A Benchmark Evaluation of Fault Tolerant Wind Turbine Control Concepts

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***Abstract*— As the world's power supply to a larger and larger degree depends on wind turbines, it is consequently and increasingly important that these are as reliable and available as possible. Modern fault tolerant control (FTC) could play a substantial part in increasing reliability of modern wind turbines. A benchmark model for wind turbine fault detection and isolation, and FTC has previously been proposed. Based on this benchmark, an international competition on wind turbine FTC was announced. In this brief, the top three solutions from that competition are presented and evaluated. The analysis shows that all three methods and, in particular, the winner of the competition shows potential for wind turbine FTC. In addition to showing good performance, the approach is based on a method, which is relevant for industrial usage. It is based on a virtual sensor and actuator strategy, in which the fault accommodation is handled in software sensor and actuator blocks. This means that the wind turbine controller can continue operation as in the fault free case. The other two evaluated solutions show some potential but probably need improvements before industrial applications.**

***Index Terms*— Adaptive fault tolerant control (FTC), FTC, Takagi–Sugeno fuzzy dynamic output feedback, virtual sensor and actuators, wind turbine control.**

I. Introduction

POWER grids around the world depend to an increasing degree on power generated by renewables. Among those wind, turbines play a very significant part. It is consequently important that these turbines are as available and reliable as possible. This implies in part that wind turbines should be as tolerant toward faults as possible. It is consequently potentially of high relevance to apply advanced fault tolerant control (FTC) schemes on modern wind turbines.

The research on model-based fault handling applied to wind turbines has until now mainly been focused on fault detection and isolation (FDI), which is the normal first step in an active fault tolerant control strategy. The FDI can also be used in manual fault accommodation and repair approaches for the wind turbine manufacturers and operators. Until a few years ago, only a small number of papers had been published on fault tolerant control of wind turbines, [1]–[3]. The FDI schemes applied to wind turbine applications are reported in a number of publications. Some examples of these are introduced in the following. In [4], a Kalman filter-based diagnosis system to detect faults in the blade root bending moment sensors was presented. An unknown input observer was designed for detection of sensor faults around the wind turbine drive train in [5]. In [6], active and passive FTC schemes were applied to a wind turbine model. More focus has been drawn on the electrical conversion system in the wind turbines; some relevant examples can be found in [7] and [8]. In the former, an observer-based solution for current sensor fault detection is presented, while the latter presents an observer-based solution for voltage sensor fault detection. In [9], a fault detection and reconfiguration solution handling faults in a doubly fed wind turbine converter is presented.

In [10], a wind turbine benchmark model for FDI and FTC was proposed. In [11], this benchmark model was described in more detail together with description and evaluation of some proposed solutions to the FDI problem, which were made for an international competition. The evaluated solutions can be seen in [12]–[16]. A high number of other FDI solutions applied to the benchmark have been published. Some of these can be seen in [17]–[27].

Fault tolerant controllers are normally divided into two main groups: 1) active and 2) passive FTC, in which the first requires detection and isolation of the fault. Based on this, relevant accommodating actions are taken when a fault is detected. Passive FTC is designed to be robust toward the faults. Recently, combinations of these two methods have emerged, in which faults are accommodated as they appear without detecting and isolating them, e.g., using adaptation to the faults. For safety reasons, it is important for the wind turbine industry that FDI is included in FTC solutions used in wind turbines. In this brief, the top three contributions from the international competition mentioned above the FTC problem given in the previously mentioned benchmark are described. These solutions can be detailed in [28]–[30]. The first uses a virtual sensor and actuator (VSA) approach, in which the fault accommodation is performed within these virtual sensors and actuators, which provides sensor and actuator interfaces from nominal controller. This approach is very interesting seen from an industrial point of view, since it does not require modification of the existing nominal controller. This solution is an active FTC approach. The second contribution uses a Takagi–Sugeno multimodel approach to deal with the nonlinear nature of the wind turbine; faults are dealt with by estimating the faults. This solution can be considered as an active fault tolerant approach. The last contribution uses adaptive control to deal with the faults. This solution is placed in the category of active/passive combination methods. It can, consequently, be dangerous seen from a practical point-of-view since this strategy might accommodate faults in a wrong way by adaption, for example, in case of a critical fault, which requires a safety stop. These solutions will first be shortly introduced, before they are evaluated and compared on the wind turbine FDI and FTC benchmark model.

