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# Hardware–In-The–Loop Assessment of a Fault Tolerant Fuzzy Control Scheme for an Offshore Wind Farm Simulator

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**Abstract:** To enhance both the safety and the efficiency of offshore wind park systems, faults must be accommodated in their earlier occurrence, in order to avoid costly unplanned maintenance. Therefore, this paper aims at implementing a fault tolerant control strategy by means of a data–driven approach relying on fuzzy logic. In particular, fuzzy modelling is considered here as it enables to approximate unknown nonlinear relations, while managing uncertain measurements and disturbance. On the other hand, the model of the fuzzy controller is directly estimated from the input–output signals acquired from the wind farm system, with fault tolerant capabilities. In general, the use of purely nonlinear relations and analytic methods would require more complex design tools. The design is therefore enhanced by the use of fuzzy model prototypes obtained via a data–driven approach, thus representing the key point if real–time solutions have to implement the proposed fault tolerant control strategy. Finally, a high–fidelity simulator relying on a hardware–in–the-loop tool is exploited to verify and validate the reliability and robustness characteristics of the developed methodology also for on–line and more realistic implementations.

*Keywords:* Fault tolerant control, fuzzy logic, data–driven approach, hardware–in–the-loop tool, offshore wind park.

## 1. INTRODUCTION

Horizontal Axis Wind Turbines (HAWTs) have dominated the Wind Energy Con-version (WEC) industry over the last few decades. Modern HAWTs are designed larger and are located in remote places, *e.g.*, offshore sites, to increase the WEC capacity. The HAWT is a complex highly nonlinear dynamic system. So, in the presence of high wind speed variation, it is challenging to retain HAWT operation with the prescribed WEC efficiency. The high wind speed may cause HAWT out-of-control operation with catastrophic overspeeding of the rotor. In this case, either the HAWT is stalled to stop, or the mechanical brake is engaged. As a result, only a conservative WEC is achieved and the efficiency is cumulatively less than that desired.

The HAWT efficiency is a trade-off between capturing the maximum energy and satisfying the structural/operational safety. In this regard, modern HAWT manufac-turers define the so-called ideal power curve, which characterizes the HAWT operation with optimal efficiency. The key solution for the enhancement of the HAWT efficiency relies on the development of proper control strategies to retain the operation on the ideal power curve. Accordingly, in high wind speed conditions, the generated power is regulated at its nominal value to maintain safe operation and to avoid overspeeding. This region of operation is known as the full load region, where power regulation represents the main objective. In the HAWT, the power regulation is fulfilled by adjusting the pitch angle of the blades, which leads to regulating the rotor speed [5]. Therefore, it is crucial to control the pitch angle such that the rotor speed is kept within the predefined safe-to-operate bound around the nominal value and, consequently, to avoid conserva-tive WEC control solutions.

The long-term operation of HAWTs may increase the incidence of pitch actuator faults. The fault occurrence reduces the availability of the plant and increases the WEC cost. Pitch actuator bias, effectiveness loss and dynamic change are the most commonly reported pitch actuator fault types. In WTs with hydraulic actuators, the dynamic change is caused by a pressure drop due to hydraulic oil leak, high air content in the oil and pump wear, for those installations using hydraulic actuation. In the case of electric actuators, dynamic change is due, for example, to the wear or ageing of the electric motor, whose response becomes slower due to the friction increase. This, in turn, leads to a slower response of the pitch actuator, and, consequently, inefficient power regulation. The pitch actuator bias can be caused when blades are installed to the pitch actuator, and small misalignments can be thus generated. This problem can be present in both electric and hydraulic actuators. The effectiveness loss can be derived from a mechanical fault affecting the electric motor actuating the blades, e.g., some deflection

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angles (for the complete range of motion) are no longer available due to the wear out of the bearings. The same issue arises also in hydraulic actuators, where the increased friction of the mechanical parts is due to the aging of the hydraulic cylinders. On the other hand, debris build-up and blade erosion are inevitable, which leads to the Blade Aerodynamic Profile Change (BAPC). These issues motivate the need for maintenance procedures. However, the increased maintenance downtime leads to reduce the power generation rate at a higher cost, especially for offshore installations, due to the reachability difficulties of harsh environments. Therefore, the pitch angle control should integrate fault-tolerance capabilities to compensate possible fault effects.

