INTERNATIONAL JOURNAL OF ROBUST AND NONLINEAR CONTROL Int. J. Robust. Nonlinear Control (2013) Published online in Wiley Online Library (wileyonlinelibrary.com). DOI: 10.1002/rnc.2993

# Active actuator fault-tolerant control of a wind turbine benchmark model

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## SUMMARY

This paper describes the design of an active fault-tolerant control scheme that is applied to the actuator of a wind turbine benchmark. The methodology is based on adaptive filters obtained via the nonlinear geometric approach, which allows to obtain interesting decoupling property with respect to uncertainty affecting the wind turbine system. The controller accommodation scheme exploits the on-line estimate of the actuator fault signal generated by the adaptive filters. The nonlinearity of the wind turbine model is described by the mapping to the power conversion ratio from tip-speed ratio and blade pitch angles. This mapping represents the aerodynamic uncertainty, and usually is not known in analytical form, but in general represented by approximated two-dimensional maps (i.e. look-up tables). Therefore, this paper suggests a scheme to estimate this power conversion ratio in an analytical form by means of a two-dimensional polynomial, which is subsequently used for designing the active fault-tolerant control scheme. The wind turbine power generating unit of a grid is considered as a benchmark to show the design procedure, including the aspects of the nonlinear disturbance decoupling method, as well as the viability of the proposed approach. Extensive simulations of the benchmark process are practical tools for assessing experimentally the features of the developed actuator fault-tolerant control scheme, in the presence of modelling and measurement errors. Comparisons with different fault-tolerant schemes serve to highlight the advantages and drawbacks of the proposed methodology. Copyright © 2013 John Wiley & Sons, Ltd.

Received 30 May 2012; Revised 20 January 2013; Accepted 25 February 2013

KEY WORDS: active fault-tolerant control; nonlinear geometric approach; actuator fault estimation; disturbance decoupling; wind turbine

# 1. INTRODUCTION

Feedback control systems for generating units of a power grid, such as wind turbines, strongly rely on actuators, sensors and components to ensure a proper interaction between the physical controlled system and control devices. Fault conditions lead to a drastic reduction or loss of stability and performance properties, which may cause damages to the entire system, with important economic losses and safety problems. Therefore, there is a growing demand for safety and fault tolerance in control systems for the wind turbine generating units of the power grid. It is necessary to design control systems that are capable of tolerating potential faults in order to improve the reliability and availability, while providing a desirable performance. These types of control systems are often known as fault-tolerant control (FTC) systems, as they possess the ability to accommodate component faults automatically.

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In general, FTC methods are classified into two types, that is, passive FTC scheme (PFTCS) and active FTC scheme (AFTCS) [1, 2]. In PFTCS, controllers are fixed and are designed to be robust against a class of presumed faults. This approach needs neither fault detection and diagnosis (FDD) schemes nor controller reconfiguration, but it has limited fault-tolerant capabilities. In contrast to PFTCS, AFTCS reacts to the system component failures actively by reconfiguring control actions so that the stability and acceptable performance of the entire system can be maintained. A successful AFTCS design relies heavily on real-time FDD schemes to provide the most up-to-date information about the true status of the system. Therefore, the main goal in an FTC system is to design a controller with a suitable structure to achieve stability and satisfactory performance, not only when all control components are functioning normally but also in case of faults in sensors, actuators, or other system components. Regarding the AFTCS design, good FDD may be required. In fact, for the system to react properly to a fault, timely and accurate diagnosis of the fault can be needed.

Over the last three decades, the growing demand for safety, reliability, maintainability and survivability in power processes has drawn significant research in fault diagnosis strategies, which can be used for FTC designs. Such efforts have led to the development of many fault diagnosis strategies (see, e.g. [3–7]).

With reference to the generating units of power grids, and in particular to wind turbines, they are complex nonlinear dynamic systems forced by gravity, and stochastic wind disturbance, which are affected by gravitational, centrifugal and gyroscopic loads. Their aerodynamics are nonlinear and unsteady, whereas their rotors are subject to complicated turbulent wind inflow fields driving fatigue loading. Therefore, wind turbine control represents complex and challenging tasks [8].

Today's wind turbines employ different control actuation and strategies to achieve the required goals and performances. Some turbines perform the control action through passive methods, such as in fixed-pitch and stall control machines [8,9]. On the other hand, for below rated wind speed, the generator speed is fixed. Rotors with adjustable pitch are often used in constant-speed machines to provide turbine power control better than the one achievable with blade stall [10]. To maximise the power output below the wind speed, the rotational speed of the turbine must vary with wind speed. Most commercial wind turbines allow the rotational speed of the machine to vary with wind speed (the variable-speed machine). This allows the turbine to maximise the power capture over a range of wind speeds. Note also that variable-speed turbines use power converters to separate the generator speed from the grid frequency.

An important control objective, which motivates the current study, consists of its fault-tolerance properties. The fault-tolerance capabilities of the controller must include monitoring for component faults, including sensor faults, operation beyond safe operating limits, grid failure or grid problems and other undesirable operating conditions. As an example, the FTC problem was recently analysed with reference to the same benchmark (e.g. in [11–15]).

In detail, this paper addresses the development of an AFTCS that integrates a robust actuator fault estimation scheme with the design of a controller accommodation system. In particular, the methodology for on-line actuator fault estimation relies on adaptive filters designed via the nonlinear geometric approach (NLGA). The controller accommodation exploiting a second control loop depends on the on-line estimate of the fault signal itself. One of the advantages of this strategy is that, for example, the structure of the controller already developed for the wind turbine benchmark and described in [16] is maintained. Many applications require not to change or modify the existing controllers, and in the authors' opinion, this point represents an important advantage of the proposed FTC scheme.

The suggested nonlinear fault estimation procedure is based on the NLGA scheme developed in [17], which does not provide any fault size estimation. Moreover, the direct application of the suggested methodology, or any other schemes relying on analytical disturbance decoupling, is almost impossible, because of the benchmark model structure. In fact, the wind turbine aerodynamic description depends on a mapping to the power conversion ratio from tip-speed ratio and blade pitch angles [18]. This mapping is not known in any analytical form but is represented by an approximated two-dimensional look-up table implemented in the Simulink® (The MathWorks, Inc. Natick, MA) environment. Thus, this paper suggests to estimate this power conversion ratio in an analytical form as a two-dimensional polynomial. This relation is subsequently used for designing the disturbance decoupled fault estimation module. The estimation of the power conversion map was proposed also in, for example, References [19–21].

Both the NLGA adaptive filter and the AFTCS strategy are analysed with respect to the benchmark of the wind turbine process, developed by kk-electronic (Denmark) and described, for example, in [18]. The simulation scheme for the complete AFTCS design has been implemented in the Simulink® environment and tested in the presence of actuator faults, disturbances, measurement noise and modelling errors.

Because the final AFTCS design relies on both the actuator fault signal estimation and the disturbance decoupling, it is necessary to evaluate the impact on the AFTCS system of modelling uncertainties, disturbance and measurement errors. The overall AFTCS scheme verification uses extensive Monte Carlo simulations for the analysis and the assessment of the design, the robustness, the stability and its final performance evaluation.

It is worth noting that with respect to works by the same authors (e.g. [14, 22, 23]), the main contribution of this paper consists of the application of the AFTCS scheme to the wind turbine generating unit of the power grid, in order to highlight the features of the nonlinear disturbance decoupling design, which are particularly difficult in the case of the considered benchmark. It can be also observed that, for the first time, the presented disturbance decoupling problem has been solved for the considered wind turbine benchmark. This represents another important contribution of the work.

