

Model-Based Fault-Tolerant Pitch Control of an Offshore Wind Turbine

Hamed Badihi*, Youmin Zhang*, Subhash Rakheja*, and Pragasen Pillay**

* Dept. of Mechanical, Industrial and Aerospace Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada

** Dept. of Electrical and Computer Engineering, Concordia University, Montreal, Quebec H3G 1M8, Canada

Emails: {Hamed.Badihi; Youmin.Zhang; Subhash.Rakheja; Pragasen.Pillay}@concordia.ca

Abstract: Given the importance of reliability and availability issue in wind turbines, the current paper presents the design and development of a novel active fault-tolerant control scheme for an offshore wind turbine. The proposed scheme tolerates the effects of any possible fault that may happen in pitch actuators of wind turbine blades. A model-based fault detection and diagnosis system provides fault information that are accurate enough for compensation of fault effects in the pitch control loop. The effectiveness of the proposed scheme is finally evaluated through simulations on an advanced offshore wind turbine benchmark model in the presence of wind turbulences, measurement noises, and realistic fault scenarios.

Keywords: Fault detection and diagnosis (FDD), Fault-tolerant control (FTC), Wind turbine, Pitch control

1. INTRODUCTION

Today, wind turbines have become a key source of renewable power generation in the world. To guarantee power generation and reduce operation and maintenance costs, it is of great importance to improve the reliability of wind turbines by designing control systems which are able to tolerate potential faults in the wind turbines. This class of control systems is known as fault-tolerant control (FTC) systems (Zhang and Jiang, 2008). In general, FTC systems are divided into two categories, namely, passive (PFTC) and active (AFTC) systems (Zhang and Jiang, 2008). PFTC systems are fixed control systems independent of any need to fault detection and diagnosis (FDD) information or controller reconfiguration algorithms. These systems are designed to be robust against a specified class of faults or some levels of uncertainty in an overall system under control. In contrast to the PFTC systems, AFTC systems react to faults (in sensors, actuators, and system itself) by reconfiguring the controller based on the real-time information about the true state of the overall system provided by an FDD system. Generally speaking, the control reconfiguration mechanism and the FDD information used in AFTC systems facilitate the detection and accommodation of severe faults that are not possible to be handled by the PFTC systems.

Given the high importance of blade pitch control in wind turbines and the high frequency of pitch actuator faults in real operations, this paper considers the application of FTC in wind turbine pitch control.

Numerous research works are reported in the literature on the general problem of wind turbine pitch control under collective pitch control (CPC) techniques (i.e., controlling all pitch angles collectively). For example, interested readers are referred to the works using proportional-integral-derivative (PID) control (Hand, 1999; Gao and Gao, 2016), linear-quadratic-gaussian (LQG) control (Novak et al., 1995), gain

scheduling (Jonkman et al., 2009; Bianchi et al., 2005), and fuzzy logic control (Mohamed et al., 2001). In contrast, the specific problem of FTC application in wind turbine pitch control has received relatively little attention in the literature. Authors in (Sloth et al., 2011) present different FTC schemes based on multiple linear parameter-varying (LPV) control for a wind turbine with a single actuator fault. A projection-based FTC approach independent of any explicit fault diagnosis information is presented in (Jain et al., 2013). Another work in (Lan et al., 2016) presents an FTC scheme designed using the state and fault estimates obtained from an adaptive step-by-step sliding mode observer (SMO).

This paper, in particular, proposes an AFTC scheme that is based on a data-driven modelling approach by which higher nonlinearity of modern wind turbines can be addressed. The nonlinearity that is turning to be a more and more important issue in the larger and more flexible off-shore rather than on-shore wind turbines. The proposed AFTC scheme tolerates the effects of any possible fault that may happen in pitch actuators of wind turbine blades. In more details, it employs an appropriate signal correction algorithm supported by a model-based FDD system designed to estimate the fault information for compensation of fault effects in the pitch control loop. Therefore, the AFTC scheme provides a nominal baseline control system performance in fault-free operation, as well as compensates fault effects to maintain safe performance once faults occur. Moreover, the used FDD system itself can act as a stand-alone condition monitoring system to provide real-time information about true state of the overall system useful for subsequent maintenance schedules when really necessary.

