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Adaptive Signal Processing Strategy for a Wind Farm System Fault Accommodation

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***Abstract*—In order to enhance the 'sustainability' of offshore wind farms, thus skipping unplanned maintenance operations and costs, that can be important for offshore systems, the earlier management of faults represents the key point. Therefore, this work studies the development of an adaptive sustainable control scheme with application to a wind farm benchmark consisting of nine wind turbine systems. They are described via their nonlinear models, as well as the wind and wake effects among the wind turbines of the wind park. The fault tolerant (*i.e.*, sustainable) control strategy uses the recursive estimation of the faults provided by nonlinear estimators designed via a nonlinear differential algebraic tool. These estimators are not affected by the model uncertainty and the wake effects among the wind turbines. This work exploits also a data-driven method used for estimating the analytical form of these disturbance functions, which are employed for obtaining the nonlinear fault reconstructors. Note that purely analytic approaches, where the model nonlinearity and the disturbance decoupling features are directly taken into account, may lead to more complex design tools. This aspect of the study, together with the more straightforward solution based on a data-driven scheme, is the issue when online applications are proposed for a viable implementation of the proposed solutions. The benchmark is exploited to verify the features of the developed strategies with respect to various fault situations and unavoidable model-reality mismatch.**

***Keywords*—Fault reconstruction; sustainable control; nonlinear models; robustness and reliability; offshore wind farm**

I. Introduction

Generally, wind turbines of important size can be quite expensive, and thus their reliability cannot be neglected in order to optimise their energy conversion rate and minimise the lost production costs. This point could represent the key point for offshore wind parks, where Operation and Maintenance (O & M) related activities have to be reduced, since they directly affect the final energy price. The so-called cost of the capital, and the wind turbine load carrying structure of the installations constitute the main term in the price of the energy, which represents its 'fixed cost'. On the other hand, the O & M term is a 'variable cost' that affect the cost up to the 30%.

In parallel, industrial plants became more and more complex with increased price, which can barely tolerate any performance reduction to faults and disturbance, thus leading to the decrease of the production and process safety. This also yields to require increased levels of reliability and safety for the control systems, as they can be subjected to system anomalities and failures. Therefore, it is really necessary the Fault Detection and Diagnosis (FDD) task or the Fault Detection and Isolation (FDI) phase, as well as the requirement of sustainable (*i.e.*, fault-tolerant features) for reducing any possible performance reduction, thus avoiding any anomalous and dangerous situations. The development of digital control tools, computer networks and information science methodologies makes it possible to design new recursive diagnosis and sustainable strategies to be applied to industrial plants. However, it also has led to important challenges. Therefore, this paper tries to propose the design of sustainable, *i.e.*, a Fault Tolerant Control (FTC) system, with an application example to a wind park simulation model.

Quite recently, several works have been suggested for wind turbine FDI/FDD, and the most important are represented, *e.g.*, by [1], [2]. In the same way, with reference to the sustainable (FTC) problem, it was quite recently considered but for an offshore wind turbine simulated model in [3]. Generally, sustainable (FTC) strategies are divided into two schemes, *i.e.*, Passive Fault Tolerant Control Strategies (PFTCS) and Active Fault Tolerant Control Strategies (AFTCS), as summarised, *e.g.*, in [4]. In particular for PFTCS, controllers are defined and are developed to be robust with respect to a subset of fault situations. On the other hand, AFTCS are able to counteract any system malfunctions in an active or adaptive way by reconfiguring or accommodating their control laws, so that the system stability and its required performance can be met in despite of the modified working conditions.

With particular reference to wind parks, sustainable control strategies were considered, *e.g.*, in [5]. These plants have complex and nonlinear dynamic behaviours, due to their aerodynamics that are nonlinear and unsteady. Moreover, their rotors are affected by complex and turbulent wind fields and driven by extreme fatigue loading conditions. Therefore, the compensation of wind parks can require complex and challenging design strategies, as described, *e.g.*, in [6].

In particular for this work, it considers the design of an active sustainable control scheme, (*i.e.*, AFTCS) that includes a reliable fault reconstruction strategy with the development of a controller accommodation methodology. In more detail, the strategy uses a recursive fault reconstruction provided by nonlinear fault estimators achieved with the so-called Nonlinear Geometric Approach (NLGA) tool [8], a nonlinear differential algebraic method already proposed by the authors in [7]. The controller compensation method uses a further control control loop employing the recursive reconstruction of the fault itself.

The proposed nonlinear fault reconstruction approach is based on the same technique addressed in [7], but it was designed only for a single wind turbine model. Moreover, this work suggests the development of nonlinear fault reconstructors that are decoupled from both the disturbance terms and their interactions among the wind turbine systems of the wind park installation.

It is worth noting that the nonlinear fault reconstruction scheme relies on the NLGA tool addressed at the beginning, *e.g.*, in [8]. However, it is not able to provide any fault size estimation, which is strictly required for this application. Moreover, the straightforward usage of the proposed scheme, or any other method exploiting the *analytical* disturbance decoupling approach, would be impossible, mainly due to the wind park model formulation and its structure. In fact, the wind turbine aerodynamic models are nonlinear functions of the tip-speed ratio and blade pitch angle, as described, *e.g.*, [6]. Moreover, this function is not known in any analytical formulations, but it is usually describe as an approximated two-dimensional map (look-up table).