The work is organised as follows. Section 2 provides the description of the nonlinear benchmark system, followed by the original controller and the actuator faults acting on the benchmark and considered in this work. Section 3 describes the implementation of the NLGA adaptive filter for fault estimation and the structure of the AFTCS strategy. The achieved results are reported in Section 4, where the capabilities of the developed AFTCS method are investigated in simulation. Comparisons with different FTC strategies are also reported. Finally, Section 5 concludes the paper by summarising the main achievements of the work and providing some suggestions for further research topics.

# 2. WIND TURBINE BENCHMARK DESCRIPTION

The three-bladed horizontal axis turbine considered in this paper works according to the principle that the wind is acting on the blades and thereby moving the rotor shaft. To up-scale the rotational speed to the needed one at the generator, a gear box is introduced. A more accurate description of the benchmark can be found, for example, in Odgaard *et al.* (2009) and Odgaard and Stoustrup (2009) [16,18]. In particular, Section 2.1 provides the basic details of the benchmark model, whereas Section 2.2 recalls the benchmark control strategy. The considered fault scenario is recalled in Section 2.3.

## 2.1. Model brief description

The rotational speed, and consequently the generated power, is regulated by means of the two control inputs: the converter torque  $\tau_{g}(t)$  and the pitch angle  $\beta(t)$  of the turbine blades. From the wind turbine system, a number of measurements can be acquired:  $\omega_{r}(t)$  is the rotor speed,  $\omega_{g}(t)$  is the generator speed, and  $\tau_{g}(t)$  is the torque of the generator controlled by the converter, which is provided with the torque reference,  $\tau_{r}(t)$ . The estimated aerodynamic torque is defined as  $\tau_{aero}(t)$ . This estimate clearly depends on the wind speed v(t), which unfortunately is very difficult to measure with good accuracy. In fact, the wind speed is not uniform across the rotor plane. When instantaneous wind fields are analysed near the rotor plane, the wind input may vary in space and time over the rotor plane itself. The deviations of the wind speed from the nominal wind speed across the rotor plane can be considered disturbances for control design. Moreover, the aerodynamic torque depends

on another uncertain term,  $C_p$ , representing the power coefficient, as shown by (1):

$$\tau_{\text{aero}}(t) = \frac{\rho A C_{\text{p}}(\beta(t), \lambda(t)) v^{3}(t)}{2 \omega_{r}(t)}$$
(1)

where  $\rho$  is the density of the air and A is the area covered by the turbine blades in its rotation, whereas  $\lambda(t)$  is the tip-speed ratio of the blade, defined as

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

with R the rotor radius.  $C_p$  represents the power coefficient, which the wind turbine benchmark implements by means of a two-dimensional map (look-up table) [18]. Equation (1) is used to estimate

 $\tau_{aero}(t)$  based on an assumed estimated v(t) and the signals  $\beta(t)$  and  $\omega_r(t)$ . Because of the uncertainty of the wind speed v(t), the term  $\tau_{aero}(t)$  is considered affected by an unknown error, which motivates the approaches described in Section 3. Moreover, the nonlinearity represented by (1) and (2) leads to the approach suggested in Section 3.

If a simple one-body model is used to represent the drive train [16], then the complete continuous-time description of the wind turbine model has the form of (3):

$$\begin{cases} \dot{x}(t) = f_{c}(x(t), u(t)) \\ y(t) = x(t) \end{cases}$$
(3)

where  $u(t) = [\tau_{ref}(t) \beta(t)]^T$  and  $y(t) = x(t) = [\omega_r(t) \tau_g(t)]^T$  are the control inputs and the monitored output measurements, respectively.  $f_c(\cdot)$  represents the continuous-time nonlinear function that will be used for acquiring the N sampled data u(k) and y(k), with k = 1, 2, ..., N, and exploited for the estimation of the analytical description of the two-dimensional nonlinear map  $C_p(\beta, \lambda)$  presented in Section 3.

Finally, the model parameters and the map  $C_p(\beta, \lambda)$  are chosen to represent a realistic turbine benchmark [18].

#### 2.2. Wind turbine benchmark control strategy

The controller for a wind turbine operates in principle in different zones. Because the focus of the benchmark model is on the normal operation, only two regions are considered, as described, for example, in Odgaard *et al.* (2009) [18]. In region 1, the turbine is controlled to obtain optimal power production, obtained if the blade pitch angle  $\beta$  is equal to 0 degrees and if the tip-speed ratio is constant at its optimal value  $K_{opt}$ . It is determined as the maximal value point in the power coefficient mapping of the wind turbine. This optimal value is achieved by setting the reference torque to the converter,  $\tau_g = \tau_r$ , that is,

$$\tau_{\rm r} = K_{\rm opt} \,\omega_{\rm r}^2 \tag{4}$$

In this way, the power reference is achieved, and the controller can be switched to control region 2. In this zone, the control objective consists of following the power reference,  $P_r$ , which is obtained by controlling  $\beta$ , such that the  $C_p$  is decreased. In a traditional industrial control scheme, the controller maintains the rotor speed  $\omega_r$  at the prescribed value by changing  $\beta$ .

For the control in region 2, the following strategy is exploited [18]:

$$\begin{cases} \beta(k) = \beta(k-1) + k_{\rm p} e(k) + (k_i T_{\rm s} - k_{\rm p}) e(k-1) \\ e(k) = \omega_{\rm g}(k) - \omega_{\rm nom} \end{cases}$$
(5)

with k = 1, 2, ..., N, and  $\omega_{nom}$  is the reference generator speed. The parameters for this PI speed controller are  $k_i = 0.5$  and  $k_p = 3$ , with sampling time  $T_s = 0.01$  s, as described in [16].

#### WIND TURBINE BENCHMARK ACTIVE FAULT TOLERANT CONTROL

Table I. List of the considered fault conditions.

Fault case	Description
Fault case 1	Offset on pitch actuator 1
Fault case 2	Offset on pitch actuator 2
Fault case 3	Offset on pitch actuator 3
Fault case 4	Changed dynamics of pitch actuator 2
Fault case 5	Changed dynamics of pitch actuator 3
Fault case 6	Offset in converter torque control

Regarding the control of the input  $\tau_g$ , a second PI regulator is implemented, as the one of (5):

$$\begin{cases} \tau_{\rm r}(k) = \tau_{\rm r}(k-1) + k_{\rm p} \, e(k) + \left(k_i \, T_{\rm s} - k_{\rm p}\right) \, e(k-1) \\ e(k) = P_{\rm g}(k) - P_{\rm r} \end{cases}$$
(6)

The parameters for this second PI *power controller* are  $k_i = 0.014$  and  $k_p = 447 \times 10^{-6}$ , according to [16].

Finally, the wind turbine benchmark controller considered in this study was implemented with a sample frequency of 100 Hz, that is,  $T_s = 0.01$  s.

#### 2.3. Benchmark fault conditions

The benchmark model presented in [18] and considered in this work implements a number of realistic malfunctions, which can cover different kinds of possible faults of wind turbines. However, only the fault modes that will be investigated in the present study are summarised in Table I.

With reference to Table I, fault cases 1, 2 and 3 affect the control signal  $\beta(t)$  regarding the blade pitch actuators through an offset. Fault cases 4 and 5 modify the dynamics of the blade pitch actuator systems and thus again the signal  $\beta(t)$ . On the other hand, fault case 6 concerns the generator/converter system and therefore the signal  $\tau_g(t)$  through an offset.

It is worth noting that, because the main focus of the paper concerns the application of the AFTCS to the benchmark model, this work will consider the example of actuator faults described as additive rectangular pulses with variable amplitude and length, as shown in Section 4.1. Moreover, the benchmark considers only the occurrence of single faults, even if the proposed procedure can be extended to multiple fault situations.

## 3. ACTIVE FAULT-TOLERANT CONTROL DESIGN

This section consists of three parts. Section 3.1 describes the estimation procedure of the nonlinear disturbance distribution function, which is required for the design of the NLGA adaptive filter for fault estimation, addressed in Section 3.2. The complete structure of the AFTCS strategy is summarised in Section 3.3.