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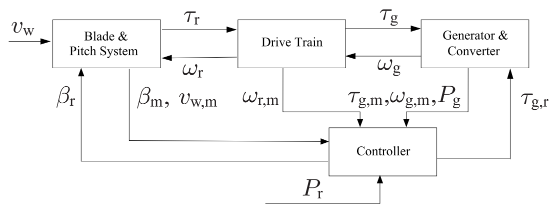

Fig. 1. Overview of the benchmark model. It consists of four parts, such as blade and pitch systems, drive train, generator and converter, and controller. The variables in the figure are defined.

A number of other FTC solutions applied to the benchmark model have been published [31]–[39].

The wind turbine FDI and FTC benchmark model is shortly introduced in Section II together with a proposed metric for evaluation of the FTC schemes applied to the benchmark model. Section III presents the evaluated FTC schemes. The schemes are evaluated in Section IV. Finally, the conclusion is drawn in Section V.

II. Wind Turbine Benchmark Description

This brief considers a generic wind turbine of 4.8 MW described in [10]. This turbine is a variable speed three blade pitch controlled turbine, with a front horizontal axis rotor.

The used wind turbine model is from [10]. It is not described in details in this brief, as the details can be found in the mentioned paper. An overview of the model can be observed in Fig. 1, in which v_w denotes the wind speed, τ_r denotes the rotor torque, ω_r denotes the rotor speed, τ_g denotes the generator torque, ω_g denotes the generator speed, β_r denotes the pitch angle control reference, β_m denotes the measured pitch angles, $\tau_{w,m}$ denotes the estimated rotor torque, $\omega_{r,m}$ denotes the measured rotor speed, $\tau_{g,m}$ denotes the measured generator torque, $\omega_{g,m}$ denotes the measured generator speed, P_g denotes the measured generated electrical power, $\tau_{g,r}$ denotes the generator torque reference, and P_r denotes the power reference. Each element of the model is shortly described as follows.

1) Wind Model: The wind speed is given by a wind model, including mean wind trends, turbulence, wind shear, and tower shadow.

A. Aerodynamic and Pitch Actuator Model

Aerodynamics and pitch actuators are modeled in the blade and pitch system model. The pitch actuator is modeled as a second-order transfer function with constraints. The aerodynamics are modeled by a static mapping from the pitch angle, rotor, and wind speeds to the torque acting on the wind turbine rotor.

B. Drive Train Model

The drive train, which is used to increase the speed from rotor to generator, is modeled with a flexible two-mass system. The drive train model includes the inertia of the rotor (which includes blades and main shaft) and generator.

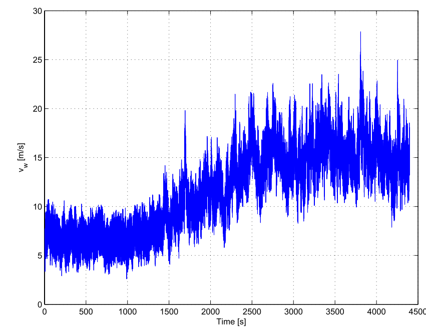

Fig. 2. Wind speed sequence used in the benchmark model. It can be seen that the wind speed covers the range from 5 to 20 m/s, with a few spikes at 25 m/s, which provides a good coverage of normal operational of a wind turbine.

C. Converter Model

The converter, which controls the generator torque, is modeled by a first-order system with constraints. This model covers both the electrical behavior of the generator and converter.

D. Sensor Models

This model is not shown on the figure, since models of each sensor in the figure are included in the relevant submodels. The model contains a number of sensors, generator and rotor speed, pitch angles, wind speed, converter torque, and electrical power. All the sensors are modeled as the measured variable added with random Gaussian noise.

E. Controller

The wind turbine operates in principle in four regions: 1) Region 1 in which wind speed is too low for the wind turbine to operate; 2) Region 2 in which the turbine operates up to a nominal wind speed (partial load); 3) Region 3 between nominal and rated wind speed, where the nominal power can be produced; and 4) Region 4 above rated wind speed, where the wind turbine is shut down to limit extreme loads on the wind turbine.

The controller is active in Regions 2 and 3. In Region 2, the optimal rotor speed is obtained using the converter torque as control signal. In Region 3, the rotor speed is kept at a given reference value by pitching the blades (the converter keeps the power at the reference taking care of fast variations in the speed). The basic controller in the different regions is described in [40].

F. Fault Scenarios

In the test signal definition described in [11], the defined faults are present at a predefined time. In this test, bench model setup a predefined wind speed sequence is used. This wind sequence consists of real measured wind data from a wind park. It can be observed in Fig. 2.

