault-free operation. In other words, to maintain the nominal performance of the system, there is no need to modify/compensate the nominal reference torque control signal \( \tau_{q} \) in (10) under fault-free operation. Finally, to avoid any inconsistencies in the generated powers from the turbines, but also the turbines’ reference power signals.

As already mentioned, the faulty turbine and its relevant fault magnitude are all determined by the FDD system, which itself is required to consider not only the generated power responses from the turbines, but also the turbines’ reference power signals. In this regard, an efficient approach is to monitor in real-time the consistency of generated powers among all turbines in a given wind farm in real-time. Then, any inconsistencies in the generated powers will be detected, isolated and identified to generate FDD information. Such a monitoring can be achieved by either a model-free algorithm or a model-based algorithm that are presented in the following segment of this section.

It should be noted that real-time monitoring of the consistency of generated powers from different turbines in a wind farm is not a straightforward process, even in the case of adjacent turbines where wind conditions may be similar. In fact, the reference power signals are not necessarily identical for the turbines in a farm, hence the turbines’ generated powers may be different even under fault-free conditions. Therefore, in order to monitor the consistency of generated powers from any two arbitrary wind turbines, it is required to consider not only the generated power responses from the turbines, but also the turbines’ reference power signals. In this regard, an efficient approach is to monitor in real-time the consistency of generated powers from any individual wind turbine and all other remaining turbines in the farm simultaneously. More precisely, considering a wind farm with \( N \) turbines that are arbitrarily labeled as \( T_1, T_2, \ldots, T_N \), the consistency of generated powers needs to be monitored through \( R \) similar modules:

\[
R = 1 + 2 + 3 + \ldots + (N - 1) = \frac{N(N - 1)}{2} \tag{11}
\]

Table 1 shows the formation of modules (each denoted by a \( M \)) for such a wind farm with \( N \) turbines. Here, each particular module monitors the consistency of the powers generated by two different wind turbines in the farm (e.g., \( M_{ij} \) represents a module that monitors the consistency of the powers generated by turbine \( T_i \) and turbine \( T_j \) in a farm \( i \neq j \)). For example, in a wind farm with ten working turbines (\( N = 10 \)), 45 modules (\( R = 45 \)) are required to monitor the consistency of generated powers among all turbines in the entire wind farm.

Fig. 7 shows the general structure of the FDD system that is composed of \( R \) modules (presented in Table 1) and a set of decision making (DM) blocks (\( D_{M_1}, D_{M_2}, \ldots, D_{M_R} \)) that each corresponds to an individual turbine and is used for analysing the module output (MO) signals and making decision about the real-time status of the
turbine. In Fig. 7, \( \text{Mes} \) is a vector of performance data including measured variables and control commands/references in wind turbines. However, the FDD system only needs the sets of reference powers and generated powers defined in (12) and (13), respectively.

\[
\begin{align*}
P_r(k) &= [P_{r,q}(k)], \quad q = 1, 2, \ldots, N \\
P_g(k) &= [P_{g,q}(k)], \quad q = 1, 2, \ldots, N
\end{align*}
\]

The reference powers \( P_{r,q} \) in (12) are computed as:

\[
P_{r,q}(k) = \tau_{r,q}(k) \cdot \omega_{g,q}(k)
\]

in which \( \tau_{r,q} \) and \( \omega_{g,q} \) are the reference generator torque and generator angular speed for \( q \) th wind turbine in the farm, respectively. Each particular module in the FDD system shown in Fig. 7 has its relevant inputs and outputs. For example, Fig. 8 shows the relevant inputs and outputs for the example module \( M_{ij} \) that monitors the consistency of the powers generated by turbine \( T_i \) and turbine \( T_j \) in a farm (\( i \neq j \)). In this figure, the inputs include the reference powers and generated powers corresponding to turbines \( T_i \) and \( T_j \) that the module is monitoring them for power consistency, while the module output \( M_{O_{ij}} \) includes inconsistency detection (\( ID_{ij} \)) and inconsistency magnitude (\( IM_{ij} \)) signals. The inconsistency detection signal and inconsistency magnitude signal indicate, respectively, the occurrence and magnitude of any possible inconsistency in the generated powers by turbines \( T_i \) and \( T_j \). More precisely, regardless of details of the monitoring process conducted in the module that are presented in two next subsections, the

| Rule No. | If | \( \Delta P_{r,s} \) and | \( P_r \) | and | \( P_g \) | is | then | \( S_i \) | is |
|---------|----|----------------|------|------|------|---|------|------|
| 1       | Z  | Z              | Z    | Z    | 0    |
| 2       | Z  | NZ             | Z    | 0.5  |
| 3       | Z  | NZ             | NZ   | 0.5  |
| 4       | Z  | Z              | NZ   | 1    |
| 5       | NZ | Z              | Z    | 1    |
| 6       | NZ | Z              | NZ   | 1    |
| 7       | NZ | NZ             | NZ   | 1    |
| 8       | NZ | NZ             | NZ   | 1    |
module output \( \text{MO}_{ij} \) can attain the values described in Table 2 under two possibilities for the consistency of power generation by turbines.