Fault Tolerant Control (FTC) solutions are divided into two types of schemes, *i.e.* Passive Fault Tolerant Control (PFTC) and Active Fault Tolerant Control (AFTC) systems. On one hand, PFTC does not need for Fault Detection and Diagnosis (FDD) or Fault Detection and Isolation (FDI) task, or even controller re–design, but it has quite limited FTC features. On the other hand, AFTC is able to manage the fault on the system component in an active way and it rearrange the control laws such that the stability is maintained and acceptable performances of the entire process are kept. Therefore, a successful strategy of AFTC exploits real–time FDD/FDI modules in order to provide the updated information regarding the health status of the dynamic process. Over the last decades, the increasing demand for safety, stability, reliability, and availability in power plants has motivated important research activities in the FTC area, as described *e.g.* in (Mahmoud et al. (2003)). In particular, with special attention to wind park installations, they represent complex nonlinear dynamic processes, with aerodynamics that are nonlinear, partially unknown, and unsteady.

In more detail, this work recalls the design of a FTC module, which includes a fault estimation solution with the generation of the controller law that is able to compensate the plant after the fault occurrence. In particular, the methodology proposed in this paper implements an on–line fault estimation strategy that is solved by means of fuzzy prototypes. These models are obtained and estimated by using the input–output data acquired from the process under investigation.

On the other hand, the same solution considers the controller that is accommodated by including a second control that injects the on–line reconstructions of the estimated fault signals. The proposed nonlinear fault reconstruction procedure has the same logic as the solution already proposed by the same authors in (Simani and Castaldi (2014)), even if the former paper designed the nonlinear filters using nonlinear differential tools, whilst in this paper the nonlinear fault estimators are modelled by means of fuzzy prototypes that are estimated directly from the data acquired from the process under investigation. Therefore, the implementation and the application of the complete FDI/FDD and FTC solutions in particular developed for the wind park benchmark that rely on the fuzzy models obtained via identification approaches justify the novel characteristics of this work.

The developed methodologies will be also compared by considering the different techniques already addressed in another work by the same authors, and in particular (Simani and Castaldi (2012); Simani et al. (2021)). By considering this former approach, the first scheme considers recursive algorithms that include adaptive laws implemented via on–line estimated linear systems; in this way, they are trying to compensate for any fault cases and their effects. On the other hand, the passive approach uses a fuzzy controller obtained via off–line batch modes, which tries to tolerate in a passive way all the possible fault cases affecting the monitored dynamic process.

It is worth noting that this paper further develops the achievements obtained *e.g.* in (Simani et al. (2014b)), but concerning the FDD design for a wind farm. On one hand, another FTC design using the input–output data achieved from a single wind turbine was also proposed *e.g.* in (Simani et al. (2013)), by considering again the achievements addressed in (Simani et al. (2014a)). On the other hand, this manuscript considers the verification and the validation of the proposed methodologies by including an innovative and original Hardware–In–the–Loop (HIL) tool, as considered in a preliminary work by the same authors, *e.g.* in (Simani (2012)). Other approaches were considered in (Harrabi et al. (2018); Simani et al. (2018)) and (Castaldi et al. (2021); Farsoni et al. (2021); Farsoni and Simani (2021)).

## 2. WIND PARK SYSTEM

The wind park simulator implements two scenarios with two different wind directions that are both fed by the same wind speed process and sequence, $v_w(t)$. It includes a possible time shift. The process of the driving wind consists of a sequence with mean speed increasing from 5 m/s to 15 m/s, with peak value of 23 m/s. More details on the process are not further addressed here as already available in (Odgaard and Stoustrup (2013)).