Therefore, this study suggests to describe this function, that represents the power conversion ratio, in an analytical formulation as two-dimensional polynomial. This function is thus exploited for developing the disturbance decoupled fault reconstruction model. The same data-driven identification estimation procedure is used for the derivation of the analytical formulation of the wake models describing the relations among the different wind turbines of the wind farm, this highlighting the novel aspect of this work.

The interactions among the wind turbines of the wind park are regarded as a disturbance terms, since, followed by the wind model, they reduce the performances of the control scheme. Note that different FDI/FDD solutions, which also enhance the features the same wind park, were recently used with application to the same wind park challenge competition, as summarised by the contributions represented, *e.g.*, in [9], [10], [11].

It is worth noting also that the active nonlinear filters and the sustainable control strategy are applied to the wind farm benchmark simulator proposed in [6], in the presence of faults and model-reality mismatch conditions. A similar FTC solution proposed for the same benchmark but relying on fuzzy logic tools was addressed in [12]. Therefore, the development of the sustainable active strategy for the wind farm benchmark and relying on nonlinear fault reconstructors are the novel aspects of this contribution.

Moreover, the developed solution are compared with respect to the former techniques designed by the same authors, *e.g.*, in [11], [12]. On one hand, the strategy described in this work uses adaptive fault reconstructors that are able to counteract in an recursive way any fault situations. On the other hand, the strategy relying on the fuzzy logic tool is obtained in a batch way, in order to compensate in a passive way all the possible fault situations regarding the controlled process, thus being a PFTCS solution. Moreover, it is worth observing also that, the disturbance decoupling approach addressed in this study has been firstly described and solved for the considered wind park model. This issue is another key aspect of the study.

Finally, it is worth observing that this work tries to generalise the solutions proposed by the same authors, *e.g.*, in [11], [12] and it compares the achievements already addressed by the same authors in [13], [14].

The paper has the following organisation. Section II describes the wind farm benchmark. Section III addresses the fault reconstruction scheme, as well as the design of the sustainable control strategy, which represents the main structure of the AFTCS solution. The obtained results are summarised and discussed in Section IV, where comparisons with respect to different sustainable control schemes are also presented. Finally, Section V ends the paper by highlighting the main points of the paper, and it suggests open problems and future issues that could require further investigations.

II. Wind Park Description

The application benchmark consists of a small wind park of 9 wind turbines located in a coordinate system of a square matrix 3×3, as explained in [6]. The distance between two wind turbines in both directions is $7\,L$, where L represents the wind turbine rotor diameter. Two measuring devices (masts) are placed in front of the wind turbines, and located in each of the two wind directions, *i.e.*, 0^o and 45^o. These masts, which provide a measurement of the wind speed, are located $10\,L$ in front of the wind park, in order to avoid the effect of the wind park wakes. The wind turbines of the wind park are generic 4.8 MW systems described in [3]. They are three bladed horizontal axis, pitch controlled variable speed wind turbines. The diagram of the wind farm is shown in Fig. 1.

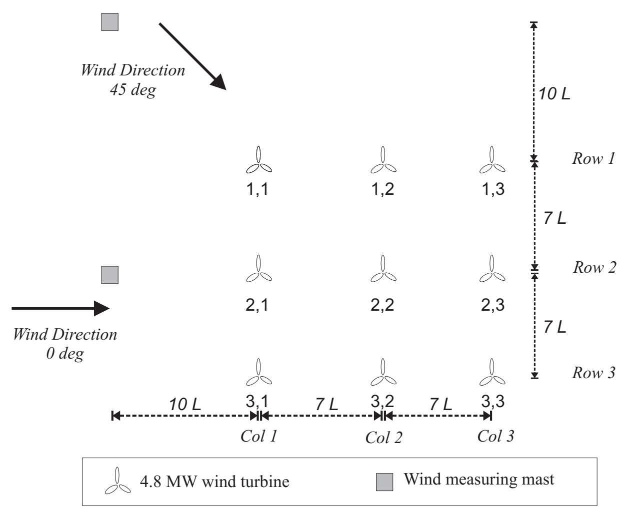

Fig. 1. The wind farm scheme.

A. Benchmark Model

The i-th wind turbine system is represented as a dynamic model that includes control logics, variable parameters and three state variables. Therefore, the i-th wind turbine model produces the electrical power $P_{i\,g}(t)$, is controlled by the collective pitch angle $\beta_i(t)$, and the generator speed $\omega_{i\,g}(t)$. For each turbine, only one measured pitch angle β_i is exploited as the i-th wind turbine controller regulates the pitch angles in the same way [6].

Two different wind distribution scenarios are considered for each direction of 0^o and 45^o, but the wind park is driven by the same wind process $v_w(t)$, and possibly affected by a time shift. The considered wind process contains a wind sequence with a mean speed value increasing from 5 m/s to 15 m/s, and with possible maximum peaks of about 23 m/s.