As it is observed in Table 2, when power generation is inconsistent between \( T_i \) and \( T_j \), the inconsistency detection and inconsistency magnitude signals indicate the faulty turbine and the absolute value of estimated power loss \( |\Delta P_{ij}| \), respectively. Conversely, when power generation is consistent between \( T_i \) and \( T_j \), both inconsistency detection and inconsistency magnitude signals are zero. This does not necessarily mean that both turbines are healthy. In fact, when power generation is consistent between two turbines \( T_i \) and \( T_j \), they can be either both healthy or both faulty. Therefore, as it is shown in Fig. 7, the DM blocks are required to further analyse the output results of modules all together in real-time, and consequently determine faulty turbine(s). In particular, Fig. 7 shows the distribution and contribution of MO signals in the decision making process in each particular DM block. As already mentioned, each DM block corresponds to an individual turbine and is exclusively used for analysing the MO signals related to that specific turbine, and then makes an appropriate decision about the real-time status of the turbine. Such a decision is simply made based on the logic which states that as long as at least one of the relevant modules detects a turbine as a faulty turbine, then that turbine is faulty and its power loss due to the fault (i.e., \( \Delta P \) in (10)) is conservatively the maximum power loss estimated by the modules. In connection with Fig. 7 and mentioned information about Fig. 8 and Table 2, the mentioned logic of decision making is formulated in (15)–(17) for \( T_1 \), \( T_Z \) and \( T_N \), respectively. Note that turbine \( T_Z \) with \( (2 < Z < N) \) represents any turbine except \( T_1 \) and \( T_N \).

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**Fig. 14.** Structure of module \( M_j \) designed using model-based algorithm.

**Fig. 15.** Flowchart of post-processing on residuals \( r \) at the time-step \( k \).
If \( (ID_{1,2} = 1) \text{ OR } (ID_{1,3} = 1) \text{ OR } (ID_{1,4} = 1) \text{ OR } \ldots \text{ OR } (ID_{1,N} = 1) \),
Then \( T_1 \) is faulty and its power loss is maximum of \( \{IM_{1,2} , IM_{1,3} , IM_{1,4} , \ldots , IM_{1,N} \} \)

(15)

If \( (ID_{1,2} = Z) \text{ OR } (ID_{2,2Z} = Z) \text{ OR } (ID_{2,1,Z} = Z) \text{ OR } (ID_{2,2,Z} = Z) \text{ OR } \ldots \text{ OR } (ID_{2,N} = Z) \),
Then \( T_Z \) is faulty and its power loss is maximum of \( \{IM_{1,2} , IM_{1,3} , IM_{1,4} , \ldots , IM_{1,N} \} \)

(16)

If \( (ID_{1,N} = N) \text{ OR } (ID_{N-3,N} = N) \text{ OR } (ID_{N-2,N} = N) \text{ OR } (ID_{N-1,N} = N) \),
Then \( T_N \) is faulty and its power loss is maximum of \( \{IM_{1,2} , IM_{1,3} , IM_{1,4} , \ldots , IM_{1,N} \} \)

(17)

Results obtained from DM blocks in Fig. 7 constitute FDD information vector \( I \) as follows:

\[ I(k) = [I_1(k), I_2(k), \ldots, I_N(k)] \]  

(18)

The FDD system discussed here is highly dependent on the monitoring process in each module. From a design point of view, all modules used in the FDD system shown in Fig. 7 are essentially the same, but each corresponds to a particular group of two turbines. As already mentioned, each module (e.g., module \( M_j \)) monitors the consistency of the powers generated by two different wind turbines (e.g., \( T_i \) and \( T_j \) in a farm \( i=j \)). To address such a monitoring process, this paper proposes two different algorithms. The first one is basically a model-free algorithm based on a rule-based threshold testing technique, while the second one is a model-based algorithm based on an FMI technique. As shown in

<table>
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<th>Item</th>
<th>No.</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td>Antecedent part</td>
<td>2</td>
<td>( u(k-1), n = 1 )</td>
</tr>
<tr>
<td>Knowledge base</td>
<td>2</td>
<td>( y(k-1), m = 1 )</td>
</tr>
<tr>
<td>Tuning rules</td>
<td>2</td>
<td>( y_i(k) = a_i y_{i-1}(k) + a_{i2} u(k-1) + b_i )</td>
</tr>
<tr>
<td>Consequent part</td>
<td>-</td>
<td>Defuzzification method</td>
</tr>
<tr>
<td>Membership functions per input</td>
<td>2</td>
<td>-</td>
</tr>
<tr>
<td>Linear equation form in ith rule</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 4

Configuration properties of T-S fuzzy model (SISO model). Note that \( u(k) = P_s(k) \), and \( y(k) = P_n(k) \).

Fig. 16. A general outline of the simulation platform from MATLAB/Simulink.
the following subsections, each individual algorithm can be used in the FDD system and thereby either a model-free or a model-based FDD system can be established.

5.1. Model-free monitoring of power consistency

From \( R \) modules used in the FDD system shown in Fig. 7, consider an example module \( M_{ij} \) as shown in Fig. 8 that monitors the consistency of the powers generated by turbines \( T_i \) and \( T_j \) in a farm \( (i \neq j) \). This subsection addresses the design of such a module using a model-free algorithm based on a rule-based threshold testing technique. A block diagram illustrating the overall structure of the module designed using the mentioned model-free algorithm is shown in Fig. 9.