Note that this benchmark is quite simple, but it is able to describe with arbitrary accuracy a wind park where a controller is also included, which requires a power reference defined by the signal $P_{i\,ref}(t)$. In this way, when the wind park has to provide a power lower than the available one, the reference power signals are equally divided among the wind turbine control modules. More details on this benchmark can be found in (Odgaard and Stoustrup (2013)). However, as already remarked, the wind farm recalled in this paper could be seen as a too simplistic model. However, it can be shown that this simulator is able to fit any actual and realistic wind farms, as properly explained in (Odgaard and Stoustrup (2013)) and reported in Table 1.

Table 1. Fault effects on the WT measurements.

| Wind turbine indices | Fault Case | Affected Measurement |
|---|---|---|
| $i = 2,\, 7$ | 1 | $\{v_w(t),\, \omega_9(t),\, P_{4\,g}\}$ |
| $i = 1,\, 5$ | 2 | $\{v_w(t),\, \beta_2(t),\, P_{6\,g}\}$ |
| $i = 6,\, 8$ | 3 | $\{v_w(t),\, \beta_3(t),\, P_{7\,g}\}$ |

Note that the measurements are affected by uncertainty and measurement errors. Therefore, the relations between faults and input–output measurements cannot be determined in a straightforward way. In this way, the results summarised in Table 1 were computed by analysing in a practical way the effects of the faults on the wind park measurements. More in detail, Table 1 is computed by considering the fault cases (1, 2, and 3) and selecting the most sensitive measurement ($u_i$ or $y_j$).

It is worth noting that this approach represents the key point of the paper, as it enhances the fault isolation task, whilst simplifying the identification procedures. In fact, it can be solved in an easier way by using the fuzzy scheme recalled in this paper, thus justifying one of the main motivations and contributions of the methodology proposed in this study.

Of course, if it is required to include fault cases different from the ones already considered in this work, in general, different input and output measurements should be tested and verified. In fact, measurements different from the ones reported in Table 1 will be probably affected by different fault cases. Moreover, the FTC strategies proposed in Section 3 will be analysed using the simulations and the experimental tools considered in Section 5.

## 3. FAULT ACCOMMODATION METHODOLOGY

The proposed FTC strategy is based on two stages. The first step achieves the estimation of the fuzzy prototypes for fault reconstruction, which are thus exploited for the unknown signal estimation. In this way, the FDI/FDD module is designed to provide the reconstruction of the fault, which is employed by the FTC strategy to compensate the changes of the output measurements and the control signals generated by the faults.

The estimation approach used in this paper derives fuzzy models, which are first determined by implementing a fuzzy clustering technique. In this way, the partition of the available data into subsets characterised by linear or affine behaviours is performed as first stage. The partition into clusters allows to determine linear regressions for the different clusters, which roughly represent the different working conditions of the considered plant. This approach allows to integrate fuzzy logic with system identification. Moreover, this task is enhanced by the availability of the Matlab Toolbox of Fuzzy Modeling and IDentification (FMID), which is useful to implement the strategies recalled in this paper (Babuška (1998)). This paper proposes to use Takagi–Sugeno (TS) fuzzy prototypes, which are exploited to determine the nonlinear (dynamic) relations between the input–output measurements and the considered fault cases. The description of the methodology proposed in the paper was described in detail in (Simani et al. (2021)) and reconsidered here for its real time implementation.

## 4. FAULT TOLERANT CONTROL DESIGN

The problem can be solved by considering the generic current state $\mathbf{x}(k)$ and the output $y(k)$, when the unknown fault signal $\hat{f}(k)$ is expressed by the relation of Eq. (1):

$$\hat{f}(k) = F^{-1}\left(\mathbf{x}(k),\, u(k),\, y(k)\right) \tag{1}$$

As already remarked, in general it is difficult to find the analytical inverse function $F^{-1}$ of Eq. (1). However, as suggested in Section 4, the solution proposed here uses identified TS fuzzy models. Therefore, as remarked in Section 4, this fuzzy modelling and identification procedure is able to provide the inverse mapping of Eq. (1) as TS fuzzy prototype.