The simulated benchmark considered in this work contains a simple wind farm controller that regulates the power reference $P_{i\,ref}(t)$. If the generated power is lower than the one requested, the reference signals $P_{i\,ref}(t)$ are evenly distributed among the different wind turbine controllers. More details regarding this wind park benchmark, whose description is beyond the scope of this work, are addressed in [6]. It is worth observing that the description of the considered wind park could be quite simple. However, the benchmark is able to accurately represent realistic wind park systems, as remarked, *e.g.*, in [15].

The simulated benchmark is composed of three blocks. The wake description is recalled in the following, as addressed in [6]. It provides the mathematical formulation of the wind distribution among the wind turbines of the park, thus representing the interactions among the different wind turbines and their wakes. This wakes distribution is a function of the different control laws, so that up-wind turbines can affect their wakes, thus increasing or decreasing the control actions of the down-wind turbines.

The scheme of the wind park is represented in Fig. 2, with v_w describing the wind speed vector, whose components are $v_{i,\,w}$. On the other hand, $v_{w,\,m}$ represents the wind speed vector provided by the masts, whose components are $v_{i,\,w,\,m}$. The variable P_r is the vector of the power references required by the i-th wind turbine of the wind park, $P_{i\,r}$. P_g is the vector containing the generated electrical powers with reference to the i-th wind turbine, $P_{i\,g}$. Finally, the signal β is the pitch angle vector for each wind turbine, controlled by the signal β_i, whilst ω_g is the generator speed vector from the measured wind turbine velocities, $\omega_{i\,g}$.

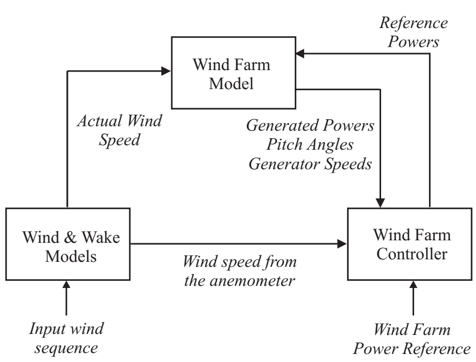

Fig. 2. The overall benchmark model.

The wake distribution is described as the effect of a wind efficacy decrease between the wind turbines of a factor 0.9. On the other hand, the wind turbulence effect is modelled by random process of zero mean and variance of 0.2 [6].

With reference to the two other blocks in Fig. 2, the wind turbine systems are quite simple and modelled according to the mathematical description addressed, *e.g.*, in the works [3]. As shown in Fig. 2, each wind turbine systems consists of three blocks: a power system, a pitch model, and a generator speed module [6]. Finally, the benchmark includes a simple controller that regulates the requested power. If the power required by the wind park is lower than the generated power and below the available power, the power reference signals are evenly sent to the remaining wind turbine regulators.

After these considerations, the overall model of the wind park under consideration has the form of (1):

$$\left\{ \begin{array}{lcl} \dot{x}_c(t) & = & f_c\left(x_c(t), u(t)\right) \\ y(t) & = & x_c(t) \end{array} \right. \tag{1}$$

with $u(t) = [v_{i\,w}(t),\, v_{j\,w\,m}(t),\, P_{i\,r},\, \beta_i(t)]^T$ and $y(t) = x_c(t) = [\omega_{i\,g}(t),\, P_{i\,g}(t)]^T$ representing the input and the measured output signals, respectively. The subscript i indicates the generic i-th wind turbine of the wind park that is affected by the j-th wind wake effect, with $i,\, j = 1, \ldots, 9$, and $i \neq j$. $f_c(\cdot)$ is a continuous-time nonlinear function used to describe the nonlinear behaviour of the considered dynamic process. A number of N sampled data $u(k)$ and $y(k)$, with $k = 1, 2, \ldots N$, will be acquired from the system of (1). They will be used for deriving the mathematical models of the disturbance effects depending on both the wind process $v_w(t)$ by means of the nonlinear aerodynamic behaviour and the wind turbine wakes $v_{w,m}$, *i.e.*, the wind turbine interactions, as described in Sections III and IV.

B. Fault Scenario

This wind park benchmark implements three fault cases that affect the wind turbine measurements, *i.e.*, the signals $\beta_i(t)$, $\omega_{i\,g}(t)$, and $P_{i\,g}(t)$. It is worth noting that these fault conditions may be diagnosed by considering the overall wind park system, for example by comparing the different wind turbine performances; however, they are difficult to be detected by considering the single wind turbine models. Moreover, these fault cases regard different wind turbines at different time instants, as addressed in [6].

Table I summarises the relations among the fault cases considered in the paper and the i-th wind turbine of the wind farm. Section III will exploit this analysis and will show how the disturbance decoupling method proposed in this work is able to improve the fault diagnosis stage, thus employed for the controller compensation task. This aspect highlights the key point of the contribution of this paper.

TABLE I. FAULT CASES OF THE WIND FARM SIMULATOR

Fault case #	1	2	3
Faulty wind turbine i	2 7	1 5	6 8

In this way, Table I represents the fault effects among the wind turbines, by considering the single fault case occurrence.