#### 3.1. Disturbance distribution estimation

As described in Section 2, to achieve a robust FTC solution, the disturbance acting on the system has to be decoupled. As already remarked earlier, the main source of uncertainty is represented by the wind signal v(t). It is often assumed that the wind speed is uniform across the rotor plane. However, when instantaneous wind fields are analysed near the rotor plane, the wind input may vary in space and time over the rotor plane itself. The deviations of the wind speed from the nominal wind speed across the rotor plane can be considered disturbances for control design. Therefore, because the wind speed varies across the rotor plane, wind speed point measurements convey only a small part of the information about the wind inflow.

Section 2 shows that the disturbance signal v(t) affects the model through the power coefficient  $C_p$ . Initially, the  $C_p$ -surface values are most often not actually measured but computed, and if measured, only a few blades in an entire series are considered but without performing any measurement

on the actual turbine. Secondly, these values can be assumed to change slowly with time, although only a few per cent per year [8]. These changes are due to wear and tear of the blades, as well as debris build-up on them.

Solutions dealing with this problem were based on the estimation of the  $C_p$  values and the wind speed v(t), as described, for example, in [9, 11, 19]. It was assumed that their effect could be separated, because, for example, of the slow change in the  $C_p$  values, whereas the wind speed variations are relatively faster. Fault diagnosis schemes based on unknown input observers were also suggested, as shown, for example, in [16].

On the other hand, a different disturbance decoupling strategy based on the NLGA scheme is proposed here. The approach follows the same concept of the estimation of the disturbance distribution matrix proposed for the linear case in [3, 4]. In particular, as described in Section 3.2, this approach requires the analytical knowledge of the nonlinear disturbance distribution relation of the unknown input v(t).

In detail, the  $C_p(\beta, \lambda)$  map appearing in (1) is estimated by means of a two-dimensional polynomial representation, which is a function of the tip-speed ratio  $\lambda$  and the blade pitch angle  $\beta$ . This polynomial structure (coefficients and degrees) has to be determined to minimise the errors between the actual and simulated measurements, which are acquired from the wind turbine simulator described in Section 2.

The Parameter Estimation<sup>TM</sup> tool of the Simulink<sup>®</sup> environment has been used for performing the suggested estimation. In particular, the  $C_p$ -map entries have been estimated to minimise the model-reality mismatch as represented in Figure 1, that is, in order to minimise the difference between the monitored outputs y(t) from the wind turbine simulator and the outputs generated by the wind turbine model containing the  $C_p$  map described in Section 2.1.

Therefore, the  $C_p$  map entering into (1) is approximated by using a two–dimensional polynomial in the form of (7):

$$\hat{C}_{p}(\lambda,\beta) = \sum_{i=1}^{n_{\lambda}} w_{\lambda,i} \lambda^{i} + \sum_{i=1}^{n_{\beta}} w_{\beta,i} \beta^{i} + \sum_{i=1}^{n_{\lambda}} \sum_{j=1}^{n_{\beta}} w_{\lambda\beta,i+j-1} \lambda^{i} \beta^{j}$$
(7)

where the unknown coefficients  $w_{\lambda,i}$ ,  $w_{\beta,j}$ ,  $w_{\lambda\beta,k}$ , as well as the degrees  $n_{\lambda}$  and  $n_{\beta}$  were estimated as shown in the work by the same authors [21]. However, to obtain a model in the form of (8) required for the design of the NLGA filter, as described in Section 3.2, some coefficients  $w_{\lambda,i}$ ,  $w_{\beta,j}$ and  $w_{\lambda\beta,k}$  in (7) are forced to be equal to zero.

Finally, because the main point of the paper consists of the design of the fault estimation and the AFTCS scheme, more details regarding the  $C_p$ -surface approximation can be found in [21].



Figure 1. Logic diagram of the scheme used for the approximation of the  $C_p$  map.

## 3.2. Robust fault estimation strategy

The presented disturbance decoupling scheme suggested here belongs to the NLGA framework, where a coordinate transformation, highlighting a subsystem affected by the fault and decoupled by the disturbances, is the starting point to design an adaptive filter for fault estimation. This filter is able to both detect additive fault acting on a single actuator and estimate its magnitude. It is worth observing that, by means of this NLGA approach, the fault estimate is decoupled from the disturbance d.

The proposed approach is applied to a general nonlinear model in the form of (8):

$$\begin{cases} \dot{x} = n(x) + g(x)c + \ell(x)f + p_d(x)d\\ y = h(x) \end{cases}$$
(8)

where the state vector  $x \in \mathcal{X}$  (an open subset of  $\mathbb{R}^{\ell_n}$ ),  $c(t) \in \mathbb{R}^{\ell_c}$  is the control input vector,  $f(t) \in \mathbb{R}$  is the fault,  $d(t) \in \mathbb{R}^{\ell_d}$  is the disturbance vector and  $y \in \mathbb{R}^{\ell_m}$  is the output vector, whereas n(x),  $\ell(x)$ , the columns of g(x) and  $p_d(x)$  are smooth vector fields, with h(x) is a smooth map.

The design of the NLGA strategy for the design of the fault f estimator with the decoupling of the disturbance d is organised as follows:

- (1) computation of  $\Sigma_*^P$ , that is, the minimal conditioned invariant distribution containing *P* (where *P* is the distribution spanned by the columns of  $p_d(x)$ );
- (2) computation of  $\Omega^*$ , that is, the maximal observability codistribution contained in  $(\Sigma_*^P)^{\perp}$ ;
- (3) if  $\ell(x) \notin (\Omega^*)^{\perp}$ , fault detectability condition, then the fault is detectable, and a suitable change of coordinate can be determined.

 $\Sigma^{P}_{*}$  can be computed by means of the following recursive algorithm:

$$\begin{cases} S_0 = \bar{P} \\ S_{k+1} = \bar{S} + \sum_{i=0}^m \left[ g_i, \bar{S}_k \cap \ker\{dh\} \right] \end{cases}$$
(9)

where *m* is the number of inputs,  $\bar{S}$  represents the involutive closure of *S*,  $[g, \Delta]$  is the distribution spanned by all vector fields  $[g, \tau]$ , with  $\tau \in \Delta$ , and  $[g, \tau]$  the Lie bracket of  $g, \tau$ . It can be shown that if there exists a  $k \ge 0$  such that  $S_{k+1} = S_k$ , then the algorithm described by (9) terminates, and  $\sum_{*}^{P} = S_k$  [17].

Once  $\Sigma_{P}^{P}$  has been determined,  $\Omega^{*}$  can be obtained by exploiting the algorithm of (10):

$$\begin{cases} Q_0 = (\Sigma_*^P)^{\perp} \cap \operatorname{span} \{dh\} \\ Q_{k+1} = (\Sigma_*^P)^{\perp} \cap \sum_{i=0}^m \left[ L_{g_i} Q_k + \operatorname{span} \{dh\} \right] \end{cases}$$
(10)

where  $L_g \Gamma$  denotes the codistribution spanned by all covector fields  $L_g \omega$ , with  $\omega \in \Gamma$ , and  $L_g \omega$  is the derivative of  $\omega$  along g.

If there exists an integer  $k^*$  such that  $Q_{k^*} = Q_{k^*+1}$ ,  $Q_{k^*}$  is indicated as o.c.a.  $((\Sigma_*^P)^{\perp})$ , where the acronym o.c.a. stands for *observability codistribution algorithm*. It can be shown that  $Q_{k^*} = \text{o.c.a.}((\Sigma_*^P)^{\perp})$  represents the maximal observability codistribution contained in  $P^{\perp}$ , that is,  $\Omega^*$  [17]. When  $\ell(x) \notin (\Omega^*)^{\perp}$ , the disturbance d can be decoupled, and the actuator fault f is detectable.