In the listing of the possible faults, a subset is chosen for the benchmark test sequence. In the following, Test Set 1 is defined and the different measurement signals are plotted as well. The test includes five sensors faults and three actuator faults.

1) *Fault 1:* Fault type 1a), a fixed value on $\beta_{1,m1}$ equal to 5° in the time period from 2000 to 2100 s.
2) *Fault 2:* Fault type 1b), a gain factor on $\beta_{2,m2}$ equal to 1.2 in the time period from 2300 to 2400 s.
3) *Fault 3:* Fault type 1a), a fixed value on $\beta_{3,m1}$ equal to 10° in the time period from 2600 to 2700 s.
4) *Fault 4:* Fault type 2a), a fixed value on $\omega_{r,m1}$ equal to 1.4 rad/s in the time period from 1500 to 1600 s.
5) *Fault 5:* Fault type 2b) and 3b) gain factors on $\omega_{r,m2}$ and $\omega_{g,m1}$, respectively, equal to 1.1 and 0.9 in the time period from 1000 to 1100 s.
6) *Fault 6:* Fault type 5a) change in the dynamics due to hydraulic pressure drop of Pitch Actuator 2, the fault is assumed to be abrupt and it is present in the time period from 2900 to 3000 s.
7) *Fault 7:* Fault type 5b) change in the dynamics due to increased air content in the oil on Pitch Actuator 3. The fault is slowly introduced during 30 s with a constant rate; afterward the fault is active during 40 s, and again decreasing during 30 s. The fault begins at 3400 s and ends at 3500 s.
8) *Fault 8:* Fault type 4b), an offset on τ_g of the value 100 Nm. The fault is active from 3800 to 3900 s.

In [11], six additional test series were defined to test and evaluate the proposed schemes robustness toward different operational points of the fault, which occurs due to the nonlinear behavior of the wind turbine. The faults occur in the various test series at different wind speed operational points as wind input changes with time. Consequently, this introduces uncertainties between the design and simulation models. These extra test series are defined as follows. Test Series 2 is generated by adding 100 s to the fault occurrence of all faults, Test Series 3 is defined by subtracting 100 s from the occurrence of all faults, Test Series 4 is defined by subtracting 200 s from the occurrence of all faults, Test Series 5 is defined by subtracting 300 s from the occurrence of all faults, Test Series 6 is defined by subtracting 400 s from the occurrence of all faults, and Test Series 7 is defined by subtracting 500 s from the occurrence of all faults.

It should be noticed that the FTC schemes evaluated in this brief are designed for fault occurrence in Test Series 1, meaning that the schemes could be expected potentially to have problems handling the point operations at which the faults occur in Test Series 2–7. These faults must be detected and handled according to the requirements given in [11].

The benchmark model package contains a wind speed sequence and Simulink model with a parameter file. The package can be obtained from the internet.[1]

G. FTC Requirements

In the original Benchmark model formulation, the requirements to the FTC solutions were quite simple. It was required that the system performance during faults should be as close to the nonfaulty performance as possible. It should be noticed that the model to provide a simple model for FDI and FTC benchmarking does not include models of the physical structures like blades and tower. Consequently, it cannot be evaluated by this model how the solutions influences the fatigue and extreme loads of the wind turbine. In the evaluation of the proposed schemes, a metric for comparison was developed. The evaluation metric will be described and explained in this section.

The variables considered in this evaluation are mean of generated power, P_{mean}, mean, min, and max of each pitch angle, $\beta_{\text{mean},i}$, $\beta_{\text{min},i}$, $\beta_{\text{max},i}$, where i is the blade number, and the mean of the generator speed, ω_{mean}. As the evaluation considers a number of test sets, random noise seeds and faults, the evaluated variables are evaluated over a number of indicators representing these different variables.

First, each Test Set, k, is repeated five times with different random noise seeds, j. For each time interval in which the faults, f, occurs and for each test set and noise seed a number of values are computed of some of the relevant states in the model. Note that for evaluation, the model state value is used and not the sensor signals of these states. The evaluation variables are subsequently redefined to depend on these indicators: mean of generated power, $P_{\text{mean},j,k,f}$, mean, min, and max of each pitch angle, $\beta_{\text{mean},i,j,k,f}$, $\beta_{\text{min},i,j,k,f}$, $\beta_{\text{max},i,j,k,f}$, where i is the blade number, and the mean of the generator speed $\omega_{\text{mean},j,k,f}$.