In particular, with reference to the rationale behind the fault scenario considered in this paper, the following remarks can be drawn. The fault Case 1 is due to the debris build-up, *i.e.*, the wind turbine blade dirt. This dirt modifies the aerodynamics law of the wind turbine model, usually by reducing the achieved power. The fault Case 2 effect derives form a misalignment of the wind turbine blades installed during the installation stage of the wind park. This effect is modelled as offset between the measured signal and real pitch angle of one or more blades. This may induce also a dangerous mismatch between the blade loads, thus possibly exciting the dynamics modes of the load carrying structure. Finally, the fault Case 3 is due to an alteration in the drive-train model parameters produced by wear and tear.

Note that this latest fault condition is typically detected by means of frequency methods that are able to highlight changes in the measured frequency spectra signals from load carrying structure vibration measurements. Obviously, it is fundamental to understand if if similar results are achievable by exploiting the measurements already acquired by control purpose. For example, the related works [16], [3] report several contributions regarding wind turbine FDI. They remarked that basic model-based FDI solutions as described in [26] are not able to diagnose this fault type. A more detailed description of this fault scenario can be found, *e.g.*, in [17], [6].

The following of this section analyses the links among the different fault cases reported in Table I and their effects on the measurements acquired from the simulated model of (1), and depicted in Fig. 2. In order to describe a realistic scenario, this system is also affected by uncertainty, measurement errors and the well-known model-reality mismatch. This point is fundamental when the reliability and robustness features of the proposed solutions have to be analysed for the viable application of the suggested methodologies. In fact, Section IV will demonstrate how the development of the nonlinear fault reconstructors for diagnosis purpose improves the sustainable strategy described in this paper. This is a key point of the proposed methodology.

In more detail, Table II reports the effects of the fault scenario on the input and output signals acquired from the wind farm benchmark model of (1). Moreover, these measured signals shown in Fig. 2 are used for the development of the nonlinear fault reconstructors addressed in Section III and validated in Section IV.

TABLE II. RESULTS OF THE FAILURE MODE & EFFECT ANALYSIS FOR THE WIND FARM MODEL

Fault case	1	2	3
u	$v_{2\,w},\, v_{7\,w}$ $v_{4\,w\,m},\, v_{9\,w\,m}$ $P_{2\,r},\, \beta_7$	$v_{1\,w},\, v_{5\,w}$ $v_{2\,w\,m},\, v_{6\,w\,m}$ $P_{1\,r},\, \beta_2$	$v_{6\,w},\, v_{8\,w}$ $v_{3\,w\,m},\, v_{7\,w\,m}$ $P_{6\,r},\, \beta_3$
y	$\omega_{9\,g},\, P_{4\,g}$	$\omega_{5\,g},\, P_{6\,g}$	$\omega_{8\,g},\, P_{7\,g}$

It is worth noting that the results summarised in Table II were achieved by performing the *Failure Mode & Effect Analysis* (FMEA), which represents an important engineering and powerful tool applied to dynamic processes, as described in [18]. In practice, for each fault case, the measurements reported in Table II represent the most sensitive signals acquired from the model of (1) in the presence of the considered fault situations. Obviously, when a different fault scenario has to be analysed, different measurements should probably be considered.

Finally, it is worth noting that the disturbance decoupling procedure considered in this work and addressed in Section III represents the key contribution of this paper. This strategy was not considered in the work by the same authors [11], [12] and that it was only partially investigated in [13], [14]. In fact, the proposed methodology is fundamental since the disturbance and the uncertainty effects due to the interactions among the wind turbines of the wind farm can reduce the capabilities of the sustainable control scheme. In fact, these disturbance terms can mask the effects of the fault conditions regarding the wind turbines, as highlighted in the following.

III. SUSTAINABLE CONTROL DESIGN

The proposed sustainable control scheme is developed in three steps. The first stage concerns the identification of the mathematical description of the nonlinear disturbance terms, which are used for the development of the NLGA fault reconstructors. Thus, the estimated faults are employed for the compensation of both the measured and control signals affected by the faults themselves.

In order to obtain reliable and robust solutions, the disturbance terms affecting the model under diagnosis need to be cancelled out. Section II shown how these terms derive from two effects: one is due to the wind signal $v_{i\,w}$ regarding the i-th wind turbine system via its power coefficient factor C_p. The elimination of this term was already addressed by the same authors in [7] but developed only for a single wind turbine model. The same strategy will be exploited here and developed for the different wind turbines of the park; the second disturbance term is generated by the interactions among the wind turbine systems, and described by the wind signals $v_{j\,w\,m}(t)$ of the different wakes.