As mentioned earlier, the considered NLGA to the fault diagnosis problem, described in [17], is based on a coordinate change in the state space and in the output space,  $\Phi(x)$  and  $\Psi(y)$ , respectively. They consist in a surjection  $\Psi_1$  and a function  $\Phi_1$  such that  $\Omega^* \cap \text{span}\{dh\} = \text{span}\{d(\Psi_1 \circ h)\}$  and  $\Omega^* = \operatorname{span} \{ d \Phi_1 \}$ , where

$$\begin{cases} \Phi(x) = \begin{pmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \bar{x}_3 \end{pmatrix} = \begin{pmatrix} \Phi_1(x) \\ H_2h(x) \\ \Phi_3(x) \end{pmatrix} \\ \Psi(y) = \begin{pmatrix} \bar{y}_1 \\ \bar{y}_2 \end{pmatrix} = \begin{pmatrix} \Psi_1(y) \\ H_2y \end{pmatrix}$$
(11)

are (local) diffeomorphisms, whereas  $H_2$  is a selection matrix; that is, its rows are a subset of the rows of the identity matrix. By using the new (local) state and output coordinates  $(\bar{x}, \bar{y})$ , the system of (8) is transformed as follows:

$$\begin{cases} \dot{\bar{x}}_{1} = n_{1}(\bar{x}_{1}, \bar{x}_{2}) + g_{1}(\bar{x}_{1}, \bar{x}_{2}) c + \ell_{1}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) f \\ \dot{\bar{x}}_{2} = n_{2}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) + g_{2}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) c + \\ + \ell_{2}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) f + p_{2}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) d \\ \dot{\bar{x}}_{3} = n_{3}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) + g_{3}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) c + \\ + \ell_{3}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) f + p_{3}(\bar{x}_{1}, \bar{x}_{2}, \bar{x}_{3}) d \\ \bar{y}_{1} = h(\bar{x}_{1}) \\ \bar{y}_{2} = \bar{x}_{2} \end{cases}$$

$$(12)$$

with  $\ell_1(\bar{x}_1, \bar{x}_2, \bar{x}_3)$  not identically zero. As described in [17], this procedure yields to the observable subsystem of (12), which, if it exists, is affected by the fault f and not affected by disturbance d.

This transformation can be applied to the system of (8), if and only if the fault detectability condition is satisfied. The system of (8) in the new reference frame is decomposed into three subsystems of (12), where the first one (the so-called  $\bar{x}_1$  subsystem) is always decoupled from the disturbance *d* and affected by the fault *f*, as described by (13):

$$\begin{cases} \dot{\bar{x}}_1 = n_1(\bar{x}_1, \bar{y}_2) + g_1(\bar{x}_1, \bar{y}_2) c + \ell_1(\bar{x}_1, \bar{y}_2, \bar{x}_3) f \\ \bar{y}_1 = h(\bar{x}_1) \end{cases}$$
(13)

where, as the state  $\bar{x}_2$  in (12) is assumed to be measured, the variable  $\bar{x}_2$  in (13) is considered as an independent input and denoted with  $\bar{y}_2$ .

With reference to (13), the NLGA adaptive filter can be designed if the condition in [17] and the following new constraints are satisfied:

- (1) The  $\bar{x}_1$  subsystem is independent from the  $\bar{x}_3$  state components.
- (2) The fault is a step function of the time; hence, the parameter f is a constant to be estimated.
- (3) There exists a proper scalar component  $\bar{x}_{1s}$  of the state vector  $\bar{x}_1$  such that the corresponding scalar component of the output vector is  $\bar{y}_{1s} = \bar{x}_{1s}$  and the following relation holds [24]:

$$\bar{y}_{1s}(t) = M_1(t) \cdot f + M_2(t) \tag{14}$$

where  $M_1(t) \neq 0, \forall t \ge 0$ . Moreover  $M_1(t)$  and  $M_2(t)$  can be computed for each time instant, because they are functions only of input and output measurements. The relation of (14) describes the general form of the system under diagnosis. Under these conditions, the design of the adaptive filter is achieved, with reference to the wind turbine model, in order to provide a fault estimation  $\hat{f}(t)$ , which asymptotically converges to the magnitude of the fault f. The proposed adaptive filter is based on the least-squares algorithm with forgetting factor [25], and it is described by the adaptation law of (15):

$$\begin{cases} \dot{P} = \beta P - \frac{1}{N^2} P^2 \check{M}_1^2, \quad P(0) = P_0 > 0 \\ \dot{\hat{f}} = P \epsilon \check{M}_1, \qquad \hat{f}(0) = 0 \end{cases}$$
(15)

with (16) representing the output estimation and the corresponding normalised estimation error

$$\begin{cases} \hat{\bar{y}}_{1s} = \check{M}_1 \, \hat{f} + \check{M}_2 + \lambda \, \check{\bar{y}}_{1s} \\ \epsilon &= \frac{1}{N^2} \left( \bar{y}_{1s} - \hat{\bar{y}}_{1s} \right) \end{cases}$$
(16)

where all the involved variables of the adaptive filter are scalar. In particular,  $\lambda > 0$  is a parameter related to the bandwidth of the filter,  $\beta \ge 0$  is the forgetting factor and  $N^2 = 1 + \check{M}_1^2$  is the normalisation factor of the least-squares algorithm. Moreover, the proposed adaptive filter adopts the signals  $\check{M}_1$ ,  $\check{M}_2$  and  $\check{y}_{1s}$ , which are obtained by means of a low-pass filtering of the signals  $M_1$ ,  $M_2$  and  $\bar{y}_{1s}$  as follows:

$$\begin{cases} \breve{M}_{1} = -\lambda \, \breve{M}_{1} + M_{1}, & \breve{M}_{1}(0) = 0 \\ \dot{\breve{M}}_{2} = -\lambda \, \breve{M}_{2} + M_{2}, & \breve{M}_{2}(0) = 0 \\ \dot{\breve{y}}_{1s} = -\lambda \, \breve{y}_{1s} + \bar{y}_{1s}, & \breve{y}_{1s}(0) = 0 \end{cases}$$
(17)

The considered adaptive filter is described by the systems of (15), (16) and (17).

It can be proved that the asymptotic relation between the normalised output estimation error  $\epsilon(t)$  and the fault estimation error  $f - \hat{f}(t)$  has the form of (18):

$$\lim_{t \to \infty} \epsilon(t) = \lim_{t \to \infty} \frac{M_1(t)}{N^2(t)} \left( f - \hat{f}(t) \right)$$
(18)

Appendix B shows that the adaptive filter described by (15), (16) and (17) provides an estimation  $\hat{f}(t)$  that asymptotically converges to the magnitude of the step fault f. This point is important because, as remarked in Section 3.3, the fault estimation error  $f - \hat{f}(t)$  has to be bounded and asymptotically converge to zero, in order to guarantee the stability of the complete AFTCS system.

## 3.3. Controller accommodation strategy

This section summarises the complete structure of the AFTCS strategy, which requires the information provided by the fault estimation module of Section 3.2.

It is worth noting that the NLGA adaptive filter scheme proposed in Section 3.2 is used here for fault estimation, even if in general could be exploited for fault detection and isolation. In particular, if the *fault isolation* task is required, a bank of NLGA adaptive filters in the form of (15), (16) and (17) can be exploited as residual generators, allowing to estimate the magnitude of different faults acting on the considered actuators. The decoupling of the effect of both the disturbance d and the fault f (important for fault isolation) from the nonlinear filters is provided by the selection of the proper state component from the  $\bar{x}_1$  subsystem. However, as the main point of the work is the design of an AFTCS with application to the considered benchmark, the problem of the fault isolation will not be addressed. Moreover, the simulated benchmark considers only the occurrence of single faults, as described in Section 2.3 [18].