As it is shown in Fig. 9, a fuzzy inference mechanism is used for conducting the rule-based threshold testing over three different inputs including the difference of reference powers \( P_{ri,j} \), the difference of generated powers \( P_{gi,j} \), and their difference denoted by \( \Delta P_{ij} \). Appropriate scaling gains A, B, and C are applied to normalize the mentioned inputs between \( [-1/2, +1/2] \). The fuzzy inference mechanism provides an output indicating inconsistency signature \( S_{ij} \) that includes all traces of inconsistency in generated powers. As it is shown in Fig. 10, trapezoidal membership functions that are simple for implementation and fast for computation are used for the mentioned inputs. Moreover, Fig. 11 shows singleton membership

Fig. 17. Nacelle wind speeds for turbines of the wind farm shown in Fig. 1. (Note: \( V_{nac,i} \) denotes nacelle wind speed for turbine \( T_i \)).

Fig. 18. A typical grid load and total generated active power response by the wind farm under fault-free conditions.

5.1. Model-free monitoring of power consistency

From \( R \) modules used in the FDD system shown in Fig. 7, consider an example module \( M_{ij} \) as shown in Fig. 8 that monitors the consistency of the powers generated by turbines \( T_i \) and \( T_j \) in a farm \( (i \neq j) \). This subsection addresses the design of such a module using a model-free algorithm based on a rule-based threshold testing technique. A block diagram illustrating the overall structure of the module designed using the mentioned model-free algorithm is shown in Fig. 9.

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functions used for the output in which each function represents a single-valued constant.

With respect to the shown membership functions in Figs. 10 and 11, the complete set of rules used in the fuzzy inference mechanism is presented in Table 3. The rules are formulated based on an expert’s knowledge obtained through observing and understanding the relation between the consistency of generated powers and variations in the inputs. Each rule corresponds to a particular condition. In total, three different possibilities are considered: (1) consistent power generation represented by \( S_{ij} = 0 \), (2) inconsistent power generation represented by \( S_{ij} = 1 \), and (3) either consistent or inconsistent power generation represented by \( S_{ij} = 0.5 \). More precisely, when \( S_{ij} \) attains a value of 0 or 1 (i.e., rule 1 or rules 4–8 in Table 3), the power generation is directly determined as consistent or inconsistent, respectively. Conversely, when \( S_{ij} \) attains a value of 0.5 (i.e., rules 2 and 3 in Table 3), the power generation cannot be directly determined as consistent or inconsistent. In fact, rules 2 and 3 in Table 3 are related to the so-called response time of the whole wind farm system. That is the time the wind farm system takes to react to its given inputs. In other words, the wind farm system takes a short period of time (i.e., the response time) for \( P_{in} \) and \( \Delta P_{ij} \) to react to any change in \( P_{out} \) by the reference power signal(s) commanded from the wind farm control system. During such a short response time, it is not possible to directly determine the consistency of generated powers in a model-free way. Therefore, as it is shown in Fig. 9, the output of fuzzy inference mechanism (i.e., inconsistency signature \( I_{ij} \)) needs to be post-processed in order to obtain absolute inconsistency information \( I_{ij} \) that can be either 0 (consistent power generation) or 1 (inconsistent power generation). The post-processing conducted on \( S_{ij} \) at the time-step \( k \) is coded based on the flowchart shown in Fig. 12.

As shown in the flowchart in Fig. 12, to achieve a more reliable conclusion on \( I_{ij} \) and in response to any possible occurrence of inconsistency in power generation, \( I_{ij} \) changes from 0 to 1 when \( S_{ij} \) stays at its relevant values presented in the flowchart for \( T_{in} \) consecutive sample-times (i.e., the number of repetitions satisfies \( T_{in} \geq T_{diff} \)). Similarly, \( I_{ij} \) changes from 1 to 0 when \( S_{ij} \) stays at its relevant values presented in the flowchart for \( T_{out} \) consecutive sample-times (i.e., the number of repetitions satisfies \( T_{out} \geq T_{diff} \)). The appropriate values for \( T_{in} \) and \( T_{out} \) are determined by the user through considering that the greater the values of \( T_{in} \) and \( T_{out} \), the higher the required time for changing \( I_{ij} \) from 0 to 1 and 1 to 0 (i.e., higher conservatism). As it is shown in the flowchart in Fig. 12, when \( S_{ij} \) attains value of 0.5 (i.e., during short periods of response time of the wind farm system described by rules 2 and 3 in Table 3), \( I_{ij} \) stays at its previous value obtained in the previous time-step (i.e., \( I_{ij}(k) = I_{ij}(k - 1) \)). With respect to the flowchart shown in Fig. 12, an example of inconsistency signature and its absolute inconsistency information are shown in Fig. 13. The figure corresponds to module \( M_{14} \) for turbines \( T_{1} \) and \( T_{4} \) while considering the fault scenario shown in Fig. 4. As it is shown in Fig. 13, \( S_{ij} \) only attains value of 0.5 for very short periods of time when the inputs of fuzzy inference mechanism activate rules 2 and 3 in Table 3.

The absolute inconsistency information \( I_{ij} \) obtained from the post-processing of inconsistency signature \( S_{ij} \) only determines the presence of consistency or inconsistency in the generated powers by turbines \( T_{1} \) and \( T_{4} \). However, in the case of inconsistency in the generated powers, \( I_{ij} \) does not provide any information about isolation of faulty turbine and magnitude of fault (power loss). Therefore, it is required to further analyse \( I_{ij} \) through inconsistency analysis and isolation block as shown in Fig. 9. The functionality of this block is very simple in comparison with the already mentioned post-processing block. In fact, in the presence of any inconsistency in the generated powers (i.e., \( I_{ij} = 1 \)), the inconsistency analysis

---

Table 5
Estimated consequent parameters for the identified T-S fuzzy model with the structure given in Table 4.