The effectiveness of the proposed AFTC scheme is finally evaluated through simulations on an advanced offshore wind turbine benchmark model in the presence of wind turbulences, measurement noises, and realistic fault scenarios.

The remainder of the paper is organized as follows: In Section 2, the wind turbine plant model and its baseline control system are introduced briefly. A short description about the considered fault scenario is presented in Section 3. System modelling and FDD design is discussed in Section 4. The AFTC scheme is presented in Section 5. Section 6 presents and discusses the simulation results. Finally, conclusions are drawn in Section 7.

2. OVERVIEW OF THE BENCHMARK MODEL

This paper considers an advanced simulation benchmark model representing a three-bladed horizontal axis wind turbine with full generator and converter. The benchmark is developed based on the U.S. National Renewable Energy Laboratory’s “FAST 5 MW Wind Turbine” model (Odgaard and Johnson, 2013). It contains a collective pitch controller (CPC), a torque controller, and a yaw controller, used to regulate blade-pitch angles, generator torque, and nacelle yaw angle, respectively.

In *below rated* wind speeds (i.e., partial load region), the torque controller is designed by varying the generator torque to maximize power capture as shown in (1). The reference generator torque is defined as:

$$\tau_{ref}(t) = K_{opt} \omega_r^2(t) \quad (1)$$

in which ω_r is the rotor angular speed (i.e., measured generator speed divided by gearbox ratio), and the gain K_{opt} is an optimally selected constant with more details in (Odgaard and Johnson, 2013).

In *above rated* wind speeds (i.e., full load region), the baseline CPC system employs the following proportional-integral (PI) control law in (2). The reference blade pitch angle is defined as:

$$\beta_{ref}(t) = K_p \omega_{g,e}(t) + K_i \int_0^t \omega_{g,e}(\tau) d\tau \quad (2)$$

where the generator speed error $\omega_{g,e}$ is calculated as $\omega_{g,e} = \omega_{g,d} - \omega_{g,m}$ in which $\omega_{g,m}$ is the measured generator speed and $\omega_{g,d}$ is the desired generator speed so that the turbine operates at its rated power of 5 MW. Also, the torque controller can be set to be active in above rated wind speeds so as to produce constant power output. In this case, the reference generator torque τ_{ref} is not calculated by (1), but using (3) in which $P_{g,0}$ is the turbine rated power, ω_g is the generator speed, and η_g is the generator efficiency.

$$\tau_{ref}(t) = \frac{P_{g,0}}{\eta_g \omega_g(t)} \quad (3)$$

The benchmark model also includes a yaw controller that is a simple On-and-Off controller developed to orient the turbine’s nacelle as the wind direction changes. For a more detailed description of the benchmark and its control system please see (Odgaard and Johnson, 2013).

3. REPRESENTATION OF PITCH ACTUATOR FAULTS

In normal/nominal operation, pitch actuators would operate exactly as directed by the controller. In other words, the

actuators are ideally 100% effective in executing the control commands. However, in real operations, the pitch actuators may experience faults resulting from dynamical changes due to pressure drop in their hydraulic lines (Esbensen and Sloth, 2009, Zhang and Jiang, 2002). This leads to reduction in effectiveness of actuators (<100% effective) which makes it impossible for the pitch actuators to fulfill the control commands completely. Consequently, serious problems arise with successful tracking of the rated speed, and thus wind turbine’s stability and performance will be degraded by excessive structural loading and fluctuations on the generator speed and power output. Fig. 1 illustrates mathematical modeling of actuator faults based on reduction in control effectiveness.

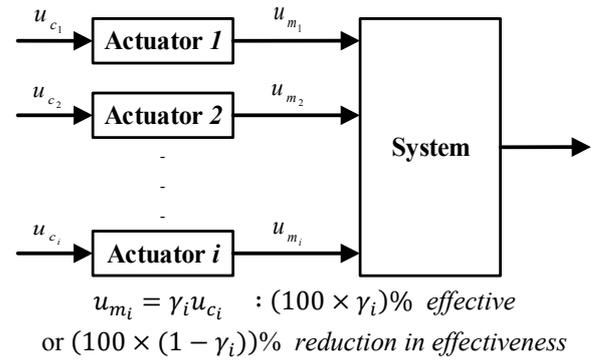


Fig. 1. Modeling of actuator faults using control effectiveness factors $\gamma_i \in (0,1]$. Here, u_{c_i} is the i th control signal and u_{m_i} is the i th manipulated variable (Note: $\gamma_i = 1$ means the actuator is 100% effective).