The next step is to compute these values for each test set defined as

$$P_{\text{mean},k,f} = \sum_{j\in\{1,2,3,4,5\}} P_{\text{mean},k,f} \tag{1}$$

$$\beta_{\text{min},i,k,f} = \sum_{j\in\{1,2,3,4,5\}} \beta_{\text{min},i,j,k,f} \tag{2}$$

$$\beta_{\text{max},i,k,f} = \sum_{j\in\{1,2,3,4,5\}} \beta_{\text{max},i,j,k,f} \tag{3}$$

$$\beta_{\text{mean},i,k,f} = \sum_{j\in\{1,2,3,4,5\}} \beta_{\text{mean},i,j,k,f} \tag{4}$$

$$\omega_{\text{max},k,f} = \max_{j\in\{1,2,3,4,5\}} (\omega_{\text{mean},j,k,f}). \tag{5}$$

The fault free test set is numbered as $k = 0$.

The basic idea in the construction of the evaluation is to give credit for the accommodation of each fault in each test set. To make the description and formulation of the evaluation metric easier to understand, the metric is described for a fault number f.

First, the ratio of mean generated power during the fault relatively to the mean generated power in the fault free case for the same time interval is computed. A number of multiplicative reductions are subsequently introduced to deal with a number of constraints, which should be enforced by the control solutions. This means that the metric, $C_{f,k}$ for fault f in Test Set k can be formulated as

$$C_{f,k} = \frac{P_{\text{mean},k,f}}{P_{\text{mean},0,f}} \cdot r_1(\sigma_1) \cdot r_2(\sigma_2) \cdot r_3(\sigma_3) \cdot r_4(\sigma_4) \cdot r_5(\sigma_5) \cdot r_6(\sigma_6) \tag{6}$$

[1]Available at http://www.es.aau.dk/project/wtbenchmarkmodels/

in which

$$\sigma_1 = P_{\text{mean},k,f} \tag{7}$$
$$\sigma_2 = [\beta_{\text{mean},1,k,f} \quad \beta_{\text{mean},2,k,f} \quad \beta_{\text{mean},3,k,f} \quad P_{\text{mean},k,f}] \tag{8}$$
$$\sigma_3 = P_{\text{mean},k,f} \tag{9}$$
$$\sigma_4 = \omega_{\text{max},k,f} \tag{10}$$
$$\sigma_5 = [\beta_{\text{min},1,k,f} \quad \beta_{\text{min},2,k,f} \quad \beta_{\text{min},3,k,f}] \tag{11}$$
$$\sigma_6 = [\beta_{\text{mean},1,k,f} \quad \beta_{\text{mean},2,k,f} \quad \beta_{\text{mean},3,k,f}]. \tag{12}$$

In the following, all the functions r_1–r_6 are defined, explained, and motivated. In these functions, a number of weights are used. These are elements in a vector W. The different weights are found by trial and error, with the objective of punishing very critical operation during faults higher than less critical behavior. Our experience with industrial wind turbine control design is as well considered selecting the used weights. In addition, they are adjusted such that a clear conclusion can be drawn from the comparison. The choice of weights clearly influences the value of the cost for the different solutions. It should be pointed out that due to the sensitive of results to weight selection, the weights should be retuned, if other wind turbine platforms should be considered. The relative ordering, however, of the presented results would be fairly robust.

The function r_1 is included to enforce a constraint on the max power, which is equal to 4.8 MW. If the power increased with >20%, a penalty is inferred. Such a large overproduction can not be accepted. Consequently, it will result in a full reduction of the obtained points

$$r_1(P_{\text{mean},k,f}) = \begin{cases} 0, & \text{if } P_{\text{mean},k,f} > 1.2, 4.8 \\ 1, & \text{else.} \end{cases} \tag{13}$$

The function r_2 is included to ensure that the power production is optimal, i.e., that the mean pitch angle is <1° if the mean power is <4.6 MW, which is slightly lower than the rated power, to allow a slight power reduction for obtaining other objectives, $W(1) = 0.75$

$$r_2(\gamma_2) = \begin{cases} W(1), & \text{if } \text{mean}_{i\in\{1,2,3\}}(\beta_{\text{mean},i,k,f}) \\ & > 1 \wedge P_{\text{mean},k,f} > 4.6 \\ 1, & \text{else} \end{cases} \tag{14}$$
$$\gamma_2 = (\beta_{\text{mean},1,k,f}, \beta_{\text{mean},2,k,f}, \beta_{\text{mean},3,k,f}, P_{\text{mean},k,f}). \tag{15}$$

The next function r_3 is introduced to punish usage of generator torque is used to lower the production, $W(2) = 0.75$

$$r_3(P_{\text{mean},k,f}) = \begin{cases} W(2), & \text{if } P_{\text{mean},k,f} < 4.8 \\ 1, & \text{else.} \end{cases} \tag{16}$$