Under these assumptions, the complete form of the fault reconstructor has the form of Eq. (2):

$$\hat{f}(k) = \frac{\sum_{i=1}^{M} \mu_i^{(r)}\left(\mathbf{x}^{(r)}(k)\right)\left(\mathbf{a}_i^{(r)}\,\mathbf{x}^{(r)}(k) + b_i^{(r)}\right)}{\sum_{i=1}^{M} \mu_i^{(r)}\left(\mathbf{x}^{(r)}(k)\right)} \tag{2}$$

where the inputs are the state vector $\mathbf{x}^{(r)}(k)$, as well as the current inputs $u(k)$ and outputs $y(k)$. Note that the representation of Eq. (2) uses the subscript $(r)$ for highlighting the estimated membership functions $\mu_i^{(r)}$, as well as the parameters $\mathbf{a}_i^{(r)}$ and $b_i^{(r)}$ of the identified prototype.

Note that these identified nonlinear filters for fault reconstruction are also able to perform the fault isolation task, as described *e.g.* in (Simani (2013)). The complete FTC scheme relying on the FDI/FDD module and the fault accommodation strategy is summarised in Fig. 1.

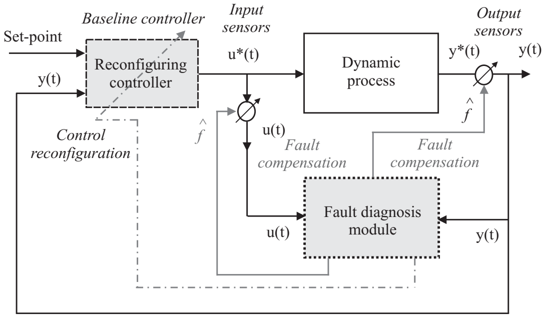

Fig. 1. The proposed fault accommodation scheme.

## 5. SIMULATION AND EXPERIMENTAL RESULTS

In order to show the achievements of the developed FDI/FDD and FTC solutions, the dynamic process has been simulated taking into account the required fault–free and faulty conditions. Extended simulations and experimental tests have been also conducted by the authors by following the more realistic test–rig presented in (Simani (2012)) and implemented for the wind park considered in this paper. This point represents a further contribution of this study.

### *5.1 Simulated Results*

This section summarises a first example where the identified nonlinear fuzzy filter is able to provide the reconstruction $\hat{f}(k)$ of the fault case 1 of Table 1. This reconstruction is decoupled from the effect of both the wind speed $v(t)$ and the model–reality mismatch. Moreover, the following results consider the simulation of the designed FDD when included in the FTC scheme proposed in the paper in the presence of the fault case 1 of Table 1.

Hence, after the estimation of the fuzzy residual generator parameters, the nonlinear TS fuzzy estimator generates the reconstruction of the fault signal $f(k)$. The simulations regard the generation of a sequence of rectangular pulses with variable amplitude and length that represent the fault effect. Fig. 2 depicts the reconstruction of the fault when compared with the actual signal. The achieved results show that the FDD module implemented via the TS fuzzy model is able to provide a good reconstruction of the actual fault.

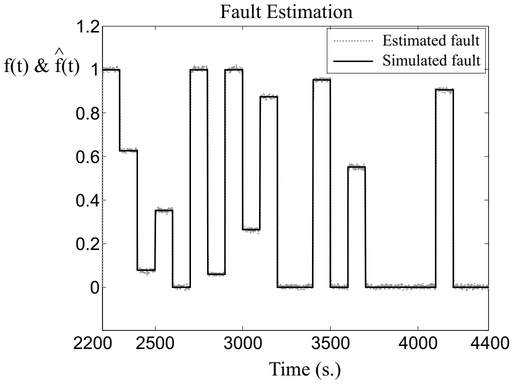

Fig. 2. Example of comparison of the actual and estimated fault case 1.