Unit step responses of a pitch actuator with different values of control effectiveness factors are shown in Fig. 2. As can be seen in the figure, the less the control effectiveness factor is, the higher the severity of the actuator fault is. This paper considers a fault scenario based on pressure drop (loss of effectiveness) in pitch actuators with more details in Section 6. In the presence of these faults, a conventional pitch control system cannot maintain the desired pitch action. Therefore, an appropriate FTC strategy needs to be considered to compensate the actuator faults so that the safe wind turbine performance can be maintained under both fault-free and faulty conditions.

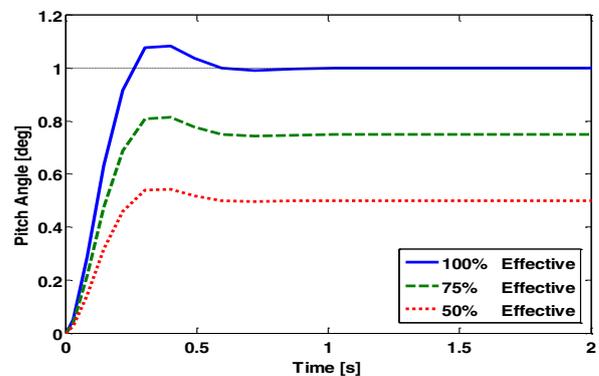


Fig. 2. Unit step responses of a pitch actuator under different control effectiveness factors ($\gamma_i = 1.0, 0.75$ and 0.50)

4. SYSTEM MODELING AND FDD DESIGN

A variable-speed wind turbine is relatively complex aero-electromechanical system immersed in a fully-stochastic wind field. It is often difficult, or even impossible to identify a single nonlinear model for such a system over its entire operation envelope. One effective way to address this difficulty is to use multiple-model networks that handle uncertain and time-varying conditions of the system using different models for different operating points. This paper suggests a data-driven fuzzy modeling and identification (FMI) method based on Takagi-Sugeno (TS) modeling that generates multiple models as a network of fuzzy *if-then* rules (Takagi and Sugeno, 1985; Babuska, 1998). As it is already shown in other works (Badihi et al., 2014; Badihi et al., 2015; Badihi et al., 2013b; Badihi et al., 2013a; Simani, 2012; Simani et al., 2012; Kamal et al., 2014; Kamal et al., 2012), the dynamic models designed using this method are accurate enough for FDD and FTC design purposes in wind turbines. In the following subsections, dynamic models of the wind turbine system are designed, and then they are used as nominal models in the design of a model-based FDD system against actuator faults.

4.1 Dynamic Model Design using FMI Method

Consider a multi-input single-output (MISO) nonlinear dynamic system including m inputs $\mathbf{u} \in U \subset \mathbb{R}^m$ and one output $y \in Y \subset \mathbb{R}$. This system can be expressed by an input-output nonlinear auto-regressive type model with exogenous inputs (NARX) (Ljung, 1999):

$$y_{(k+1)} = F(\boldsymbol{\psi}_{(k)}) + \varepsilon \quad (4)$$

where $F(\cdot)$ denotes a nonlinear function, k is the discrete time-instant (step), and ε is the modeling error. Also, the past inputs and outputs are included in the regression vector $\boldsymbol{\psi}$ as follows:

$$\boldsymbol{\psi}_{(k)} = [y_{(k)}, \dots, y_{(k-n_y+1)}, u_{i,(k)}, \dots, u_{i,(k-n_{u,i}+1)}] \quad , \quad (5)$$

$$i = 1, 2, \dots, m$$

in which $n_{u,i}$ and n_y are integers corresponding to the system's order.

As it is shown in (6), the unknown function $F(\cdot)$ in (4) can be approximated by a TS type fuzzy model in terms of R rules which are characterized by linear function rule consequents (Babuska, 1998). This forms a collection of local linear models.