On one hand, in [19] it was shown that the derivation and the cancellation of the first disturbance effect can rely on the analytical identification of both the C_p factor and the wind velocity $v_w(t)$. On the other hand, with reference to the wind wakes, a new methodology using the NLGA tool is proposed in this work. In more detail, by following the same strategy used for the cancellation of the uncertainty of wind speed $v_w(t)$ described in [7], this scheme needs for the nonlinear mathematical description of the disturbance distribution relation of the signals $v_{j\,w\,m}(t)$. Therefore, as described in [7], the function $C_p\,(\beta,\, \lambda)$ entering into the aerodynamic models of the wind turbines and included in (1) was obtained as a two-dimensional polynomial description. It depends on the tip-speed ratio λ and the blade pitch angles β of the i-th wind turbine system. The same strategy was used for removing the effect of the other inputs $v_{j\,w\,m}(t)$ by exploiting the identification procedure presented for the first time in [20].

Once the disturbance distribution term has been derived in mathematical form, the next step of the sustainable control scheme development requires the design of the nonlinear fault reconstructors for fault diagnosis purpose. Their models are achieved via the disturbance cancellation strategy originally traced back to the NLGA methodology [8]. This procedure allows to design a coordinate transformation that highlights a subsystem depending only on the faults but insensitive to the disturbance signals, which represents the first step in the development of the fault reconstructors. Note that, in this way, the fault reconstructors do not depend on the disturbance d, that in this paper represent the vector $[v_{i\,w},\, v_{j\,w\,m}]$.

This scheme applies to the general nonlinear system of (2):

$$\begin{cases} \dot{x} &= n(x) + g(x)\, c + \ell(x)\, f + p_d(x)\, d \\ y &= h(x) \end{cases} \tag{2}$$

with $x \in \mathcal{X}$ is an open subset of $\mathbb{R}^{\ell_n}$, the signal $c(t) \in \mathbb{R}^{\ell_c}$ represents the input vector, the term $f(t) \in \mathbb{R}$ is the fault signal, whilst the vector $d(t) \in \mathbb{R}^{\ell_d}$ is the disturbance effect, and the vector $y \in \mathbb{R}^{\ell_m}$ is the system output. The nonlinear functions $n(x)$, $\ell(x)$, $g(x)$, and $p_d(x)$ are smooth vector fields, whilst $h(x)$ is a smooth map.

The derivation of the nonlinear fault reconstructors for the fault signal f that are decoupled from the disturbance d relies on the algorithm addressed in [21]. In that work the original NLGA scheme of [8] was modified to be applied to the FDI problem. By means of a suitable coordinate change, the model of (2) is transformed into a new system in the local coordinates $(\bar{x}, \bar{y})$ in the form of (3) [21]:

$$\begin{cases} \dot{\bar{x}}_1 &= n_1(\bar{x}_1, \bar{x}_2) + g_1(\bar{x}_1, \bar{x}_2)\, c + \ell_1(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, f \\ \dot{\bar{x}}_2 &= n_2(\bar{x}_1, \bar{x}_2, \bar{x}_3) + g_2(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, c + \\ & \quad + \ell_2(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, f + p_2(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, d \\ \dot{\bar{x}}_3 &= n_3(\bar{x}_1, \bar{x}_2, \bar{x}_3) + g_3(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, c + \\ & \quad + \ell_3(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, f + p_3(\bar{x}_1, \bar{x}_2, \bar{x}_3)\, d \\ \bar{y}_1 &= h(\bar{x}_1) \\ \bar{y}_2 &= \bar{x}_2 \end{cases} \tag{3}$$

where $\ell_1(\bar{x}_1, \bar{x}_2, \bar{x}_3)$ is not identically zero. The system of (3), when this transformation exists, is observable. Moreover, it depends on the faults f and insensitive to the effect of the disturbances d [21].

The feasibility of this transformation depends on some fault detectability conditions, that need to be satisfied, as remarked in [21]. Moreover, the system of (2) consists of three submodels of (3), where this $\bar{x}_1$-subsystem is always insensitive to the disturbance effects d, but depending on the fault signals f, as highlighted by the relation of (4):

$$\begin{cases} \dot{\bar{x}}_1 &= n_1(\bar{x}_1, \bar{y}_2) + g_1(\bar{x}_1, \bar{y}_2)\, c + \ell_1(\bar{x}_1, \bar{y}_2, \bar{x}_3)\, f \\ \bar{y}_1 &= h(\bar{x}_1) \end{cases} \tag{4}$$

where the state vector $\bar{x}_2$ in (3) can be measured, whilst $\bar{x}_2$ in (4) is an exogenous input, that is indicated as $\bar{y}_2$.

The developed nonlinear fault reconstructors obtained via the modified NLGA tool implement the least-squares algorithm with forgetting factor described in [22], which rely on the adaptation law of (5):

$$\begin{cases} \dot{P} &= \beta\, P - \frac{1}{N^2} P^2 \breve{M}_1^2, & P\,(0) = P_0 > 0 \\ \dot{\hat{f}} &= P\, \epsilon\, \breve{M}_1, & \hat{f}\,(0) = 0 \end{cases} \tag{5}$$

where the (6) is the estimation of the output signal, whilst the corresponding normalised estimation error has the form of (6):

$$\begin{cases} \hat{\bar{y}}_{1s} &= \breve{M}_1\, \hat{f} + \breve{M}_2 + \lambda\, \breve{\bar{y}}_{1s} \\ \epsilon &= \frac{1}{N^2}\left(\bar{y}_{1s} - \hat{\bar{y}}_{1s}\right) \end{cases} \tag{6}$$

