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# Hardware–In–The–Loop Assessment of Fuzzy and Neural Network Fault Diagnosis Schemes for a Wind Turbine Model

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**Abstract:** The fault diagnosis of wind turbines includes extremely challenging aspects that motivate the research issues considered in this paper. In particular, this work studies fault diagnosis solutions that are considered in a viable way and used as advanced techniques for condition monitoring of dynamic processes. To this end, the work proposes the design of fault diagnosis techniques that exploits the estimation of the fault by means of data–driven approaches. These fuzzy and neural network structures are integrated with auto–regressive with exogenous input regressors, thus making them able to approximate unknown nonlinear dynamic functions with arbitrary degree of accuracy. The capabilities of fault diagnosis schemes are validated by using a real–time simulator of a wind turbine system. Moreover, at this stage the benchmark is also useful to analyse the robustness and the reliability characteristics of the developed tools in the presence of model–reality mismatch and modelling error effects featured by the wind turbine simulator. This realistic simulator relies on a hardware–in–the–loop tool that is finally implemented for verifying and validating the performance of the developed fault diagnosis strategies in an actual environment.



*Keywords:* Fault diagnosis, fuzzy logic, neural network, data–driven approach, hardware–in–the–loop tool, wind turbine system.

## 1. INTRODUCTION

Horizontal Axis Wind Turbines (HAWTs) have dominated the Wind Energy Conversion (WEC) industry over the last few decades [1,2]. 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 manufacturers 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 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. 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 conservative WEC control solutions. To this end, advanced control solutions relying on Fault Detection and Isolation (FDI) and Fault Tolerant Control (FTC) approaches represent the key point for WEC systems.

In the last decades several papers have investigated the problem of fault diagnosis for wind turbine systems, as addressed *e.g.* in (Lan et al. (2018); Harrabi et al. (2018)). Some of them have investigated the diagnosis of particular faults, see *e.g.* (Hossain et al. (2018); Leite et al. (2018); Lan et al. (2018)). In fact, sometimes the FDI can be enhanced if the WT subsystems are compared to other modules of the whole plant (Niemann et al. (2018)).

The first data–driven strategy proposed in this work exploits Takagi–Sugeno (TS) fuzzy prototypes (Babuška (1998)), which are estimated via a clustering algorithm and exploiting the data–driven algorithm developed in (Simani et al. (1999)). For comparison purpose, a further approach is designed, which exploits Neural Networks (NNs) to derive the nonlinear dynamic relations between the input and output measurements acquired for the process under diagnosis and the faults affecting the plant. The selected structures belong to the feed–forward Multi–Layer Perceptron (MLP) neural network class that include also Auto–Regressive with eXogenous (ARX) inputs in

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order to model nonlinear dynamic links among the data. In this way, the training of these Nonlinear ARX (NARX) prototypes for fault estimation can exploit standard back–propagation training algorithm, as recalled *e.g.* in (Korbicz et al. (2004)).

The designed fault diagnosis schemes are tested via a high–fidelity simulator of a wind turbine process, which describes its behaviour in healthy and faulty conditions. This simulator, which represents a benchmark (Odgaard et al. (2013)), includes the presence of uncertainty and disturbance effects, thus allowing to verify the reliability and robustness characteristics of the proposed fault diagnosis methodologies. Moreover, this work proposes to validate the efficacy of the designed fault diagnosis techniques by exploiting a more realistic scenario, which consists of a Hardware–In–the–Loop (HIL) tool.

## 2. WIND TURBINE SYSTEM

The Wind Turbine (WT) benchmark considered in this work for validation purposes was earlier presented in (Odgaard et al. (2009)) and motivated by an international competition. Despite its quite simple structure, it is able to describe quite accurately the actual behaviour of a three–blade horizontal–axis wind turbine that is working at variable–speed and it is controlled by means of the pitch angle of its blades. The plant includes several interconnected subsystems, namely the wind process, the wind turbine aerodynamics, the drive–train, the electric generator/converter, the sensor and actuator systems and the baseline controller. The overall system is sketched in Figure 1, which represents the fault diagnosis target developed in this work. Further details of the WT benchmark will not be provided here, as they were described in detail in (Odgaard and Stoustrup (2015)) and the references therein.