Rule j : *If* $y_{(k)}$ *is* $A_{j,1}$ **and** ... $y_{(k-n_y+1)}$ *is* A_{j,n_y} **and** $u_{1,(k)}$ *is* $B_{j,1,1}$ **and** ... $u_{1,(k-n_{u,1}+1)}$ *is* $B_{j,1,n_{u,1}}$ **and** ... $u_{m,(k)}$ *is* $B_{j,m,1}$ **and** ... $u_{m,(k-n_{u,m}+1)}$ *is* $B_{j,m,n_{u,m}}$ **then** (6)

$$\hat{y}_{j,(k+1)} = \sum_{l=1}^{n_y} a_{j,l} y_{(k-l+1)} + \sum_{i=1}^m \sum_{l=1}^{n_{u,i}} b_{j,i,l} u_{i,(k-l+1)} + c_j$$

In (6), **Rule j** is the j th rule from R rules ($j = 1, 2, \dots, R$), A and B are the antecedent membership functions, \hat{y}_j is the output of the j th rule, and a , b and c are the consequent parameters.

Finally, the aggregated output of the model denoted by \hat{y} is inferred using the following weighted average over all rule contributions (Babuska, 1998),

$$\hat{y} = \frac{\sum_{j=1}^R \mu_j(\boldsymbol{\psi}) \hat{y}_j}{\sum_{j=1}^R \mu_j(\boldsymbol{\psi})} \quad (7)$$

in which μ_j are membership functions that each represents the degree of fulfillment of a rule.

According to the above-mentioned fuzzy modeling method, the dynamic model of pitch actuation process in the wind turbine is designed and developed as follows: first, a suitable model structure to represent the dynamics of the process (e.g., an input-output regression model, and the number of tuning rules) is determined, and second, the parameters of the model are identified by an appropriate parameter estimation algorithm.

The model structure is determined based on available knowledge of the process/system. Generally, as much knowledge as possible should be incorporated in this step. With respect to the details presented in Section 3, the considered actuator fault results in disturbed pitch actuation and incorrect blade-pitch angle. Therefore, the dynamic model needs to serve as a numerical predictor of the nominal (fault-free) blade-pitch angle. As it is shown in Table 1, the dynamic model is represented by a MISO fuzzy model. The multiple inputs include reference blade pitch angle β_{ref} , reference generator torque τ_{ref} and generator speed ω_g that represent real-time control and operating conditions of wind turbine, while the single output is the estimated blade-pitch angle $\hat{\beta}$.

Table 1. Dynamic model structure for pitch actuation process (MISO fuzzy model)

Antecedent Part	Knowledge Base	Consequent Part
Candidate Inputs: $\hat{\beta}_{(k)}$ $\beta_{ref,(k)}$ $\tau_{ref,(k)}$ $\omega_{g,(k)}$	Tuning Rules: $j = 1, 2, \dots, R$ $R = 4$	Linear Equation Form in j th Rule: $\hat{\beta}_{j,(k+1)}$ $= a_{j,1} \hat{\beta}_{(k)}$ $+ b_{j,1,1} \beta_{ref,(k)}$ $+ b_{j,2,1} \tau_{ref,(k)}$ $+ b_{j,3,1} \omega_{g,(k)} + c_j$
Membership Functions per Input: 4		Defuzzification Method: $\hat{\beta} = \frac{\sum_{j=1}^R \mu_j(\boldsymbol{\psi}) \hat{\beta}_j}{\sum_{j=1}^R \mu_j(\boldsymbol{\psi})}$

Once the structure is determined, the model parameters including antecedent fuzzy sets and consequent parameters of the fuzzy model are identified. Since the process data are corrupted by noise and high frequency excitations, it is suggested that the original data be preprocessed using the

following recursive, single-pole low-pass filter with exponential smoothing (Jonkman et al., 2009):

$$y(k) = (1 - \alpha)u(k) + \alpha y(k-1) , \quad \alpha = e^{-2\pi T_s f_c} \quad (8)$$

where α is the low-pass filter coefficient, T_s is the discrete time constant, f_c is the corner frequency, and u and y are the unfiltered input and filtered output measurements, respectively. The preprocessed data from simulation of the wind turbine benchmark (under fault-free operation) are used for identification process based on fuzzy clustering with the well-established Gustafson-Kessel (GK) algorithm (Gustafson and Kessel, 1978). In more details, first, the data set partitioning into fuzzy clusters is conducted in an iterative way, and then the antecedent membership functions and parameters of the local linear models are extracted and identified from such clusters (Babuska, 1998).