Note that all the variables of the adaptive fault reconstructor of (6) are scalar. In particular, the variable $\lambda > 0$ is a parameter regarding the bandwidth of the filter. The variable $\beta \geq 0$ represents the forgetting factor, whilst $N^2 = 1 + \breve{M}_1^2$ describes the normalisation parameter of the least-squares method. Moreover, the developed fault reconstructor uses the input signals $\breve{M}_1$, $\breve{M}_2$, $\breve{\bar{y}}_{1s}$, that are achieved via a low-pass processing of the variables M_1, M_2, $\bar{y}_{1s}$ as described by (7):

$$\begin{cases} \dot{\breve{M}}_1 &= -\lambda\, \breve{M}_1 + M_1,\ \breve{M}_1(0) = 0 \\ \dot{\breve{M}}_2 &= -\lambda\, \breve{M}_2 + M_2,\ \breve{M}_2(0) = 0 \\ \dot{\breve{\bar{y}}}_{1s} &= -\lambda\, \breve{\bar{y}}_{1s} + \bar{y}_{1s},\ \breve{\bar{y}}_{1s}(0) = 0 \end{cases} \tag{7}$$

The fault reconstructor systems are adaptive filters consisting of the relations of (5), (6), and (7). Note also that the same authors in [21] showed that this adaptive filter generates a signal $\hat{f}(t)$ that asymptotically approximates the real fault f. Moreover, these reconstructed faults have general models, as remarked in [23]. Note that this methodology is valid for the reconstruction of both actuator and sensor faults, as described in [24].

Once the fault reconstructor block has been designed, these reconstructed fault signals can be exploited for the accommodation of the control signals P_g, β, and ω_g that are altered by the faults themselves of the wind park system of Fig. 2. This step is the third stage in the development of the complete sustainable control strategy. Moreover, the simulation results of Section IV will be obtained by considering the sustainable control scheme reported in Fig. 3. This scheme implements the wind park controller developed in [6].

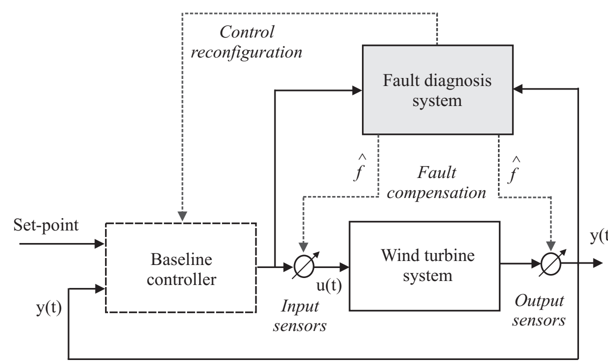

Fig. 3. The developed sustainable control scheme.

The complete scheme reported in Fig. 3 shows that the sustainable control scheme is implemented by integrating the fault reconstruction task with the existing control system. This fault reconstruction block (FDI) gives the reconstruction of the actuator and sensor faults $\hat{f}$, that are injected into the control loop. In this way, they are able to accommodate the effect of the faults themselves, that have modified the measured and controlled signals. After this compensation, the wind turbine controller is able to guarantee the nominal tracking of the reference signal, as for the nominal or fault-free case.

Finally, note that in steady-state conditions, once the fault effects are completely cancelled out, the performances of the control scheme coincide with the fault-free situation. Therefore, the stability issues of the sustainable control scheme have to be considered only during the transient phases, since the faults have not yet accommodated. In fact, during this phase, the reconstruction errors of the faults could destabilise the closed-loop system of Fig. 3. However, by following, *e.g.*, the demonstration presented in [25], it is possible to demonstrate that the fault reconstruction error is limited and convergent to zero, and the stability of the overall closed-loop system is thus achieved.

IV. Simulation Experiments

This section summarises the development and the results achieved from the sustainable control scheme applied to the wind farm benchmark model. In more detail, the first part of this section describes the derivation of the disturbance distribution functions in (2).

In particular, the entries of the C_p-map of the wind turbine aerodynamic system has been described by means of two-dimensional polynomial of (8):

$$\hat{C}_p\left(\lambda_i,\, \beta_i\right) = -0.0013\,\lambda_i^3 + 0.0003\,\lambda_i^3\,\beta_i + 0.010\,\lambda_i^2 \tag{8}$$

with reference to the i-th wind turbine system. More details on the procedure for achieving this polynomial were described in [20]. In the same way used for the estimation of this term, the disturbance functions representing the $p_d(x)$ term of (2) and derived from the wind wakes are described as $\hat{C}_{p\,i}$ in (9):

$$\hat{C}_{p\,i}\left(\lambda_j,\, \beta_j\right) = -0.0011\,\lambda_j^2 + 0.0027\,\beta_j\,\lambda_j^2 \tag{9}$$

for the the j-th turbine wake affecting the i-th turbine of the farm.