The next function r_4 is introduced to punish generator overspeed. The nominal speed is 162 rad/s, overspeed is weighted with two scales, one for 16%, $W(3) = 0.75$, and one for 28% overspeed, where the latter results in a higher reduction, $W(4) = 0.5$

$$r_4(\omega_{\text{textmax},k,f}) = \begin{cases} W(3), & \text{if } 207 \geq \omega_{\text{max},k,f} > 186 \\ W(4), & \text{if } \omega_{\text{max},k,f} > 207 \\ 1, & \text{else.} \end{cases} \tag{17}$$

r_5 punishes pitch angle requests below −2°, which is the lowest possible pitch angle the actuator can provide. The used weight $W(5)$ is set equal to 0.5 for this

$$r_5(\beta_{\text{min},1,k,f}, \beta_{\text{min},2,k,f}, \beta_{\text{min},3,k,f}) = \begin{cases} W(5), & \text{if } \min_{i\in\{1,2,3\}} < -2 \\ 1, & \text{else.} \end{cases} \tag{18}$$

r_6 evaluates the correction of the pitch system faults. Since the wind turbine is controlled with collective pitch, all three pitch angles should be much alike. If the difference is >10°, it is punished, $W(6) = 0.5$, if it is <2°, it is rewarded, ($W(7) = 1.1$), and if <1°, it is rewarded even more ($W(8) = 1.2$)

$$r_6(\gamma_6) = \begin{cases} W(6), & \text{if } \|\max_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f}) \\ & -\min_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f})\| > 10 \\ W(7), & \text{if } \|\max_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f}) \\ & -\min_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f})\| < 2 \\ W(8), & \text{if } \|\max_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f}) \\ & -\min_{i\in\{1,2,3\}}(\beta_{\text{mean},k,f})\| < 1 \end{cases} \tag{19}$$
$$\gamma_6 = (\beta_{\text{mean},1,k,f}, \beta_{\text{mean},2,k,f}, \beta_{\text{mean},3,k,f}). \tag{20}$$

The weight vector W is defined as

$$W = [0.75 \quad 0.75 \quad 0.75 \quad 0.5 \quad 0.5 \quad 0.5 \quad 1.1 \quad 1.2]. \tag{21}$$

All these metrics are subsequently summarized over the different faults and Test Series.

It could be relevant to include other requirements in the evaluation cost function. This could for example be the computational burden evaluated in some way. The purpose of this brief has been to show the potential for fault accommodation using FTC methods, and handling computational complexity has been viewed being a part of the wind turbine and controller hardware specific design and implementation. Consequently, computational burden has not been included in the evaluation.

III. Evaluated FTC Methods

In this section, the three FTC solutions applied, to the benchmark model presented in [10], are introduced before they are evaluated in Section IV.

A. VSA-Based FTC

This solution has been published in [28]. It will, in the following, be denoted VSA. This solution proposes a FTC scheme based on a VSA concept, which in principle encapsulates the actual sensors and actuators in a software module, which compensates for the faults in the sensors and actuators, respectively. This can be seen as an annihilating signal to the fault being introduced in the virtual sensor/actuator such that the effect of the fault is mitigated.

This means that the wind turbine and nominal controllers would in principle not see any differences from the nonfaulty sensors and actuators. This in turn implies that the nominal controller can be used. This is especially relevant and important for industrial applications. The sensor and actuator faults are compensated by estimating the faults and then using the estimates compensating the actuators and sensors. This scheme relies on FDI such that the fault is identified. For the sensor faults in case of fixed sensor values, the measurement is replaced by estimations based on models and other sensors. The gain fault is compensated by estimating the fault gain. Subsequently, this estimate is used to compensate the measurement. The pitch actuator fault is compensated by estimating the fault dynamics and using the inverse of the fault dynamics to compensate the changed dynamics. The converter fault is compensated by subtracting the estimated offset from the control signal sent by the controller.

B. Takagi–Sugeno Fuzzy-Based FTC

Sami and Patton [30] proposes the second solution to the FTC problem, which is denoted as Takagi–Sugeno fuzzy (TSF). This solution was only designed for partial load control of the wind turbine. In this brief, the solution is nevertheless evaluated on the full test sequences. The first step in this approach is to model the wind turbine with Takagi–Sugeno multimodels representing the nonlinear behavior of the wind turbine. An effective wind speed estimator is used to select the relevant model. The generator speed sensor faults are estimated using a proportional multiple integration observer, which as well provide a robust estimate of the effective wind speed. Based on these estimates in which the fault is compensated, a TSF dynamic output feedback controller Lyapunov stability is proven with respect to H_∞ performance and D-stability constraints.