4.2 Model-Based FDD Design

The purpose here is to create a model-based FDD system that uses the MISO fuzzy model designed in the previous subsection. Since the MISO fuzzy model is designed and identified from fault-free measured data obtained from nominal operation of wind turbine system, the model estimates the nominal performance of the system. More precisely, the MISO fuzzy model acts as a nominal model which estimates the nominal values of blade-pitch angle $\hat{\beta}$ for each rotor blade. Therefore, as it is shown in Fig. 3, the FDD system uses three similar MISO fuzzy models (called pitch actuation models) that each corresponds to a blade pitch actuation process.

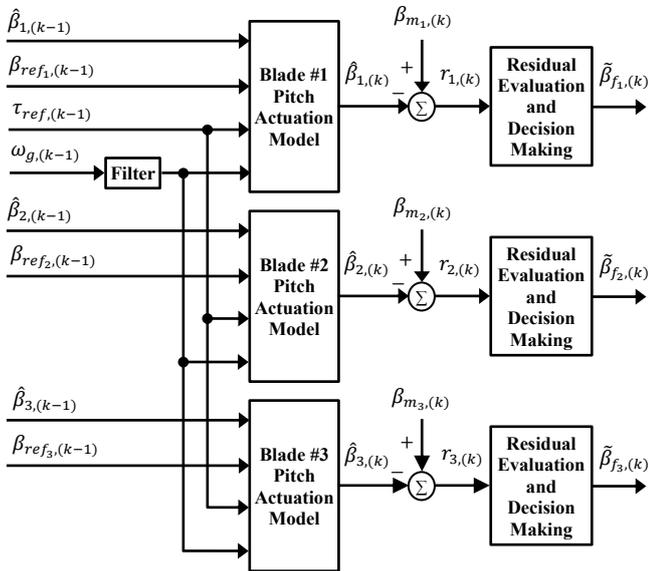


Fig. 3. Model-based FDD system

In Fig. 3, the so-called residuals r are computed as the difference between measured values β_m and estimated values $\hat{\beta}$ of blade-pitch angle. The residuals are then evaluated and appropriate decision is made in order to detect and then diagnose the actuator faults. The simple algorithm for real-time residual evaluation and decision making is outlined in Fig. 4.

The FDD system, as explained above, provides the most up-to-date condition monitoring information about the true status of the system that will enable the reconfiguration of control action whenever there are pitch actuator faults in the system.

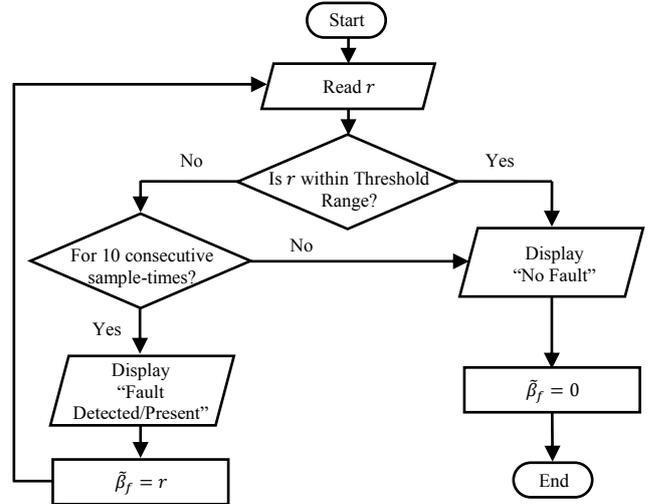


Fig. 4. Residual evaluation and decision making in the FDD system

5. AFTC DESIGN

An AFTC scheme is proposed in this section. As it is shown in Fig. 5, the proposed scheme consists of: 1) a CPC system that provides a collective pitch command β_{ref} ; 2) an FDD and automatic signal correction system that detects, isolates and estimates the considered faults $\hat{\beta}_{f_1}$, $\hat{\beta}_{f_2}$ and $\hat{\beta}_{f_3}$ in any pitch actuator while the faults are accommodated using the following signal correction (or fault compensation) process.