To compute the simulation results described in Section 4, the AFTCS scheme has been completed by means of the benchmark controller described in Section 2.2. The logic scheme of the integrated adaptive fault-tolerant approach is shown in Figure 2.



Figure 2. Logic diagram of the integrated AFTCS strategy.

With reference to Figure 2, the term u represents the actuated inputs,  $u_c$  the controlled inputs and  $u_l$  the output signals from the benchmark controller (with a switching logic). On the other hand, y is the measured outputs and f the actuator fault, whereas  $\hat{f}$  is the corresponding estimated signal.

Therefore, the logic scheme depicted in Figure 2 shows that the AFTCS strategy is implemented by integrating the fault estimator module with the existing benchmark control system. From the controlled input and output signals, the fault estimation module provides the correct estimation  $\hat{f}$  of the f actuator fault, which is injected into the control loop, in order to compensate the effect of the actuator fault itself. After this correction, the benchmark controller provides the nominal tracking of the reference signal.

Regarding the scheme shown in Figure 2, as already remarked earlier, the proposed strategy has been applied for the accommodation of additive actuator fault. However, the proposed NLGA-based methodology could be extended to the case of sensor faults. In fact, sensor faults can be modelled as additive inputs in the measurements equation (i.e. the output equation) by means of the so-called sensor fault signature (often a column with only one element equal to '1', and the remaining entries are null). Moreover, sensor faults signatures could also be modelled as an input to the system, in the same way of actuators faults. This further task could be performed following the method (a further coordinate change) described in [26].

Regarding the stability analysis of the overall AFTCS, the simulation results shown in Section 4 highlight that the model variables remain bounded in a set, which assures control performance, even in the presence of faults. Moreover, the assumed fault conditions do not modify the system structure, thus guaranteeing the global stability.

However, a few more issues can be considered here. It should be clear that in steady-state conditions, when the fault effect is completely eliminated, the performances of the AFTCS are the same of those of fault-free situation. Therefore, the performance of the complete system is the same of that of the fault-free nominal controller. The stability properties of the AFTCS should be considered only in transient conditions, when the fault is not compensated. In fact, in these conditions, the fault estimation error of (18) corresponds to a signal injected into the feedback loop of Figure 2. It is possible to show that the fault estimation error is limited and convergent to zero; thus, the stability of the complete system is maintained. Moreover, the main design parameters for the NLGA adaptive filters are represented by  $\lambda > 0$ , related to the bandwidth of the filter, and  $\beta \ge 0$ , the forgetting factor. These issues are addressed in Appendix B.

### 4. SIMULATED RESULTS

This section describes the design and the simulations of the AFTCS applied to the wind turbine benchmark. In detail, Section 4.1 shows the results achieved from the estimation of the  $C_p$  map.

Once the disturbance decoupling has been achieved, the capabilities of the AFTCS method are reported. Moreover, Section 4.2 reports the performance evaluation of the developed AFTCS scheme with respect to modelling errors and measurement uncertainty. Section 4.3 compares the proposed AFTCS with respect to two different schemes, whereas Section 4.4 summarises further issues on the stability of the proposed AFTCS.

## 4.1. Fault-tolerant control design

The  $C_p$  map entering into the relation of (1) has been approximated by using the two-dimensional polynomial in the form of (19):

$$\hat{C}_{\rm p}(\lambda,\,\beta) = 0.010\,\lambda^2 + 0.0003\,\lambda^3\,\beta - 0.0013\,\lambda^3 \tag{19}$$

It is worth noting that the degrees and the coefficients of the two-dimensional polynomial described by the expression of (19) have been optimised by comparing the approximation capabilities achieved with different sets of data directly acquired from the benchmark model. Moreover, the uncertainty structure modelled by (19) must lead to a wind turbine model of (3) in the affine form of (8) as required by the NLGA methodology.

The approximation quality of the  $\hat{C}_p$  map, with respect to the nominal look-up table  $C_p$  implemented directly in the benchmark model, is not reported here, as more details can be found in [21].

It is worth noting that the suggested scheme provides an analytical description of the look-up table  $C_p$  that takes into account all uncertainties and not only the errors due to  $C_p$  entry changes. However, because the  $C_p$  map is used for the fault estimation filter design, any kind of uncertainty must be modelled. Moreover, it followed the same procedure already proposed in [4, Chap. 4.7] and [3, Chap. 5.3], but developed only for linear state–space models. Under this consideration, the uncertainty distribution description  $p_d(x)$  for the nonlinear model of (8) is identified using the input–output data from the wind turbine. The general assumption holding for this case is that the model–reality mismatch is varying more slowly than the disturbance signals, such as d. Moreover, the estimation approach does not exploit directly the wind v(t) and the c(t) control signals but the sequences that are filtered by the dynamic simulation process (Figure 1). Another important point is the fact that the  $C_p$ -map estimation aims at describing the *structure* of the uncertainty, which should not depend on the wind size uncertainty. Only the so-called 'directions' of the disturbance represent the important effect for disturbance decoupling, that is, the  $p_d(x)$  term, and not the 'amplitude' of the uncertainty, that is, the size of the disturbance v(t) (d).

To show the capabilities of the proposed AFTCS strategy, the benchmark has been tested with the reference signals required by the wind turbine benchmark, as described in [18].

The designed NLGA adaptive filters in the form of (15), (16) and (17) allow to estimate the magnitude of the different faults acting on the wind turbine benchmark, as shown in Section 2.

As an example, for the actuator fault case 1 summarised in Table I, the nonlinear filter for f, which is decoupled from the effect of the disturbance d representing both the wind speed v(t) and the  $C_p$ -map uncertainty, has the form of (15), and it is based on (A8) reported in Appendix A.

To compute the simulation results described in the succeeding paragraphs, the AFTCS scheme has been completed by means of the standard benchmark controller described in Section 2.2. The integrated AFTCS strategy corresponds to the logic scheme shown in Figure 2. The following results refer to the simulation of the actuator fault case 1 of Table I modelled as a step signal with a size from 0 to 1, commencing at t = 66 s. In particular, Figure 3 shows the estimate of the actuator fault f (solid line), when compared with the simulated actuator fault (dashed line).

As it will be shown also in Section 4.2, after a suitable choice of the parameters of the filter of (15), (16) and (17), the nonlinear filter provides an accurate estimate of the fault size, with minimal detection delay.

Figure 4 shows the generator speed  $\omega_g$  compared with its desired value  $\omega_{nom}$ . When fault case 1 is compensated by the AFTCS scheme, the tracking error is small.

As highlighted in Figure 4, during the time interval 100 < t < 200 s, only the nominal benchmark regulator without AFTCS is working. On the other hand, when the proposed AFTCS scheme

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Figure 3. Real-time estimate  $\hat{f}$  of the simulated actuator fault f (case 1).



Figure 4. Generator speed  $\omega_{g}$  w.r.t. its reference  $\omega_{nom}$ , with and without AFTCS with fault case 1.

is acting on the control loop, during the interval 0 < t < 100 s, the tracking error due to fault case 1 is lower.

The achieved simulation results summarised in Figures 3 and 4 show the effectiveness of the presented integrated FDD and FTC strategy, which is able to improve the control objective recovery and the reference tracking in the presence of actuator fault. However, the transient and the asymptotic stability of the controlled system, which in this paper are assessed in simulation, require further theoretical studies and investigations.

It is worth observing that the suggested NLGA adaptive filter provides not only the fault detection but also the fault estimate. Moreover, a fault modelled as an additive step function has been considered, because it represents the realistic fault condition in connection with the benchmark model. However, the fault estimation module can be easily generalised to estimate, for example, polynomial functions of time, or generic fault signals belonging to a given class of faults, if the NLGA adaptive filters contain the internal model of the fault itself. The generalisation to more general fault functions is beyond the scope of this paper, and it can be investigated in further works. On the other hand, a different fault scenario for the considered benchmark has been considered in the following. In particular, the case of *intermittent fault* is presented in the following.