Under this condition, Fig. 3 depicts the power reference signal $P_r$ compared with its desired value with and without FTC.

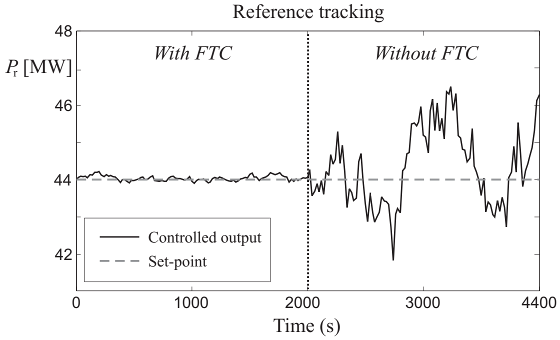

Fig. 3. Example of compensation of the fault case 1.

In particular, Fig. 3 shows the power reference of the wind park, $P_r$, which is almost constant and equal to 43.6MW until $t = 2000$ s, when it starts varying more than with fault accommodation. This paper considers faults modelled by means of sequences of pulses with variable amplitude and length, as they represent realistic fault cases. However, the FDD module is able to reconstruct more general functions. This generalisation, which is beyond the scope of this paper, was already analysed by the authors *e.g.* in (Baldi et al. (2013)). Finally, Table 2 summarises the values of the reconstruction errors of the different fault cases, with reference to the index representing the per–cent Normalised Sum of Squared Error ($NSSE$) between the actual and the reconstructed fault signals.

Table 2. $NSSE\%$ values of the fault reconstruction errors.

| Fault Case | $NSSE\%$ Error |
|---|---|
| 1 | 0.11% |
| 2 | 0.12% |
| 3 | 0.10% |

The paper considers only the fault case 1.

## 6. EXPERIMENTAL RESULTS

As final experiments, this section introduces the HIL test–rig, which has been implemented by the authors for validating the designed FDI/FDD and FTC schemes in more realistic and real–time conditions. The scheme of the implementation the test–rig is represented in Fig. 4.

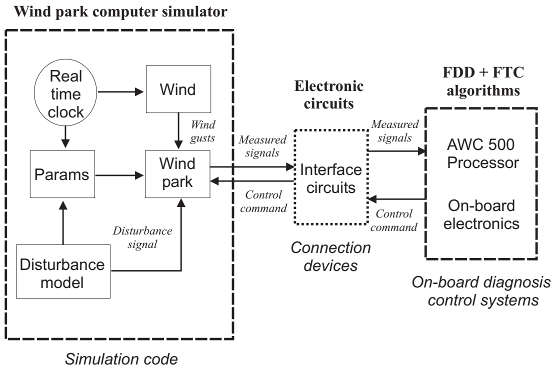

Fig. 4. The real–time wind park test case.

The considered wind speed sequence is considered in Figure 4, with the mean 17.84 (m/s) and the standard deviation of 1.94 (m/s). It is worth noting that other wind sequences can be used to study the robustness of the performance. In this work, however, the robustness is analysed via the Monte-Carlo tool in the presence of measurement errors. Therefore, for the sake of brevity, the wind speed sequence depicted in Figure 4 is only used. Under single and simultaneous fault scenarios, the results are shown in the following.

It can be seen that the tracking errors are within the considered constraints, considering the achieved results. Accordingly, both the rotor and the generator speed signals, illustrated in the paper, are quite close to the corresponding nominal values despite the wind speed variation and faults. As a result, the generated power is regulated at the nominal value, as shown in the following. These results imply that the wind turbine is successfully controlled by pitch angle regulation, *i.e.* the nominal power is generated, despite the wind speed high variation and the faults. Furthermore, the given operation bounds are not violated. This enables safe operation and avoids conservative WEC. Especially, considering the bounded rotor speed, the engagement of the mechanical brake on the rotor shaft can be avoided. On the other hand, as indicated in the following, the proposed scheme is able to construct the bounds to handle the initial conditions outside of these bounds, as discussed in the paper.