Note that the proposed strategy allows to derive the mathematical formulation of the disturbance functions for all uncertainties, and not only due to the errors from the C_p entry variations and the interferences of the wind wakes among the wind turbines of the park. This remark is important since these terms are exploited for the derivation of the fault reconstruction filters, all uncertainty effects have to be taken into account. A similar method was described in [26] but developed only for linear time-invariant systems. Therefore, the uncertainty distribution function $p_d(x)$ entering into the nonlinear system of (2) is obtained using the input-output data acquired from the wind farm. An important hypothesis that has to be valid in this situation is that the model-reality mismatch changes slower than the effects of the disturbance terms, *i.e.*, the signals d in (2). Another important issue concerns the estimated function $p_d(x)$ regarding the uncertainty structure, that should be independent from the wind size represented by the signal d. This means that the so-called disturbance directions are the most important feature of the disturbance decoupling approach proposed in this work.

In this way, the fault reconstruction adaptive filters of (5), (6), and (7) developed via the NLGA tools generate the estimate of the different fault signals affecting the the wind park simulator, as shown in Section II. The development of these fault reconstruction adaptive filters that are used for fault compensation is summarised in the following. More analytical details of the mathematical procedure are presented in [7] for the single wind turbine model.

When the model of (2) is defined, the following vectors are defined, with reference to the wind park benchmark: $x = [x_1\,x_2]^T = [\omega_{i\,g}\,P_{i\,g}]^T$, $c = [P_{i\,r}\,\beta_i]^T$, and the functions below are fixed:

$$n(x) = \begin{bmatrix} -\frac{\rho\,A}{2\,J}\,0.0010\,R^3\,x_1^2 - \frac{1}{J}\,x_2 & -p_{gen}\,x_2 \end{bmatrix}^T \tag{10}$$

$$g(x) = \begin{bmatrix} 0 & \frac{\rho\,A}{2\,J}\,0.0003\,R^3\,x_2^2 \\ p_{gen} & 0 \end{bmatrix} \tag{11}$$

and:

$$\ell(x) = \begin{bmatrix} 0 & \frac{\rho\,A}{2\,J}\,0.0003\,R^3\,x_1^2 \\ 0 & 0.0001 \end{bmatrix} \tag{12}$$

for the i-th wind turbine. Note that the subscript i is dropped. Moreover, $p_d(x)$ has the following form:

$$p_d(x) = \begin{bmatrix} \frac{\rho\,A}{2\,J}\,0.0010\,R^2\,x_1 & 0.0011 \\ 0.0002 & \frac{\rho\,A}{2\,J}\,0.0027\,x_2 \end{bmatrix} \tag{13}$$

When the model of (1) is considered, taking into account (2), (13), (12), and (11), it can be shown that:

$$S_0 = \bar{P} = \mathrm{cl}\left(p_d(x)\right) \equiv p_d(x) \tag{14}$$

Moreover, if $\ker\{dh\} = \emptyset$, it is easy to verify that $\Sigma_*^P = \bar{P}$ as $\bar{S}_0 \cap \ker\{dh\} = \emptyset$. Therefore, the expression $\left(\Sigma_*^P\right)^\perp = \left(\bar{P}\right)^\perp$ needs to be computed. However, note that for the system under diagnosis, the derivation of the observability codistribution $\left(\Sigma_*^P\right)^\perp = \left(\bar{P}\right)^\perp$ is improved by observing (14). More analytical details are similar to the results already addressed by the same authors for the case of the single wind turbine, and they will not be recalled here. The interested reader can refer to [7], [13].

Finally, as an example, with reference to the fault case 2, the development of the nonlinear fault reconstruction adaptive filter that generates the estimation of the fault signal f affecting the actuator $\beta_i(t)$ has the form of (15):

$$\dot{\bar{y}}_{1s} = M_2 + M_1 \cdot f \tag{15}$$

with:

$$\begin{cases} M_1 &= -0.0361\,x_1 + 0.8019\,x_1^2 \\ M_2 &= 0.7754\,x_1^2 - 0.3347\,x_1^3 + 15.7897\,x_2 + 1.0234\,x_2^2 \end{cases} \tag{16}$$

On the other hand, the derivation of the fault reconstruction filters for the Cases 1 and 3 is basically relying on a different choice of the vectors of (12), which lead to other forms for the nonlinear adaptive filter of (15). For example, with reference to the fault case 2 reported in Table I, the nonlinear fault reconstruction filter insensitive to the disturbance effect d describing both the wind $v_w(t)$ and the wake $v_{w,\,m}$ terms is described by the model of (5). A proper selection of the adaptation parameters entering in (5), (6), and (7), the nonlinear adaptive reconstructor generates a good approximation of the fault size, with minimal detection delay.

Therefore, the simulations reported in Fig. 4 regard the case of the actuator fault f described as a sequence of 2 rectangular pulses affecting 2 turbines, as described in Section II-B. In particular, Fig. 4 reports the fault reconstruction (dashed black line), when compared with respect to a fixed threshold used for the FDI task (grey dotted line).