C. Adaptive FTC

The adaptive FTC scheme is proposed in [29] and [41]. It is, in the following, denoted as Adaptive FTC scheme (ADA). This FTC strategy is based on an adaptive scheme, in which the online identification of the system is used. In this way, the controller reconfiguration mechanism exploits an adaptive regulator implementation, depending on the online estimate of system model. This system model is achieved using a recursive identification method exploiting an adaptive directional forgetting scheme. Modified Ziegler–Nichols rules are applied to the online adapted model to adjust the Proportional-Integral controller parameters in the control scheme. One of the advantages of this strategy is that, for example, the original structure of the logic-based switching digital controller scheme already implemented for the wind turbine benchmark can be almost preserved. Note also that this scheme does not require any FDI schemes.

IV. Evaluation of Methods

In this section, the three methods are evaluated. First, time plots of the methods are shown of the generated power and generator speed for the three methods for the Test Series 1 and 7. The two test series are plotted to show how the analyzed methods handle different operational conditions while the faults are occurring. After inspecting these plots, the computed metrics are present for comparison, from which the different methods handling of the different faults can be seen. Robustness of the schemes can be evaluated as well, based on these different Test Series, as the faults will occur at different operational conditions, and thereby different system behaviors. In the plot, the proposed FTC scheme's operation in the fault free case and baseline controller's operation in the fault free case are compared with proposed FTC schemes operation in case of Test Series 1 and 7, respectively. The fault accommodation sequences are compared both with fault free simulations of the baseline controller and proposed controller. The latter might perform better or worse than the baseline controller in the fault free case.

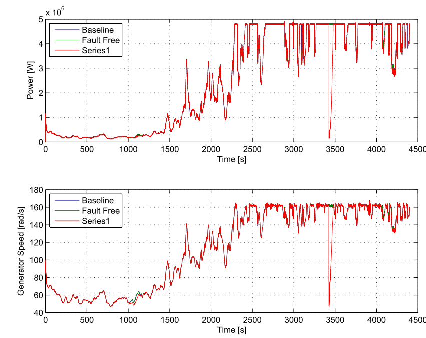

Fig. 3. Generated power and generator speed for the VSA scheme in case of Test Series 1 compared with the fault free case and the baseline controller in the fault free case.

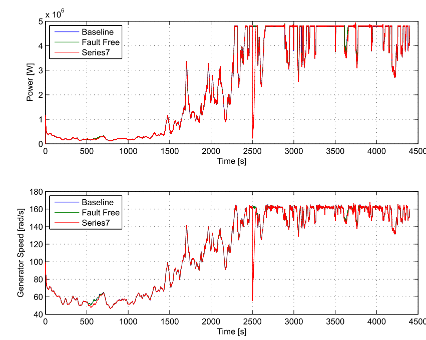

Fig. 4. Generated power and generator speed for the VSA scheme in case of Test Series 7 compared with the fault free case and the baseline controller in the fault free case.

Plots of the VSA Method: The power and generator speed for Test Series 1 can be observed in Fig. 3, and the plots for Test Series 7 can be observed in Fig. 4. These plots show that the VSA scheme accommodates the faults quite well, with respect to the generated power and as well generator speed. The only exception is the accommodation of the fault in the pitch actuator present in the time interval 3400–3500 s in Test Series 1 and 2500–2600 s in Test Series 7, which results in a clear drop in generated power and generator speed.

Plots of the TSA Method: The power and generator speed for Test Series 1 can be observed in Fig. 5, and the plots for Test Series 7 can be observed in Fig. 6. As the TSA scheme is only designed for partial load, it is expected to perform unacceptable in full load operation, which it is actually observed to do. Before 2500 s, it can be seen that the TSA scheme handles the faults by reducing generated power and increasing the generator speed, which is nonoptimal. In the

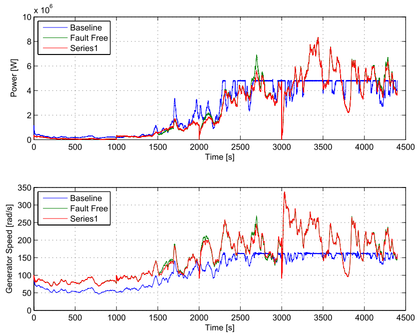

Fig. 5. Generated power and generator speed for the TSA scheme in case of Test Series 1 compared with the fault free case and the baseline controller in the fault free case.