<table>
<thead>
<tr>
<th>Rule No. (i)</th>
<th>( a_{i1} )</th>
<th>( a_{i2} )</th>
<th>( b_{i} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>+8.9 ( 10^{-1} )</td>
<td>+1.0 ( 10^{-1} )</td>
<td>+3.9 ( 10^{2} )</td>
</tr>
<tr>
<td>2</td>
<td>+9.0 ( 10^{-1} )</td>
<td>+9.1 ( 10^{-2} )</td>
<td>-4.2 ( 10^{2} )</td>
</tr>
</tbody>
</table>

Table 6
Cluster centers.

<table>
<thead>
<tr>
<th>Rule No. (i)</th>
<th>( y(k - 1) )</th>
<th>( u(k - 1) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-9.8 ( 10^{-3} )</td>
<td>-7.6 ( 10^{-3} )</td>
</tr>
<tr>
<td>2</td>
<td>-5.2 ( 10^{-3} )</td>
<td>-8.0 ( 10^{-3} )</td>
</tr>
</tbody>
</table>

Table 7
Modelling accuracy and fitting performance of the fuzzy model.

<table>
<thead>
<tr>
<th>VAF (%)</th>
<th>NRMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>99.2</td>
<td>0.004</td>
</tr>
</tbody>
</table>

![](https://example.com/fig19.png)

Fig. 19. Projected membership functions for: (a) \( y(k - 1) \), and (b) \( u(k - 1) \).

![](https://example.com/fig20.png)

Fig. 20. The process output and the fuzzy model output (showing the contribution of each local model) – time period [200,250] sec.
Fig. 21. FDD results for the model-free FDD system.
Fig. 22. FDD results for the model-based FDD system.
and isolation block computes the running mean of $\Delta P_\text{ij}$ in real-time (see Fig. 9). Then, the block determines (isolates) the faulty turbine based on the sign of the computed mean. That is, if the mean attains positive values, $T_\text{j}$ is faulty while if it attains negative values, it means that $T_\text{i}$ is faulty. Moreover, the absolute magnitude of this running mean $|\Delta P_\text{ij}|$ is used as the estimated power loss in the faulty turbine (see Table 2).

It should be noted that the module $M_\text{ij}$ designed here only determines whether powers generated from turbines $T_\text{i}$ and $T_\text{j}$ are consistent or inconsistent. When power generation is inconsistent, the module provides relevant information about detection and diagnosis of the faulty turbine. However, as previously mentioned at the beginning of Section 5, when power generation is consistent between turbines $T_\text{i}$ and $T_\text{j}$, they are either both healthy or both faulty. More precisely, if the fault happens simultaneously in both turbines $T_\text{i}$ and $T_\text{j}$, the module $M_\text{ij}$ still shows consistent power generation. For example, this is shown in Fig. 13 for module $M_{1,4}$ while both turbines $T_1$ and $T_4$ are faulty. To address this issue, as it was previously shown in Fig. 7, and formulated in (15)–(17), the DM blocks are required to analyse the output results of modules all together in real-time, and to consequently detect and diagnose faulty turbine(s).

### 5.2. Model-based monitoring of power consistency

From $R$ modules used in the FDD system shown in Fig. 7, consider an example module $M_\text{ij}$ that monitors the consistency of the powers generated by turbines $T_\text{i}$ and $T_\text{j}$ in a farm ($i \neq j$). This subsection addresses the design of such a module using a model-based algorithm based on an FMI technique. A block diagram illustrating the overall structure of the module designed using the above-mentioned model-based algorithm is shown in Fig. 14.

As shown in Fig. 14, the module employs a nominal dynamic model of the system that is developed using a data-driven modelling approach based on FMI technique. The model estimates the nominal relative performance between turbines $T_\text{i}$ and $T_\text{j}$ in a farm. In fact, powers generated from turbines $T_\text{i}$ and $T_\text{j}$ are consistent as long as $P_{\text{g}_\text{i}}$ and $P_{\text{g}_\text{j}}$ are (ideally) equal. However, they cannot be equal in practice due to the presence of noises and uncertainties inherent in real data. Therefore, a post-processing including a threshold testing is necessary to obtain absolute inconsistency information $I_\text{ij}$ that can be either 0 (consistent power generation) or 1 (inconsistent power generation). The post-processing at the time-step $k$ is coded based on the flowchart shown in Fig. 15. Similar to what was mentioned in the previous subsection, to achieve a more reliable conclusion on $I_\text{ij}$, in response to any possible occurrence of inconsistency in power generation, $I_\text{ij}$ changes from 0 to 1 when residual $r$ stays outside of its threshold for $T_a$ consecutive sample-times (i.e., the number of repetitions satisfies $T_\text{r} > T_a$). Similarly, $I_\text{ij}$ changes from 1 to 0 when residual $r$ stays within its threshold for $T_a$ consecutive sample-times (i.e., the number of repetitions satisfies $T_\text{r} > T_a$).