Note that the developed fault reconstruction adaptive filters not only allow for the fault detection and their isolation, but also the fault estimation. Moreover, the considered faults described as sequences of rectangular pulses have been included in the wind farm simulator, since they can describe actual fault situations with reference to the wind farm under investigation. However, as already highlighted, the fault reconstruction systems can be easily modified to provide, for example, the estimation of general signals, if the nonlinear adaptive filter design can include the fault internal models.

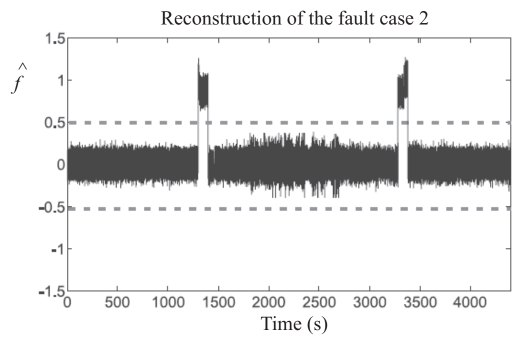

Fig. 4. Recursive reconstruction of the fault case 2.

A. Sensitivity Analysis and Comparisons

In order to highlight advantages and drawbacks of the proposed solutions, the features of the sustainable control scheme applied to the wind park benchmark were analysed with respect to the per cent Normalised Sum of Squared Error ($NSSE$) and considering different data sequences. Therefore, the achievable performances were verified by considering the benchmark simulator and the Monte-Carlo tool developed in the Matlab® environment. With these remarks, Table III summarises the nominal values of the considered benchmark model simulator parameters with reference to realistic uncertainty values. In fact, the Monte-Carlo analysis has been defined by describing the reliabilities (errors) of the benchmark model parameters as Gaussian stochastic variables, with zero-mean and standard deviations with values as reported in Table III.

TABLE III. WIND FARM PARAMETER SIMULATED ACCURACY FOR THE MONTE-CARLO ANALYSIS

Model Variable	Nominal Value & Accuracy (Error)
ρ	1.225 kg/m^3 $\pm$ 20%
J	7.794×10^6 kg/m^2 $\pm$ 30%
C_p	$C_{p\,0} \pm 50\%$
u	$u_0 \pm 20\%$
y	$y_0 \pm 20\%$

Table III also considers that the input-output signals u and y and the entries of the power coefficient C_p-map are affected by error terms described as per cent standard deviations of the corresponding nominal values u_0, y_0, and $C_{p\,0}$.

On the basis of the simulated parameter uncertainty, the verification of the control scheme performances relies on the average values of the $NSSE\%$ index that is experimentally evaluated with 500 Monte-Carlo runs. This $NSSE\%$ index is evaluated for different combinations of the model parameter as described in Table III.

Note that Table III summarises the parameter accuracy that are considered for analysing the robustness and the reliability features of the developed sustainable control scheme with reference to these parameter changes. In fact, the proposed disturbance decoupling methodology was considered for cancelling out the wind uncertainty and the wind wake effects, and not for taking into account the parameter changes of Table III.

Table IV reports the simulation results achieved via the developed Sustainable Control Method (SCM) that includes the baseline wind turbine farm controller with respect to the fault scenario. This approach considers the decoupling of both the wind and the wake effects. Moreover, Table IV compares the results from other two different methodologies, and in particular the Active FTC only with the Wind Decoupling (AFTCWD) as described in [13], and the Passive FTC approach relying on Fuzzy Logic (PFTCFL) proposed in [14].

TABLE IV. COMPARISON OF DIFFERENT FTC PERFORMANCES WITH RESPECT TO THE $NSSE\%$ INDEX AND THE FAULT CASES

Fault Case	FTC Method SMC	AFTCWD	PFTCFL
1	11.45%	15.33%	14.89%
2	12.67%	16.18%	15.46%
3	11.58%	16.45%	16.92%

In more detail, Table IV reports the $NSSE\%$ performance index values when the parameters of Table III vary according to the Monte-Carlo tool. The performances achieved with the methodology described in this work seem in general better than the ones obtained with the AFTCWD scheme presented in [7] with the simpler wind decoupling, and the fuzzy strategy (PFTCFL) presented in [12]. Therefore, it means that the scheme developed in this work presents better tracking errors when compared with the other two approaches. Further investigations will consider the analytic assessment of the stability properties for the developed sustainable control design, possibly applied also to real wind turbine installations.

V. CONCLUSION

This work considered the development of a sustainable control strategy applied to a wind farm benchmark. The proposed controller accommodation strategy employed the recursive reconstruction of the fault signals provided by nonlinear adaptive filters. They were obtained by means of differential algebraic tools that allowed to achieve important disturbance decoupling and robustness features. An identification scheme from input-output data was also exploited for deriving the mathematical description of the nonlinear disturbance distribution functions, which were necessary for the development of the nonlinear adaptive filters for fault reconstruction. These aspects represent key points when recursive applications are proposed for a viable and practical implementation of the suggested sustainable control strategy. A realistic wind park simulated model was used to assess the reliability and robustness features of the proposed methodologies, in the presence of model-reality mismatch effects. Finally, further studies will consider the analysis of the proposed methods when applied to real installations, as well as their mathematical stability and reliability characteristics.

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