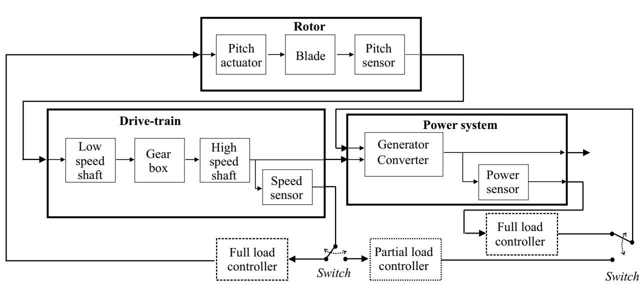


Fig. 1. The WT benchmark and its functional subsystems.

## 3. FAULT DIAGNOSIS DATA–DRIVEN SCHEMES

This section recalls the fault diagnosis strategy proposed in this paper that relies on FS and NN tools, as summarised in Section 3.1. These architectures are able to represent NARX models exploited for estimating the nonlinear dynamic relations between the input and output measurements of the WT process and the fault signals. In this sense, these NARX prototypes will be employed as fault estimators for solving the problem of the fault diagnosis of the WT system.

Under these assumptions, the fault estimators derived by means of a data–driven approach represent the residual generators $\mathbf{r}(k)$, which provide the on–line reconstruction $\hat{\mathbf{f}}(k)$ of the fault signals as described *e.g.* in (Farsoni and Simani (2021); Simani et al. (2021); Farsoni et al. (2021)).

### *3.1 Fault Estimators via Artificial Intelligence Tools*

The unknown dynamic relations between the selected input and output measurements of the WT plant and the faults are represented by means of FSs, which rely on a number of rules, antecedent and consequent functions. These rules are used to represent the inference system for connecting the measured signals from the system under diagnosis to its faults, in form of IF $\Longrightarrow$ THEN relations, implemented via the so–called Fuzzy Inference System (FIS) (Babuška (1998)). The implementation of these schemes follows the results already achieved *e.g.* in (Farsoni and Simani (2021); Simani et al. (2021); Farsoni et al. (2021)).

## 4. SIMULATION AND EXPERIMENTAL TESTS

This section presents and discusses the numerical simulations conducted on the high-fidelity 4.8 MW HAWT benchmark to evaluate the effectiveness of the proposed solutions. Different fault scenarios are applied to the benchmark, *i.e.*, single and simultaneous faults. It is shown that in both cases the considered constraints are not violated, satisfying the operation requirements. Uncertainties represent the key point in the case of offshore HAWTs. Indeed, in remote harsh locations, conversion and drivetrain efficiency reduction are unavoidable. This issue is important, as this may lead to less captured power. Accordingly, to assess the robustness of the proposed scheme, a Monte-Carlo analysis is performed with different measurement errors, modelled as Gaussian processes, and the model-reality mismatch.

### *4.1 Simulated Results*

The considered wind speed sequence 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 is only used. Under single and simultaneous fault scenarios, the results are also shown.

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, as illustrated in the addressed solutions, 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 here. 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 below, the proposed scheme is able to construct the bounds to handle the initial conditions outside of these bounds, as discussed in Section 2.

The reference pitch angle computed by the proposed controller is shown. The pitch angles are very similar to each other. Therefore, to accurately investigate the performance of the proposed solutions, the difference between these two pitch angles is considered. Considering the achieved results, it is clear that the main difference is in the periods that the pitch actuator bias and effectiveness loss commence. Considering the results below, the effects of the pitch actuator dynamic change have led to more variations.

Note that these reconstructed signals $\hat{f}(k)$ can be directly used as diagnostic residuals in order to detect and isolate the faults affecting the WT. Moreover, each fuzzy model with a number of delayed inputs and outputs $n = 3$ and $n_C = 4$ clusters. The results are shown in Figure 2.

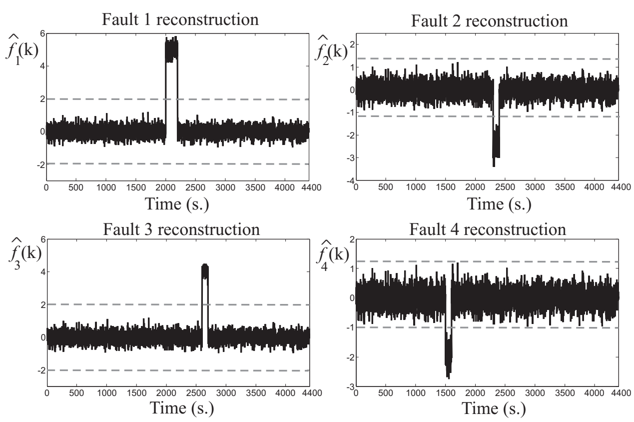


Fig. 2. Reconstructed faults $\hat{f}(k)$.