The following fuzzy fusion over all rule outputs provides the dynamics of a nonlinear system [25]:

$$y(k) = f(\Phi(k - 1)) + e$$

where $\Phi(k - 1)$ as defined in (20) is an information data vector including the past model inputs $u$ and outputs $y$, $k$ is the discrete-time-step, $(m, n) \in \mathbb{Z}$ denote the model order that are defined by the user, and $e$ denotes the modelling error.

A T-S type fuzzy model can approximate the unknown function $f(.)$ in (19) using $L$ rules (local models) as follows [25]:

**Rule i:** If $\Phi(k - 1)$ is $A_i$ then $\tilde{y}_i(k) = F_i(\Phi(k - 1))$, $i = 1, 2, \ldots, L$

where $A_i$ are the antecedent fuzzy sets of the $i$th rule. A simple but efficient linear form for $F_i(.)$ is defined by [25]:

$$F_i(.) : \tilde{y}_i(k) = a_i \Phi(k - 1) + b_i$$

where $a_i$ and $b_i$ denote the parameter vector and scalar offset of the $i$th rule, respectively.

The following fuzzy fusion over all rule outputs provides the dynamics of a nonlinear system [25]:

$$\ddot{\tilde{y}} = \left(\sum_{i=1}^{L} \mu_i(\Phi) \tilde{y}_i\right) / \left(\sum_{i=1}^{L} \mu_i(\Phi)\right)$$

<table>
<thead>
<tr>
<th>FDD system type</th>
<th>Detection time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model-free</td>
<td>2.2125</td>
</tr>
<tr>
<td>Model-based</td>
<td>1.5000</td>
</tr>
</tbody>
</table>

### Table 8

Time of fault detection (or detection time) for each FDD system (in seconds).
Fig. 23. Generator power response under fault-free and faulty conditions (3% power loss) – model-free AFTCC: (a) T1, (b) T2, (c) T3, (d) T4, (e) T7, (f) T8, and (g) T10.
Fig. 24. Generator power response under fault-free and faulty conditions (3% power loss) – model-based AFTCC: (a) $T_1$, (b) $T_2$, (c) $T_3$, (d) $T_4$, (e) $T_5$, (f) $T_6$, and (g) $T_{10}$. 

Fault-Free Operation
Faulty Operation with AFTCC
Faulty Operation without AFTCC
where \( \hat{y} \) is the aggregated output of the fuzzy model, and \( \mu_i \) denotes the degree of fulfillment of \( i \)th rule in [21].

To develop the above-mentioned T-S model for a real system, it is necessary to perform the nonlinear system identification that is the process of identifying the structure of fuzzy model, and then estimating the parameters in the model. The detailed structure of the fuzzy model developed for application in the module in Fig. 14 is presented in Table 4. It is worth mentioning that in order to identify the T-S model, the well-established Gustafson-Kessel clustering algorithm [26] is used here.

### 6. Simulation results and discussion

This section presents and discusses different simulation results for the investigation of the performance of proposed schemes under both fault-free and faulty conditions. The simulations in this work have been carried out in MATLAB/Simulink environment using the nonlinear offshore wind farm benchmark model presented in Section 2. The general outline of the simulation platform is shown in Fig. 16.

In more details, an offshore wind farm including ten 5 MW-turbines (\( N = 10 \)) is created with the layout as shown in Fig. 1. A realistic wind field with a mean speed of 15 m/s and a turbulence intensity of 10% is simulated over 1000 s of run time. The obtained wind speed profiles for each of the ten turbines in the farm are shown in Fig. 17. Moreover, a typical electrical grid load is applied to the wind farm over the simulation time. Fig. 18 shows the applied time-varying grid load as well as the relevant total generated active power response obtained from the wind farm under fault-free conditions.

In the following subsections, various simulations and numerical results for the proposed schemes are presented and discussed. The

<table>
<thead>
<tr>
<th>Faulty turbine</th>
<th>Fault period [S]</th>
<th>NRMSE [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model-based AFTCC</td>
<td>Model-free AFTCC</td>
</tr>
<tr>
<td>T1</td>
<td>[225,400]</td>
<td>0.0031</td>
</tr>
<tr>
<td>T2</td>
<td>[800,1000]</td>
<td>0.0030</td>
</tr>
<tr>
<td>T3</td>
<td>[450,1000]</td>
<td>0.0018</td>
</tr>
<tr>
<td>T4</td>
<td>[125,300]</td>
<td>0.0032</td>
</tr>
<tr>
<td>T7</td>
<td>[350,1000]</td>
<td>0.0015</td>
</tr>
<tr>
<td>T8</td>
<td>[100,1000]</td>
<td>0.0023</td>
</tr>
<tr>
<td>T9</td>
<td>[700,1000]</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Faulty turbine</th>
<th>Fault period [S]</th>
<th>NRMSE [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model-based AFTCC</td>
<td>Model-free AFTCC</td>
</tr>
<tr>
<td>T10</td>
<td>[700,1000]</td>
<td>0.0266</td>
</tr>
</tbody>
</table>

fault-free simulation with the baseline wind farm controller in (5) is used as a frame of reference to evaluate the overall performance, effectiveness, and fault-tolerance properties of the proposed FDD and FTC schemes against the considered decreased power generation faults that are already described in Fig. 4. In this regard, with respect to the considerations given in Section 3, the generator power response is chosen as a well-suited performance index to illustrate the performance of each turbine in the wind farm.