Thus, the results refer to the simulation of a fault f modelled as a sequence of rectangular pulses with variable amplitude and length. Figure 5 shows the estimate of the intermittent actuator fault  $\hat{f}$ (dotted line), when compared with the simulated actuator fault f (dashed line). Also, in this case, after a suitable choice of the parameters of the NLGA adaptive filter, the fault estimation module provides a quite good reconstruction of the fault signal.

Under this condition, Figure 6 shows the reference  $\omega_g$  compared with its desired value  $\omega_{nom}$ . The estimate feedback used by the AFTCS is applied at t = 260 s without any delay.



Figure 5. Real-time estimate  $\hat{f}$  of the intermittent actuator fault f.



Figure 6. Reference  $\omega_{g}(t)$  of the benchmark for the case of an intermittent fault, with the control signal  $\beta(t)$ .

Also, for the situation of an intermittent fault, Figure 6 shows how the AFTCS scheme is able to compensate and accommodate it.

To summarise the advantages of the proposed AFTCS strategy, the performance of the wind turbine benchmark regulator recalled in Section 2.2 with and without the fault accommodation scheme has been evaluated in terms of per cent normalised sum of squared tracking error (NSSE) values defined in (20)

NSSE% = 100 
$$\sqrt{\frac{\sum_{k=1}^{N} (r(k) - y(k))^2}{\sum_{k=1}^{N} r^2(k)}}$$
 (20)

and considering different data sequences. The achieved results for the fault cases considered in Table I are reported in Table II.

It is clear that in full-load operation, the performance depends on the generator speed  $\omega_g$  with respect to the nominal one,  $\omega_{nom} = 162$  rad/s.

The simulation results of Table II show that in faulty conditions, the control performances are improved when the proposed AFTCS strategy is exploited.

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Fault condition	without AFTCS (%)	with AFTCS (%)
Case 1 Case 2 Case 3 Case 4 Case 5	23.02 22.98 22.84 20.68 19.54	11.23 12.23 10.85 13.27 12.97
Case 6	21.01	9.17

Table II. Benchmark controller with and without fault case 1 accommodation: NSSE% values.

Variable	Nominal value	Minimal error (%)	Maximal error (%)
$ \begin{array}{c} \rho \\ J \\ C_p \\ u \\ y \end{array} $	$\begin{array}{c} 1.225 \text{ kg/m}^3 \\ 7.794 \times 10^6 \text{ kg/m}^2 \\ C_{p0} \\ u_0 \\ y_0 \end{array}$	$egin{array}{c} \pm \ 0.1 \\ \pm \ 0.1 \\ \pm \ 0.1 \\ \pm \ 0.1 \\ \pm \ 0.1 \end{array}$	$\pm 20 \\ \pm 30 \\ \pm 50 \\ \pm 20 \\ \pm 20 $

#### 4.2. Performance evaluation

In this section, further experimental results have been reported regarding the robustness evaluation of the developed scheme with respect to modelling errors and measurement uncertainty. In particular, the simulation of different data sequences has been performed by exploiting the wind turbine benchmark simulator, followed by a MATLAB® (The MathWorks, Inc. Natick, MA) Monte Carlo analysis.

In particular, the nonlinear wind turbine simulator originally developed in the Simulink® environment [16] was modified by the authors to vary the statistical properties of the signals used for modelling process parameter uncertainty and measurement errors. Therefore, in this case, the Monte Carlo analysis represents a viable method for analysing some properties of the developed AFTCS, when applied to the considered benchmark. Under this assumption, Table III reports the nominal values of the considered wind turbine model parameters with respect to their simulated uncertainty.

The Monte Carlo analysis has been performed by modelling these variables as Gaussian stochastic processes, with zero mean and standard deviations corresponding to realistic minimal and maximal error values of Table III.

Moreover, it is assumed that the input–output signals u and y and the power coefficient map  $C_p$  entries were affected by errors, expressed as per cent standard deviations of the corresponding nominal values  $u_0$ ,  $y_0$  and  $C_{p0}$  also reported in Table III.

Therefore, for performance evaluation of the control schemes, the best, average and worst values of the NSSE % index were computed and experimentally evaluated with 500 Monte Carlo runs. The value of NSSE % is computed for several possible combinations of the parameter values reported in Table III.

It is worth noting that Table III describes the uncertain parameters that have been simulated to analyse the *robustness* of the proposed scheme with respect to *parameter variations*. In fact, the disturbance decoupling approach was proposed for removing the effect of the uncertain wind term v(t) and not for handling the parameter variations summarised in Table III.

Table IV summarises the results obtained by considering the proposed AFTCS integrating the original benchmark controller for the different fault cases.

In particular, Table IV summarises the values of the considered performance index according to the best, worst and average cases, with reference to the possible combinations of the parameters

#### WIND TURBINE BENCHMARK ACTIVE FAULT TOLERANT CONTROL

Fault case/test case	Best case	Average case	Worst case
	(%)	(%)	(%)
Fault case 1	8.04	11.23	15.05
Fault case 2	9.01	12.23	14.74
Fault case 3	7.96	10.35	13.83
Fault case 4	9.87	13.02	15.91
Fault case 5	7.73	9.97	12.15
Fault case 6	8.98	11.17	13.53

Table IV. Monte Carlo analysis for the proposed AFTCS: NSSE% values with different fault cases.

described in Table III. Thus, Table IV shows that the proposed AFTCS scheme allows to maintain good control performances even in the presence of fault case 1, varying errors and uncertainty effects.

Finally, the results demonstrate also that Monte Carlo simulation is an effective tool for experimentally testing the design robustness of the proposed methods with respect to modelling uncertainty.

## 4.3. Comparative simulations

This section provides comparative results with respect to different AFTCS schemes. In detail, the properties of the methods suggested in this paper have been analysed with respect to alternative FDD approaches, in particular relying on the sliding mode observer (SMO) and the NN estimator.

Regarding the SMO used for the estimation of the fault acting on the system, it represents the alternative fault estimator module forming a part of the AFTCS strategy. Edwards and his coworkers [27,28] proposed an SMO structure and design procedures that obviates the use of symbolic manipulation, thus offering an explicit design algorithm. The SMO concept involves the design of observer gain matrices to ensure that the sliding surface is reached and maintained. During sliding, the error between the system and the observer states remains close to zero, ensuring robust estimation under conditions of matched uncertainty. For this application, the SMO has two functions: (i) robust state estimation and (ii) using the state estimation, the actuator fault is estimated using the concept of equivalent output injection [28]. The fault acting on the nominal system can be described via a linearised state-space model for the wind turbine benchmark of (3). It is assumed that the system states are unknown, and only the signals u(t) and y(t) are available. The SMO generates a state estimate and output estimate such that a sliding mode is attained in which the output error is forced to zero in finite time. The SMO structure of [28] can be obtained quite easily by choosing suitable gain matrices and the discontinuous switched component that is necessary to induce the sliding motion. The SMO design has been obtained by exploiting the MATLAB® routines described in [29, 30].