The reference pitch angle computed by the proposed controller is shown in the scheme below. The pitch angles are very similar to each other. Therefore, to accurately investigate the performance of the proposed controller, the difference between these two pitch angles is considered.

Considering the achieved results, is clear that the main difference is in the periods that the pitch actuator bias and effectiveness loss commence. Moreover, the effects of the pitch actuator dynamic change have led to more variations, compared to bias and effectiveness loss. Indeed, the dynamic change causes the slower pitch actuator dynamic response. In this case, the controller has to vary the pitch angle faster with larger values to retain the rotor speed within the bounds.

Now to extensively evaluate the performance, the Monte-Carlo analysis is performed to assess the robustness and reliability of the proposed controller, in terms of nominal power generation, considering different measurement errors and the NSSE% index. Additionally, BAPC is included as a 10% reduction in the power coefficient. On the other hand, the drivetrain decreased efficiency is considered by a 5% reduction in this parameter. Accordingly, two cases with and without FTC and drivetrain efficiency reduction are represented by the considered cases, respectively. The Monte-Carlo analysis is performed under a single fault scenario.

For each case, 100 simulations are performed. For each simulation, the NSSE% is computed over the simulation time. Then, the maximum, minimum, standard deviation and mean values of each NSSE% index for each simulation are computed. Accordingly, for the sake of brevity, the worst, the average, and the best values over 100 simulations are considered, as reported below. It is worth noting that the NSSE% index, as defined in the paper, is ideally close to zero. Therefore, the worst, the average and the best values represent the largest, average and smallest values, respectively.

The rationale behind this is that the largest NSSE% represents the largest deviation from the nominal power generation. Therefore, this is selected as the worst performance index. Similar justifications can be given for average and the best values. All Monte-Carlo simulation results reported in Table 3 highlight that the proposed control scheme is robust with respect to the model efficiency reduction, measurement errors, wind speed variations as well as faults. Indeed, in terms of nominal power generation, which is the main operational objective of the wind turbine in the full load region, the proposed pitch angle controller is able to keep the generated power very close to the nominal value.

Table 3. $NSSE\%$ index values.

| Fault Case | $NSSE\%$ |
|---|---|
| 1 | 11.31% |
| 2 | 10.14% |
| 3 | 11.85% |

Table 3 summarises the Monte-Carlo analysis results. As these simulations are performed under random noise processes 600 times, cumulatively, it can be concluded that the achievement of this objective is guaranteed by using the proposed controller. This highlights the robustness and reliability of the developed solution, in terms of nominal power generation. This is verified considering the NSSE% in Table 3. The deviation of the generated power from the nominal value is negligible for all the simulations with different measurement errors and faults. Even the worst cases, *i.e.*, the largest NSSE%, have led to small deviations.

## 7. CONCLUSION

This paper proposed a novel pitch actuator controller to improve the power regulation efficiency of the horizontal axis wind turbine. It also guaranteed safe operation with efficient wind energy conversion. The constrained control was designed, using data-driven approaches, to retain the rotor speed and the generated power within the safe-to-operate bounds. Therefore, the rotor overspeeding, the mechanical brake engagement, and the conservative energy conversion are avoided. The proposed fault tolerant controller was able to handle the uncertain wind speed variation effects without requiring accurate wind speed measurement, using the Nussbaum-type function. It was also able to compensate for pitch actuator faults and aerodynamic characteristic change. Accordingly, unplanned maintenance and consequent cost are reduced. Numerical simulations were performed to validate the effectiveness of the proposed controller under various faults. The Monte-Carlo tool was exploited for the evaluation of reliability and robustness against the model uncertainty and measurement noise. This paper suggests some future research issues that need to be investigated. One of the most crucial issues is the experimental analysis of the proposed scheme, which needs to be conducted before industrial applications. However, the development of the proposed solution for real wind turbines is promising. Furthermore, the numerical calculation of the captured wind energy can be evaluated, considering the reduced downtime, operation and maintenance costs. This can further highlight the economic benefits of the proposed controller.

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