#### 6.1. Identification and validation of the fuzzy dynamic model

As already mentioned, the nominal dynamic model used in the modules of the model-based FDD system is designed and developed using the FMI technique described in Section 5.2. In more details, to train and evaluate a model, a set of 80,000 measured data for each of the inputs and outputs were used. The data was obtained with a sampling rate of 80 Hz from the fault-free simulation of the wind farm with its baseline control system. It is worth mentioning that each set of the data was split into equal halves; one half for training and the other one for validation. The structure for the fuzzy model is already determined in Table 4. In connection to the mentioned table and the performed nonlinear system identification process, the projected membership functions (two membership functions per input) are shown in Fig. 19. The consequent parameters of the model as well as the cluster centers are also presented in Tables 5 and 6, respectively. In addition, for example, Fig. 20 shows the output of a fuzzy model during a fault-free operation of the wind farm including the contribution of each local model (rule) in the developed model over a period of 50 s of simulation time. In this figure, the noise-free measurement of process output is used for comparison with the model output.

To assess the quality of the developed fuzzy model in terms of modelling accuracy and fitting performance, the normalized root-mean-squared error (NRMSE) and the variance accounted for (VAF) index are used, respectively. The NRMSE is defined as:

![Fig. 25. Generator power response under fault-free and faulty conditions (30% power loss) in T10: (a) model-free AFTCC, and (b) model-based AFTCC.](image-url)
\[
\text{NRMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2} \quad \text{where } y_k \text{ and } \hat{y}_k \text{ are the } k\text{th true output of the system (process), and the } k\text{th estimated output of the model, respectively. The denominator in (24) represents the range of the true output defined as the maximum value } y_{\text{max}} \text{ minus the minimum value } y_{\text{min}}. \text{The percentile VAF is computed by:}
\]
\[
\text{VAF} = \left[ 1 - \frac{\text{cov}(y_k, \hat{y}_k)}{\text{cov}(y_k)} \right] \times 100\%
\]

where \text{cov} denotes the covariance of the respective vector. Table 7 presents the obtained results. From the table, it is obvious that the fuzzy model is considerably accurate for approximating the process under diagnosis.

6.2. Performance of FDD system

As it was previously presented in Section 5, the FDD system can be developed based on either model-free or model-based monitoring of power consistency in the wind farm. Both model-free FDD system and model-based FDD system are investigated under both fault-free and faulty conditions.

As it is shown by the FDD results in Figs. 21 and 22, the proposed model-free and model-based FDD systems both are able to detect and diagnose all the considered faults based on the scenario defined in Fig. 4. The faults occur in turbines T1, T2, T3, T5, T7, T8, and T10. The FDD results are shown in terms of both fault detection indicators/signals and estimated fault magnitudes that can be used for ASC and accommodation of the faults in faulty turbines.

The time of fault detection (i.e., the time required for detecting a fault after its occurrence) for each FDD system is presented in Table 8. The time of fault detection reflected in this table is directly related to the \( T_m \) consecutive sample-times considered in the design process of each FDD system. As can be seen from Table 8, the model-based FDD system requires lower time for detection of faults. The lower the detection time, the better the fault detection has scored.

With respect to the identification of faults, both model-free and model-based FDD systems provide almost similar estimates for fault magnitudes in each particular faulty turbine. The fault magnitude itself represents the estimated amount of power loss that actually happens due to the occurrence of fault in a turbine. As it is shown in Figs. 21 and 22, the fault magnitudes are estimated exactly during the time that the fault detection indicators/signals are generated. These estimates are accurate enough to be used for the fault accommodation process. This fact is quantitatively shown in the next subsection while the obtained estimates are used directly in (10) for signal correction and fault accommodation in the framework of integrated FDD and FTC approach.

6.3. Performance of AFTCC schemes based on integrated FDD and FTC approach

As already mentioned, the estimated fault magnitudes act upon the reference torque control signal (see (10)) to accommodate the fault effects in each faulty turbine in the farm. Based on the
integrated FDD and FTC approach presented in Section 4, two AFTCC schemes are designed and developed using the model-free and model-based FDD systems in Section 5. In the following figures and tables, the AFTCC scheme using the model-free FDD system is denoted by “model-free AFTCC” scheme, and the AFTCC scheme using the model-based FDD system is denoted by “model-based AFTCC” scheme.

Based on the FDD results presented in the preceding subsection, the fault accommodation is performed in the faulty turbines that include T1, T2, T3, T4, T7, T8, and T10. Figs. 23 and 24 show the generator power responses in the mentioned turbines under fault-free conditions, faulty conditions with AFTCC schemes, and faulty conditions without AFTCC schemes.

Fig. 23 represents the performance of the model-free AFTCC scheme, while Fig. 24 represents the performance of the model-based AFTCC scheme. Both figures illustrate that the accommodation of faults is successfully performed in the faulty turbines and during all periods of fault activity. In other words, the performance of the system under faulty conditions with AFTCC schemes remains as close as possible to the performance of the system under fault-free conditions (i.e., the system’s nominal performance). Moreover, as foreseen, since the control reconfiguration (signal correction) is only activated during the periods of fault activity, the nominal performance of wind turbines will be unaffected under fault-free conditions.