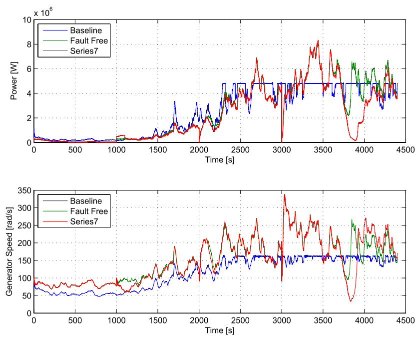

Fig. 6. Generated power and generator speed for the TSA scheme in case of Test Series 7 compared with the fault free case and the baseline controller in the fault free case.

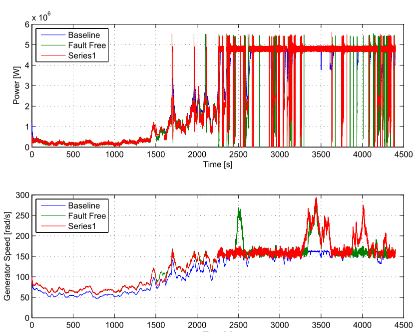

Fig. 7. Generated power and generator speed for the ADA scheme in case of Test Series 1 compared with the fault free case and the baseline controller in the fault free case.

full load time interval, it can clearly be seen that this controller does not try to use the pitch actuator, since the controller in the fault free case tries to generate up to 8 MW on this turbine rated to 4.8 MW, and as well runs with overspeed.

Plots of the ADA Method: The power and generator speed for Test Series 1 can be observed in Fig. 7, and the plots for Test Series 7 can been observed in Fig. 8. For this solution, the observations made on the two test series are quite similar. It can be seen that the ADA scheme in partial load obtains approximately the same power as the baseline controller even in the case of faults, but operates with a higher generator speed. It can as well be seen that it introduces an overshoot up to 5 MW when it switches to full load. In full load, it does

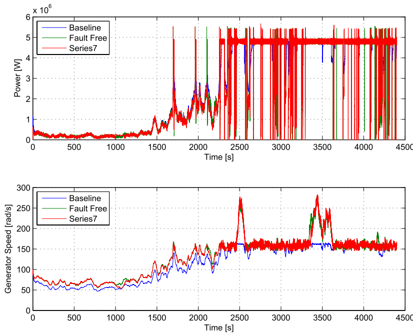

Fig. 8. Generated power and generator speed for the ADA scheme in case of Test Series 7 compared with the fault free case and the baseline controller in the fault free case.

TABLE I
EVALUATION METRICS FOR THE VSA SCHEME. F#: REFERS TO FAULT NUMBER. S: SERIES NUMBER

F #	S 1	S2	S 3	S 4	S 5	S 6	S 7	Sum
1	1.2	1.23	1.2	1.2	1.2	1.2	1.2	8.43
2	0.6	0.46	0.6	1.2	1.2	1.2	1.2	6.46
3	0.54	0.59	0.42	0.45	0.6	0.6	1.2	4.4
4	1.2	1.1	1.2	1.2	1.2	1.2	1.2	8.3
5	1.2	1.17	1.24	1.21	1.27	1.22	1.22	8.53
6	0.6	0.45	0.6	0.59	0.58	0.33	0.45	3.6
7	0.6	0.43	0.6	0.6	0.45	0.59	0.47	3.74
8	0.6	0.6	0.6	0.52	0.55	0.6	0.6	4.07
Sum	6.56	6.03	6.46	6.97	7.05	6.94	7.54	47.55

have a lot of negative spikes in the power and generator speed, probably due to the adaptive nature of this scheme. In addition, it has some significant over-speed periods both in the fault free and faulty cases.

A. Evaluation Using Metrics

After inspecting a couple of plots with time series simulations, the different schemes are now evaluated using the metrics proposed in Section II-G. The results of the evaluation of the VSA scheme can be seen in Table I, from which it can be seen that it handles Faults # 1, 4, and 5 very well. The remaining faults are handled reasonably well. This indicates that this scheme is accommodating the sensor faults better. It can also be seen that it handles the different test series with almost the same performance, but it does actually score a higher number for Test Series # 4, 5, 6, and 7 than for the nominal test series that it was designed for, which is mainly due to a better accommodation of pitch actuator faults, which are better detected in the latter test series. Compared with the two other schemes, for which the results can be seen in Table II for the TSA scheme and in Table III for the ADA scheme, the VSA scheme performs much better, which the time series plots also clearly show. The two other schemes did score almost equal in total score with a slightly higher number for the TSA scheme. The ranking of the TSA and ADA might have been influenced by the weight selections, but the ranking of the VSA scheme is not sensitive to the weight selection. The TSA scheme accommodates Faults 4 and 5 very well and Faults 2 and 3 well. It is expected that the actuator faults (Faults # 6–8)