In particular, the linearised state–space model used for the design of the SMO for fault estimation has the form of (21):

$$\begin{cases} \dot{x}_{e}(t) = A_{e} x_{e}(t) + B_{e} u_{e}(t) + R_{e} f(t) \\ y_{e}(t) = C_{e} x_{e}(t) \end{cases}$$
(21)

where  $u_e(t) = [\tau_{aero}, \tau_r]^T$ ,  $y_e(t) = x_e(t) = [\omega_r, \tau_g]^T$ . The matrices are defined as follows [16, 18]:

$$A_e = \begin{bmatrix} 0 & -1/J \\ 0 & -p_{\text{gen}} \end{bmatrix}, B_e = \begin{bmatrix} 1/J \\ p_{\text{gen}} \end{bmatrix}, R_e = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, C_e = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
(22)

The second fault estimation scheme exploited for comparison purposes has been developed by using the strategy relying on the NN tool [31]. The NN exploited as fault estimator consists of a 4-inputs 1-output time-delayed three-layer multilayer perceptron (MLP) NN with three neurons in

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Fault case	Test case	SMO (%)	NN (%)
Case 1	Best case	17.05	18.57
	Average case	18.02	19.94
	Worst case	19.04	20.44
Case 6	Best case	18.23	19.33
	Average case	19.55	20.79
	Worst case	20.96	21.84

Table V.	Monte Carlo analysis for the SMO and NN
	schemes for fault cases 1 and 6.

the input layer, five neurons in the hidden layer and 1 neuron in the output layer. The NN has been trained to provide the estimate of the fault signal on the basis of the training patterns and target sequences [31].

To provide a brief but clear insight into the aforementioned techniques, the comparison has been performed in the same previous working conditions and based on the NSSE% index of (20). It is worth recalling the main features of the alternative FDD schemes implemented via the SMO or the NN estimator. In particular, the SMO strategy is able to decouple the model reality uncertainty via the sliding motion, whereas the NN estimator was designed to *passively tolerate* disturbance and modelling errors.

From Table V, it can be seen how the different schemes are able to tolerate uncertainty and errors, trying to achieve different FTC properties. For the sake of brevity, fault cases 1 and 6 have been considered.

The comparison of Table V highlights that the scheme using the SMO allows to achieve better performances in terms of tracking error. However, the SMO can increase the computational time and the actuator signal activity with respect to the other solution.

Few further comments can be drawn here. When the modelling of the dynamic system can be perfectly obtained, in general, model-based strategies are preferred. On the other hand, when modelling errors and uncertainty are present, alternative estimation schemes relying on adaptation mechanisms, or PFTCS, have shown interesting robustness properties in the presence of unmodelled disturbance, modelling mismatch and measurement errors. With reference to the NN estimator, in the case of a system with modelling errors, the off-line learning can lead to fair results. Other explicit disturbance decoupling techniques can take advantage of their robustness capabilities, but with quite complicated and not straightforward design procedures. The NN-based scheme relies on the learning accumulated from off-line simulations, but the training stage can be computationally heavy.

#### 4.4. Stability analysis

The stability properties of the proposed AFTCS have been discussed at the end of Section 3.3. They have been analysed in Appendix B and verified here by means of a Monte Carlo campaign based on the wind turbine benchmark nonlinear simulator. Initial conditions have been changed randomly, and disturbance affecting the system has been simulated during the transient related to the stability analysis. All simulations have been performed by considering noise signals modelled as band-limited white processes, according to the standard deviations reported in Table III.

Figure 7 depicts for a single Monte Carlo run the main wind turbine model variables in full load working conditions.

Figure 7 depicts the wind signal v(t), the generator speed  $\omega_g$  and power  $P_g$ , and the control input  $\beta$ . Also, in this situation, the main wind turbine variables remain bounded around the reference values, thus assessing the overall system stability in simulation, even in the presence of modelling errors and noise signals.

Finally, it is worth noting that the AFTCS design and the analysis procedures shown in Sections 4.2, 4.3 and 4.4 were implemented using the MATLAB<sup>®</sup> and Simulink<sup>®</sup> software tools,



Figure 7. Signals of the benchmark working at full load operation.

in order to automate the overall simulation process. These feasibility and reliability studies are of paramount importance for real application of control strategies once implemented to future wind turbine installations.

## 5. CONCLUSION

This paper described the development of an active FTC scheme, which integrates a robust fault estimation method with the design of a controller reconfiguration system. The methodology was based on a disturbance decoupled adaptive filter, designed via the NLGA. The fault-tolerant strategy has been applied to a benchmark model, namely a wind turbine process provided by kk-electronic (Denmark), which simulated faults, measurement noise and modelling errors.

A data-driven approach was suggested to estimate the wind turbine power coefficient, from the input–output measurements that can be acquired from the wind turbine system. The simulation results seem to show that the proposed estimation scheme allows to obtain a sufficiently accurate analytical approximation of the power coefficient relationship.

With reference to the achieved performances of the FTC scheme, the advantages and drawbacks of the complete design scheme applied to the nonlinear wind turbine were discussed. The proposed fault-tolerant scheme allows to maintain the existing benchmark controller, because a further loop is added to the original scheme, thus providing in the faulty case, the feedback of the fault estimate.

The stability and robustness of the developed FTC scheme, followed by the evaluation of the achievable performance, were analysed. The results showed that the proposed strategy allowed to tackle disturbances and uncertainty. Comparisons with alternative FTC strategies based on an SMO and a neural estimator were also provided.

Finally, further investigations will be carried out to evaluate the effectiveness of the suggested approach when applied to real wind turbine processes, as well as its analytical stability properties, in the presence of different fault conditions.

### APPENDIX A: NLGA ADAPTIVE FILTER COMPUTATION EXAMPLE

This appendix provides some mathematical details regarding the example of the design of the nonlinear adaptive filter for fault case 1. However, the Symbolic Toolbox<sup>™</sup> of MATLAB® has been exploited to obtain several results concerning the computation of the vector subspaces required by the NLGA scheme.

With reference to the input–affine model of (8),  $x = [x_1 x_2]^T = [\omega_r \tau_g]^T$ ,  $c = [\tau_{ref} \beta]^T$  and with

$$n(x) = \begin{bmatrix} -\frac{\rho A}{2J} \ 0.0010 \ R^3 \ x_1^2 - \frac{1}{J} \ x_2 \\ -p_{\text{gen}} \ x_2 \end{bmatrix}$$
(A1)

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$$g(x) = \begin{bmatrix} 0 & \frac{\rho A}{2J} \ 0.0003 \ R^3 \ x_2^2 \\ p_{\text{gen}} & 0 \end{bmatrix}$$
(A2)

and:

$$\ell(x) = \begin{bmatrix} 0 & \frac{\rho A}{2J} & 0.0003 & R^3 & x_1^2 \\ 0 & 0.0001 \end{bmatrix}$$
(A3)

Moreover,  $p_d(x)$  is defined as

$$p_d(x) = \begin{bmatrix} \frac{\rho A}{2J} \ 0.0010 \ R^2 \ x_1 \\ 0.0002 \end{bmatrix}$$
(A4)

In the case of the model of (3), with reference to (8), and recalling (A4), (A3) and (A2), the following is obtained:

$$S_0 = \bar{P} = \operatorname{cl}\left(p_d(x)\right) \equiv p_d(x) \tag{A5}$$

By recalling that ker $\{dh\} = \emptyset$ , it follows that  $\Sigma_*^P = \overline{P}$  as  $\overline{S}_0 \cap \text{ker}\{dh\} = \emptyset$ . Thus, algorithm 9 stops with  $\tilde{S}_1 = S_0 = \Sigma_*^{\dot{P}}$ .

On the other hand, to solve (10), it is necessary to compute the expression  $(\Sigma_*^P)^{\perp} = (\bar{P})^{\perp}$ . However, it is worth noting that, for the case under investigation, the determination of the codistribution  $(\Sigma_*^P)^{\perp} = (\bar{P})^{\perp}$  is enhanced because of the sparse structure of (A5). Moreover, by means of (10), the computation of  $(\Sigma^P_*)^{\perp} = (\bar{P})^{\perp}$  leads to a codistribution  $\Omega^* = \text{o.c.a.}((\Sigma^P_*)^{\perp})$  spanned by exact differentials. Finally, any codistribution  $\Omega$  that is a conditioned invariant contained in  $\bar{P}^{\perp}$ spanned by exact differentials, with  $\Omega = \text{o.c.a.}((\Omega) \text{ and } \ell(x) \notin (\Omega)^{\perp}$ , can be used to define the coordinate change (11). Therefore, the computation of the maximal observability codistribution is not required.