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 per-formed to assess the robustness and reliability of the proposed controller, in terms of nominal power generation, considering different measurement errors and the VAF% index. Additionally, it 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 FDI and drivetrain efficiency reduction are represented by the considered cases. The Monte-Carlo analysis is performed under a single fault scenario. For each case, 100 simulations are performed. For each simulation, the VAF% is computed over the simulation time. Then, the maximum, minimum, standard deviation and mean values of each VAF% index for each simulation are computed.

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 VAF% 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 below 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.

As for the FS case, it is reported also the values of the standard deviation of the estimation errors achieved by the neural network fault estimators.

Also in this case, Figure 3 depicts some of the residual signals $\hat{f}(k) = r_i(k)$ provided by the NARX NNs for the fault conditions 6, 7, 8, and 9, and compared with respect to the fixed detection thresholds (dotted lines).

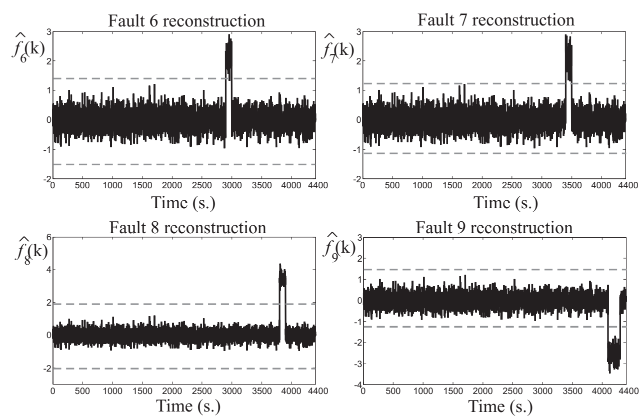


Fig. 3. Estimated faults for cases 6, 7, 8, and 9.

### 4.2 Hardware–In–The–Loop Experiments

The considered test–bed allows to reproduce experimental tests that are oriented to the verification of the results achieved in simulations. This test–bed is sketched in Figure 4, which highlights its 3 main modules.

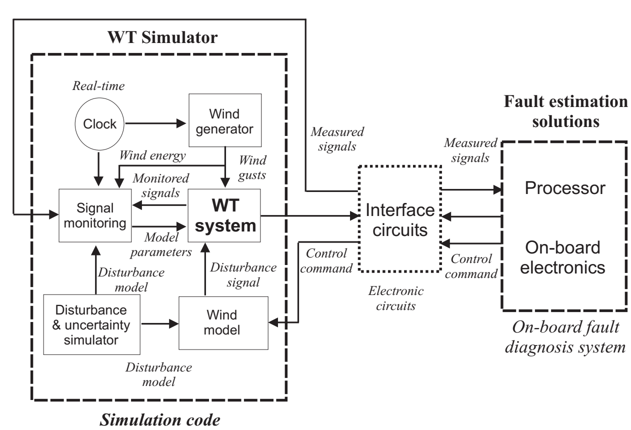


Fig. 4. HIL tool for real–time validation.

Table 1 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 VAF%. 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 VAF%, have led to small deviations.

The results achieved via this HIL tool are reported in Table 1 that summarises the capabilities of the fault diagnosis algorithms by means of the NSSE % performance index.

Table 1. RMSE % index for the HIL tool.

| Fault Case | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| TS FSs | 1.69% | 2.29% | 2.01% | 1.94% | 1.99% |
| NARX NNs | 0.99% | 0.98% | 0.99% | 1.28% | 1.21% |
| Fault Case | 6 | 7 | 8 | 9 | |
| TS FSs | 2.22% | 1.81% | 2.21% | 2.03% | |
| NARX NNs | 1.69% | 1.02% | 1.01% | 1.51% | |

## 5. CONCLUSION

This paper proposed a novel approach 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 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 controller was able to handle the uncertain wind speed variation effects without requiring accurate wind speed measurement, using data–drive approaches. 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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