TABLE II
EVALUATION METRICS FOR THE TSA SCHEME.
F#: FAULT NUMBER. S: SERIES NUMBER

F #	S 1	S 2	S 3	S 4	S 5	S 6	S 7	Sum
1	0.33	0.34	0.46	0.48	0.34	0.45	0.45	2.85
2	0.3	0.3	0.3	0.9	0.3	1.18	1.19	4.47
3	1.19	1.1	1.09	1.1	0.1	0.11	0.29	4.98
4	1.2	0.83	1.2	1.2	1.2	1.2	0.23	7.06
5	1.2	1.2	1.19	1.2	1.2	1.25	1.21	8.45
6	0.30	0.3	1.19	0.3	0.29	0.3	1.25	3.93
7	0.30	0.0	0.0	0.0	0.3	0.3	0.29	1.19
8	0.27	0.29	0.9	0.0	0.3	0.0	0.30	2.06
Sum	5.09	4.36	5.62	4.51	4.43	5.15	5.21	34.37

TABLE III
EVALUATION METRICS FOR THE ADA SCHEME.
F#: FAULT NUMBER. S: SERIES NUMBER

F #	Ss 1	S 2	S 3	S 4	S 5	S 6	S 7	Sum
1	0.59	0.6	0.46	0.6	0.6	0.6	0.59	4.04
2	0.60	0.59	0.6	0.6	0.6	0.47	0.59	4.05
3	0.44	0.15	0.12	0.44	0.44	0.15	0.15	1.89
4	1.2	1.2	1.2	1.11	1.2	1.2	1.2	8.31
5	1.19	1.19	1.15	1.19	1.19	1.19	1.19	8.29
6	0.6	0.6	0.45	0.6	0.23	0.6	0.6	3.68
7	0.15	0.15	0.15	0.15	0.15	0.15	0.15	1.05
8	0.45	0.32	0.6	0.13	0.68	0.68	0.37	3.23
Sum	5.22	4.8	4.71	4.81	4.99	4.94	4.84	34.31

would be handled poorly as they occur in full power, which this scheme was not designed for. It can also be seen that the scheme is somewhat robust toward changes in the time location of the faults, and thereby toward the operational condition at which the different faults occur. The ADA scheme accommodates Faults # 4 and 5 very well and # 1 and 2 reasonably well. The actuator faults are again not handled as well as the sensor faults. It seems to be a general trend of these solutions, which might indicate that the sensor faults in the benchmark model are easier to accommodate than the actuator faults. The ADA scheme scores at the same level for all Test Series, but the nominal Test Series scores slightly better than the others. Based on these evaluations, it is found that the VSA scheme performs the best on the used wind turbine FDI/FTC Benchmark model, both by inspection on various time series plots, and the proposed evaluation metrics. A drawback on this benchmark is that it does not include models of the structural parts of the wind turbine, so fatigue and extreme loads on important components like tower and blades cannot be investigated and evaluated. Future work would consequently be to redesign the schemes for a benchmark including more detailed wind turbine models, like the one proposed in [42]. Evaluating the schemes on such a more detailed wind turbine model will consequently evaluate the schemes on a model closer to a real wind turbine, and as well introduce larger difference between design and simulation models. Thereby, the robustness toward model uncertainties could be investigated to a larger extent.

V. CONCLUSION

In this brief, the top three solutions for an international competition on fault tolerant wind turbine control, applied to a known benchmark model, where presented and evaluated on this benchmark model. Based on these evaluations, it can be seen that the winner of the competition performs very well on the benchmark model problem. This solution has a concept relevant for industrial usages, as it uses virtual sensors and actuators for accommodating the faults, whereby the nominal controller does not have to be modified to deal with the faults. The second solution is based on TSF dynamic output feedback. This solution is only designed for partial load operation of the wind turbine. Consequently, it has difficulties handling the full load operation, which it is also evaluated on. The last solution is based on an adaptive scheme, which in a practical setup might lead to accommodation by adaption of faults, which should result in safety stop of the wind turbine. A natural next step in the evaluation of the proposed schemes would be to evaluate them on a more detailed wind turbine model like the one in [42], or on experiments on a test turbine.

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