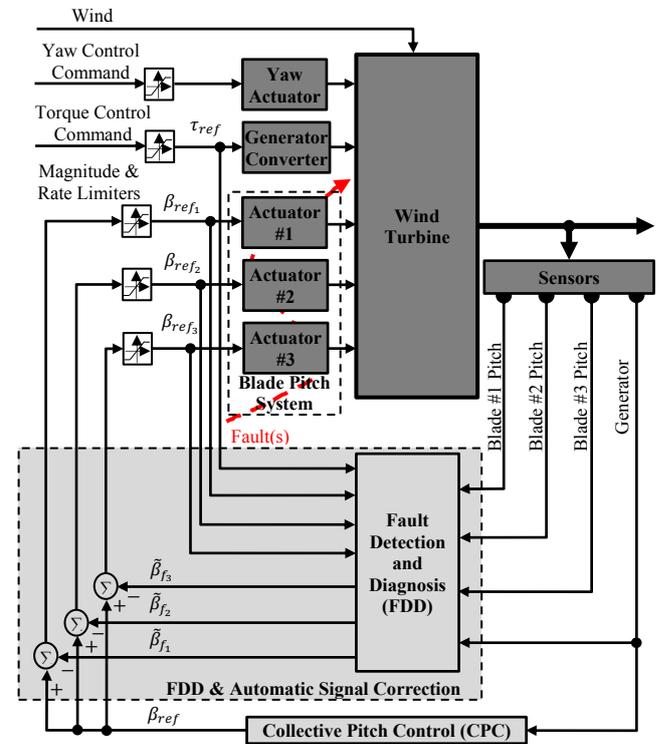


Fig. 5. Active fault-tolerant control (AFTC) scheme for pitch regulation

where

$$\begin{cases} \beta_{ref_1} = \beta_{ref} - \tilde{\beta}_{f_1} & \text{Blade \#1} \\ \beta_{ref_2} = \beta_{ref} - \tilde{\beta}_{f_2} & \text{Blade \#2} \\ \beta_{ref_3} = \beta_{ref} - \tilde{\beta}_{f_3} & \text{Blade \#3} \end{cases} \quad (9)$$

In the above AFTC scheme, the CPC system may be designed based on whatever collective pitch control algorithm. However, this paper uses the already developed conventional PI control system described in Section 2. Also, the FDD system used in the AFTC scheme is the model-based system shown in Fig. 3 with the decision-making logic shown in Fig. 4.

6. SIMULATION RESULTS

This section presents the evaluation of the AFTC scheme based on simulation tests performed in MATLAB/Simulink using the nonlinear benchmark model described in Section 2. Simulations were performed for a wind speed profile (see Fig. 6) with mean speed of 14 m/s, and over 630 seconds of run time.

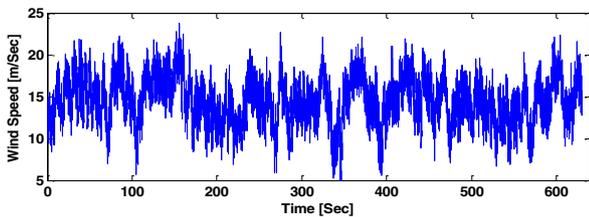


Fig. 6. Wind speed profile

6.1 Identification and Validation of the MISO Model

As already mentioned, the dynamic pitch actuation models used in the model-based FDD system are basically the same and developed using the MISO fuzzy modelling and identification technique described in Section 4. A MISO model is trained and evaluated using a set of 50,400 measured data for each of inputs and output. The data are obtained from the fault-free simulation of the wind turbine with a sampling rate of 80 Hz. Each set of the data are split into equal halves. One half is used for training and the other one for validation.

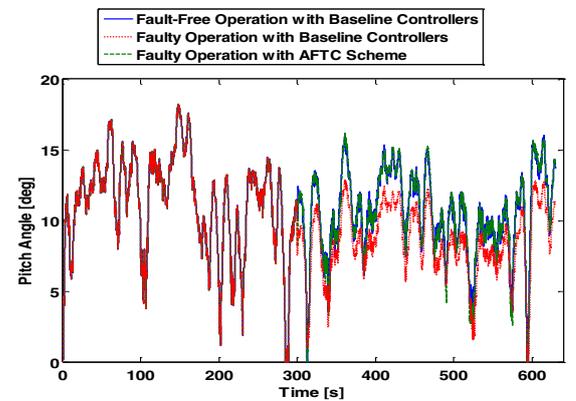
The modelling accuracy of the identified MISO models are demonstrated in terms of the Variance Accounted For (VAF) index (Babuska, 1998). The developed models have VAF of 98.2% that points out satisfactory accuracy.