To further investigate the performance of the proposed schemes in a comparative perspective, Table 9 presents a precise quantitative comparison between both schemes in terms of NRMSE during the periods of fault activity in the faulty wind turbines. Note that the lower the NRMSE, the better the fault-tolerance has scored. Based on the results presented in Table 9, the model-based AFTCC scheme provides a more efficient accommodation of faults compared to the model-free AFTCC scheme. This is due to the fact that the performance of each scheme was highly dependent on the speed and accuracy of its FDD system. As already discussed in the previous subsection, the model-based FDD system demonstrates better performance compared to the model-free FDD system that does not employ any dynamic model of the system. However, this superior performance of the model-based FDD system may be subject to modelling uncertainties, while the model-free system does not deal with any difficulties related to system modelling.

In addition to the presented results, Fig. 25 together with the numerical results presented in Table 10 show the fault-tolerance
capability of the proposed AFTCC schemes against a more serious fault with 30% power loss in turbine T10 as an example. This demonstrates that both of the schemes can also satisfactorily accommodate larger magnitudes of the considered type of fault in turbines. However, this does not eliminate the final necessity for maintenance of the blades before the amount of debris build up and/or erosion reaches a highly serious level.

6.4. Evaluation of wind farm structural dynamics and loading results

While evaluating the performance and effectiveness of the proposed schemes, it is also necessary to evaluate the functionality of the proposed schemes in terms of wind farm structural dynamics and loading. With respect to the implementation of control schemes, the recommended rate and magnitude limiters are...
employed in the benchmark model under consideration. Such an implementation aims to avoid intense control command, and thereby preventing extreme structural loading on the wind turbines' actuators. Different structural safety measures such as blade root bending moments, nacelle acceleration, drivetrain torsion, and tower bending moments have been considered and evaluated in this study and found to be well within their safe ranges. However, some of the evaluated structural dynamics and loading results are presented in this subsection. In particular, the drivetrain torsion rates and tower bending moments under both fault-free and faulty conditions are presented here. Fig. 26 shows the results of drivetrain torsion rate in turbine T1 for both the proposed model-free and model-based schemes. This figure also includes the zoomed-in views of the torsion rate response around the time instants in which the fault accommodation begins and finishes. Based on the scenario defined in Fig. 4, the fault period for T1 is [225,400] sec. However, as already discussed, the accommodation of fault is delayed by the fault detection time related to the FDD process. As it is seen in the zoomed-in views, in reference to the torsion rate response under fault-free conditions, the process of fault accommodation has been conducted safely, although the beginning and end of the fault accommodation show minor deviations because of activating and deactivating of the ASC process, respectively. Similar results for drivetrain torsion rates from other turbines in the farm have also been obtained that are not shown here for the sake of brevity.

Figs. 27 and 28 show the tower bending moment results for the model-free AFTCC scheme and model-based AFTCC scheme, respectively. In connection with these figures, a quantitative comparison in terms of mean and standard deviation (STD) for each of the considered results is also presented in Table 11.

The results shown in Figs. 26–28 together with the numerical results presented in Table 11 all demonstrate that both AFTCC schemes have minimal impact on the wind turbine structural dynamics and loading during fault accommodation. In other words, the shown structural safety measures have remained almost the same under both fault-free conditions and faulty conditions with AFTCC.

### Table 12
The results of Monte Carlo simulation studies under wind field shown in Fig. 17.

<table>
<thead>
<tr>
<th>Faulty turbine</th>
<th>Fault period [S]</th>
<th>NRMSE [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Model-based AFTCC</td>
</tr>
<tr>
<td>T1</td>
<td>[225,400]</td>
<td>0.00308</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.00323</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.00331</td>
</tr>
<tr>
<td>T2</td>
<td>[800,1000]</td>
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<td>0.00331</td>
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<td>T3</td>
<td>[450,1000]</td>
<td>0.00164</td>
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<td>0.00171</td>
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<td></td>
<td></td>
<td>0.00191</td>
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<tr>
<td>T4</td>
<td>[125,300]</td>
<td>0.00285</td>
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<tr>
<td></td>
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<td>0.00311</td>
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<td>0.00323</td>
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<tr>
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<td>0.00152</td>
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<td>T8</td>
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<td></td>
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<td>0.00226</td>
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<td></td>
<td>0.00231</td>
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<tr>
<td>T10</td>
<td>[700,1000]</td>
<td>0.00235</td>
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<td>0.00248</td>
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<td>0.00257</td>
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### Table 13
Quantitative comparison of generator power responses for AFTCC schemes during the specified fault periods with 3% power loss and under wind field with mean speed of 16 m/s, a turbulence intensity of 12%, and over 2000 s of run time.