By observing the structure of  $(\bar{P})^{\perp}$  and noting that span $\{dh\} = I_2$ , from (10), it follows that  $\Omega^* = (\Sigma^P_*)^{\perp} = (\bar{P})^{\perp}$ , and  $(\Omega^*)^{\perp} = \Sigma^P_* = \bar{P}$ . The fault in (3) is detectable if  $\ell(x) \notin (\Omega^*)^{\perp} =$  $\Sigma_*^P = \overline{P}$ . This condition is fulfilled because of the expression of  $\ell(x)$  in (A3).

As dim  $\{\Omega^*\} = 1$ , and dim  $\{\Omega^* \cap \text{span}\{dh\}\} = 1$ , it follows that  $\Phi_1(y) : \mathbb{R}^2 \to \mathbb{R}^1$ . Moreover, as  $\Omega^* \cap \text{span}\{dh\} = \text{span}\{d(\Psi_1 \circ h)\}, H_2 y : \mathbb{R}^2 \to \mathbb{R}^1$ . Thus, as  $h(x) = I_2 x$ , the surjection  $\Psi(y(x))$  is given by

$$\Psi(y(x)) = \begin{pmatrix} \Psi_1(x) \\ H_2 x \end{pmatrix}$$
(A6)

where  $H_2 = [0 \ 1]$ .

Note that, because  $dh = I_2$ , the diffeomorphism  $\Phi_1(x)$  such that  $\Omega^* = \text{span} \{ d(\Phi_1) \}$  is given by

$$\Phi_1(x) = \Psi_1(y(x)) = \Psi_1(x)$$
(A7)

Hence, the  $\bar{x}_1$ -subsystem state variable can be computed.

It is worth observing that only  $\bar{x}_{11}$  is affected by the fault and that its differentials span an observability codistribution  $\Omega$  contained in  $P^{\perp}$  with  $\Omega = \text{o.c.a.}(\Omega)$ . Hence, as previously remarked, in order to estimate the fault, it is possible to use the scalar subsystem defined by the coordinate  $\bar{x}_{11}$ , from which, by assuming that the whole state is measured, the NLGA adaptive filter is computed.

With reference to (13), the NLGA adaptive filter can be designed if the condition in [17] and the conditions stated in Section 3.2 are satisfied.

To decouple the effect of the disturbance d = v(t) from the fault estimator, it is necessary to select from the  $\bar{x}_1$  subsystem the suitable state component. Hence, it is possible to specify the specific expression of the fault dynamics (14). Finally, the design of the NLGA adaptive filter for the reconstruction of the fault f affecting the actuator  $\beta(t)$  is based on the expression of (A8):

$$\bar{y}_{1s} = M_1 \cdot f + M_2 \tag{A8}$$

In the same way, the design of the NLGA adaptive filter for the reconstruction of the actuator fault  $\tau_g$  is based on a different selection of the vector of (A3).

## APPENDIX B: AFTCS STABILITY ISSUE

This appendix shows that the fault estimation error is limited and asymptotically converges to zero. In fact, if the controlled system is stable in fault-free conditions, also the AFTCS is stable in faulty conditions.

The auxiliary model in the form of (B1) is defined as follows:

$$\begin{cases} \dot{y}'_1 = -\lambda \, y'_1 + \dot{\bar{y}}_{1s}, & y'_1(0) = 0\\ \dot{y}'_2 = -\lambda \, y'_2 + \lambda \, \bar{y}_{1s}, & y'_2(0) = 0\\ y' = y'_1 + y'_2 \end{cases}$$
(B1)

It follows that

$$y'(t) = \int_{0}^{t} e^{-\lambda(t-\tau)} \dot{\bar{y}}_{1s}(\tau) d\tau + \int_{0}^{t} e^{-\lambda(t-\tau)} \lambda \, \bar{y}_{1s}(\tau) d\tau =$$
  
=  $\int_{0}^{t} e^{-\lambda(t-\tau)} (M_{1}(\tau) f + M_{2}(\tau)) d\tau + \lambda \, \check{\bar{y}}_{1s} =$   
=  $\check{M}_{1}(t) f + \check{M}_{2}(t) + \lambda \, \check{\bar{y}}_{1s}(t)$  (B2)

The function of (B3)

$$V = \frac{1}{2} \left( y' - \bar{y}_{1s} \right)^2$$
(B3)

is positive definite and radially unbounded. Moreover, its first time derivative is

$$\dot{V} = (y' - \bar{y}_{1s})(\dot{y}'_1 + \dot{y}'_2 - \dot{\bar{y}}_{1s}) = = (y' - \bar{y}_{1s})(-\lambda y'_1 - \lambda y'_2 + \lambda \bar{y}_{1s}) = -\lambda (y' - \bar{y}_{1s})^2$$
(B4)

Because  $\dot{V}$  is negative definite  $\forall y' \neq \bar{y}_{1s}$ , V is a Lyapunov's function so that y'(t) globally asymptotically tends to the output function  $\bar{y}_{1s}(t)$ . From (B2), (B5) holds:

$$\lim_{t \to \infty} \bar{y}_{1s}(t) = \check{M}_1(t) f + \check{M}_2(t) + \lambda \, \bar{y}_{1s}(t)$$
(B5)

From Equations (16) and (B5), the asymptotic behaviour of the normalised output estimation error  $\epsilon(t)$  has the form

$$\lim_{t \to \infty} \epsilon(t) = \lim_{t \to \infty} \frac{1}{N^2} \left( \bar{y}_{1s} - \check{M}_1 \hat{f} - \check{M}_2 - \lambda \, \check{\bar{y}}_{1s} \right) =$$
$$= \lim_{t \to \infty} \frac{1}{N^2(t)} \left( \check{M}_1(t) f - \check{M}_1(t) \hat{f}(t) \right)$$
(B6)

Moreover, the function of (B7)

$$W = \frac{1}{2} \left( \hat{f} - f \right)^2 \tag{B7}$$

is trivially positive definite and radially unbounded. Moreover, its first time derivative is

$$\dot{W} = \left(\hat{f} - f\right) \left(P \ \epsilon \ \breve{M}_1 - 0\right) \tag{B8}$$

It is worth noting that the smoothness property of the involved functions allows to apply the asymptotic approximation of (18) to the expression of (B8). In fact,  $\exists t_* > 0$  so that the sign of  $\dot{W}(t)$ ,  $\forall t \ge t_*$  is not affected by the asymptotic approximation of (18). Hence, it follows that

$$\dot{W}(t) = -P(t)\frac{\dot{M}_{1}^{2}(t)}{N^{2}(t)}\left(\hat{f}(t) - f\right)^{2}, \qquad \forall t \ge t_{\star}$$
(B9)

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Int. J. Robust. Nonlinear Control (2013) DOI: 10.1002/rnc which is negative definite  $\forall \hat{f} \neq f$ . In fact,  $\breve{M}_1(t)$  is a low-pass filtering of the signal  $M_1(t)$ , which is a smooth function and always not null by the assumptions of Section 3.2. Moreover,  $N^2(t) = 1 + \breve{M}_1^2(t) > 0$  and

$$P(t) = \left(e^{-\beta t} P_0^{-1} + \int_0^t e^{-\beta (t-\tau)} \frac{\breve{M}_1^2(\tau)}{N^2(\tau)} \mathrm{d}\tau\right)^{-1} > 0$$
(B10)

Therefore, W is a Lyapunov's function and  $\hat{f}(t)$  globally asymptotically tends to f.

This proves that the fault estimation error is bounded and asymptotically converges to zero, thus guaranteeing the stability of the AFTCS system.

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