6.2 Fault-Tolerance Performance of the AFTC Scheme

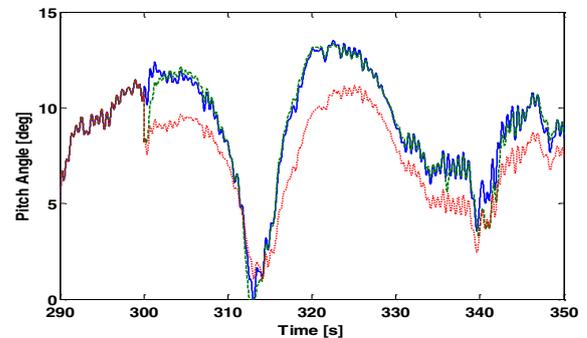
In this subsection, the AFTC scheme is tested and evaluated against faults in actuators. As it was explained in Section 3, the wind turbine's actuators may experience faults resulting in reduction in effectiveness of actuators. This paper considers an example fault scenario with reduction in effectiveness of pitch actuator #2 in Fig. 5. In more details, a fault with 25% reduction in effectiveness of actuator #2 happens within time period of [300,630] s. This fault causes disrupted pitch actuation in blade #2 and then drop the wind turbine's performance measures.

According to the obtained results during simulations under both fault-free and faulty operations, the proposed AFTC

scheme can effectively detect, diagnose and accommodate the considered fault in the faulty actuator (i.e., actuator #2). Fig. 7 shows the measured pitch angle during the overall simulation time as well as around the fault activity period. As it is observed in Fig. 7(a), the autonomous structure of AFTC scheme that is basically due to its automatic signal correction algorithm does not affect the nominal performance of the baseline controllers under fault-free conditions. This feature can be favourable in terms of easier acceptance and validation & verification (V&V) by the industry. The quality of fault accommodation is better seen in Fig. 7(b). Some less serious deviations still exist due to the common pitch offset and modelling errors. In Fig. 8, the measured generator speed is shown during the fault period. As it is observed in this figure, the AFTC scheme can successfully accommodate the fault effects on the dynamics of the wind turbine system as well.



(a)



(b)

Fig. 7. Pitch angle response in pitch actuator #2 during: (a) [0,630] s and (b) [290,350] s

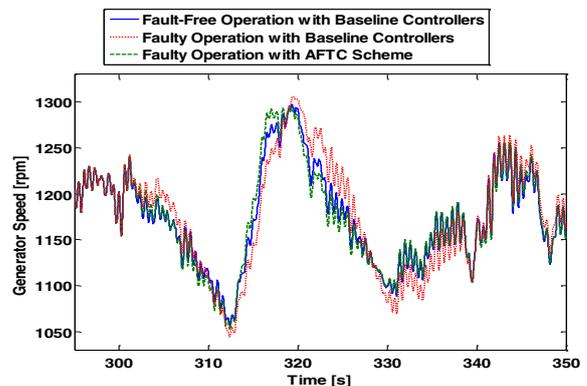


Fig. 8. Generator speed response during [290,350] s

7. CONCLUSIONS

This paper addressed the design and development of a novel active fault-tolerant control (AFTC) scheme for an offshore wind turbine against actuator faults in its pitch system. A model-based FDD system and an appropriate signal correction algorithm are designed to estimate the fault information and then compensate the fault effects in the pitch control loop. The proposed scheme provides a nominal baseline control system performance in fault-free operation, as well as compensates fault effects to maintain safe performance once faults occur. This feature makes the proposed AFTC scheme a favourable option in terms of easier acceptance and validation & verification by wind turbine industry. All simulations have been conducted in using an advanced 5 MW turbine model. Numerical results and simulation studies clearly indicate the effectiveness of the proposed schemes over the entire range of tested wind speeds and in both the fault-free and faulty conditions. Further investigations under real case studies remain as one of future works.

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