<table>
<thead>
<tr>
<th>Faulty turbine</th>
<th>Fault period [S]</th>
<th>NRMSE [-]</th>
</tr>
</thead>
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<tr>
<td></td>
<td></td>
<td>Model-based AFTCC</td>
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<tr>
<td>T1</td>
<td>[225,1400]</td>
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<td>T2</td>
<td>[800,2000]</td>
<td>0.0019</td>
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<tr>
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<td>[450,2000]</td>
<td>0.0017</td>
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<tr>
<td>T4</td>
<td>[125,1300]</td>
<td>0.0020</td>
</tr>
<tr>
<td>T7</td>
<td>[350,2000]</td>
<td>0.0015</td>
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<tr>
<td>T8</td>
<td>[100,2000]</td>
<td>0.0016</td>
</tr>
<tr>
<td>T10</td>
<td>[700,2000]</td>
<td>0.0018</td>
</tr>
</tbody>
</table>

### 6.5. Robustness
This subsection deals with further evaluation of the proposed AFTCC schemes in terms of robustness to disturbances and measurement uncertainties. Extensive Monte Carlo simulations have been performed using the wind farm nonlinear benchmark model that was modified to include the stochastic features of the signals used for the modelling of the process parameter variations and measurement uncertainties. In this regard, sensors are modeled as noise-contaminated uncertain measurement systems, and some model parameters in turbines' drivetrain and aerodynamic models are stochastically varied around their nominal values. In total, 100 Monte Carlo simulations have been performed for each of the schemes under both fault-free and faulty (3% power loss) conditions. The best, average, and the worst values of NRMSE are presented in Table 12.

Although the wind speed profile with a mean speed of 15 m/s and a turbulence intensity of 10% over 1000 s of run time (see Fig. 17) was used for the above-mentioned Monte Carlo study, an additional simulation trial was also made in order to test the robustness in performance of the proposed schemes in terms of external disturbances (e.g., wind changes). In this regard, a new wind field with a mean speed of 16 m/s and a turbulence intensity of 12% is simulated over 2000 s of run time. For the mentioned
wind field, similar simulations as described in Section 6.3 are conducted with the exception of fault activity periods that are extended by an extra 1000 s of run time. Table 13 presents the quantitative comparison between the proposed schemes in terms of NRMSE during the mentioned periods of fault activity in the faulty wind turbines (the simulation plots are not shown here for the sake of brevity).

All results presented in Tables 12 and 13 confirm that both model-free and model-based AFTCC schemes are not only robust in the presence of modelling errors, measurement uncertainties, and external disturbances, but also can successfully maintain reliable wind farm performance under faulty conditions.

7. Conclusions and future works

This paper proposed a novel integrated fault detection and diagnosis (FDD) and fault-tolerant control (FTC) approach in a cooperative framework referred to as active fault-tolerant cooperative control (AFTCC) oriented to the design and development of two AFTCC schemes for an offshore wind farm. The designed AFTCC schemes can address decreased power generation faults caused by turbine blade erosion and debris build-up on the blades over time. Each of the designed schemes employs a FDD system to provide accurate and timely diagnosis information to be used in an appropriate automatic signal correction algorithm for accommodation of faults in the farm. The first scheme is based on a model-free FDD system that incorporates a rule-based threshold testing technique for residual evaluation. Conversely, the second scheme is based on a model-based FDD system that incorporates data-driven models developed using fuzzy modelling and identification technique.

Different simulations have been performed using a high-fidelity offshore wind farm benchmark model in the presence of wind turbulence, measurement noises, and realistic fault scenarios. Moreover, extensive Monte Carlo simulations are performed to evaluate the robustness of the designed schemes with respect to modelling errors, disturbances and measurement uncertainties. All simulation studies and numerical results clearly indicate the effectiveness and robustness of the schemes over the entire range of tested wind profiles for both the fault-free and faulty conditions.

Both AFTCC schemes are superior to the baseline wind farm control system designed using classical methods. The fault-tolerance and nominal performance provided by the schemes make them an efficient and practical choice for wind farms. In particular, the fact that the proposed schemes employ an automatic signal correction algorithm for fault accommodation, and hence do not disturb the nominal performance of a wind farm under normal (fault-free) operating conditions, is a remarkable feature. This feature is particularly favorable in the case of any already designed wind farm control systems whose structures are well-defined, for optimizing power capture in a farm while achieving fault-tolerance capability without sacrificing the optimal performance of the wind farm. However, it is worth mentioning that the performance of the proposed AFTCC schemes is highly dependent on the speed and accuracy of their FDD systems. Obviously, it may be impossible in practice to measure or obtain the instant precise values of faults in a system. In fact, the FDD systems only determine an online estimate for the magnitude of faults after their occurrence while accepting a detection time delay.

It is worth mentioning that the considered fault of blade erosion and debris build-up on the blades actually happens over the operation time of a wind turbine in a wind farm. The AFTCC schemes proposed in this paper are basically developed for timely detection and diagnosis and accommodation of such a fault in a wind farm, and finally, extending the operation time (availability) of any faulty wind turbine with an acceptable (probably degraded) performance until the next maintenance time is reached or scheduled for faulty parts replacement and/or investigating the root causes which might also include blade material failure. The proposed AFTCC schemes in fact lessen the downtime of wind turbines and extend their availability in a wind farm, in order to achieve higher cost-efficiency in energy generation. However, it does not eliminate the final necessity for maintenance of the blades before the amount of debris build-up and/or erosion reaches a highly serious level.

With respect to future research topics related to this presented work, it can be promising to extend the proposed AFTCC approach to accommodation of other frequent faults in wind farms, such as misalignment of one or more blades originated at the time of installation and/or change in the drivetrain due to wear and tear. Moreover, it should be noted that in order to practically implement and benefit from such a fault-tolerant control approach, the FDD system and real-time control system reconfiguration as a whole needs to be designed and developed along with the so-called techniques related to fault-tolerant computing and fault-tolerant communication networks that are followed by hardware-in-the-loop testing for complete evaluation before real system tests.

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References