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Residual Generator Fuzzy Identification for Wind Farm Fault Diagnosis

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Abstract: In the recent years the wind turbine industry has focused on optimising the cost of energy. One of the important factors in the achievement of this task consists of increasing the reliability of the wind turbines, which can be obtained using advanced fault detection and isolation strategies. Clearly, most faults are managed quite easily at a wind turbine control level. However, some faults are better dealt with at wind farm level, when the wind turbine is located in a wind farm. This paper aims at proposing a fault detection and isolation solution with application to a wind farm benchmark model. The considered benchmark includes a small wind farm of nine wind turbines, based on simple models of wind turbines, as well as the wind and interactions between wind turbines in the wind farm. The solution relies on a set of piecewise affine Takagi–Sugeno models, which are identified from the noisy measurements acquired from the simulated wind park. The design of the fault isolation strategy is also enhanced by the use of the proposed fuzzy approach. Finally, the wind park simulator is exploited for validating the achieved performances of the suggested methodology.

1. INTRODUCTION

A consequence of the increased level of wind generated power in power grids is that it has become more and more important that wind farms are reliable. It is clear that wind farms should be able to generate the power continuously, given the wind speed level. This means that possible faults in the wind turbines of the wind farm should be detected and isolated, in order to avoid any change in the generated power without introducing additional and more critical faults.

In the recent years, the research focus has been oriented to advanced Fault Detection and Isolation (FDI) of wind turbines. As an example, a model–based fault diagnosis system that detects faults was presented in (Chen et al. [2011]). An unknown input observer was designed for the detection of sensor fault of the wind turbine drive train in (Odgaard et al. [2009]). With reference to a wind turbine benchmark model described in (Odgaard and Stoustrup [2009]), several solutions were recently proposed in (Chen et al. [2011], Svard and Nyberg. [2011], Zhang et al. [2011]), whilst the achieved results were summarised in (Odgaard and Stoustrup [2012]). It is worth noting that regarding the wind farm issue, only a few works on condition monitoring and fault detection have been reported, see *e.g.* in (Kusiak and Verma [2011], Kusiak and Li [2011]).

In particular, many papers on model–based FDI were published over the last decade, using both signal– and process model–based methods. Unsurprisingly, these show that the more accurate the model is at describing the process behaviour, the better its performance will be in detecting anomalous conditions. Unfortunately, an accurate and complete mathematical model of such a complex system is usually unavailable, typically because of the assumptions introduced to reduce mathematical complexity. Hence, FDI schemes that relate to first principle models are costly to develop, while current alternatives tend to be mathematically complex or require considerable a priori knowledge to be incorporated into the monitoring scheme.

In this paper, the use of fuzzy identification is proposed through the wind farm process for finding a viable solution of the FDI problem. To this aim, three practical aspects of the presented work are stressed. Firstly, the system complexity may not indicate a requirement for a sophisticated physical model. In fact, as shown in this work, a fuzzy identification method can be successfully used, thus obviating the requirement for physical descriptions. In particular, the Errors–In–Variables (EIV) framework (Van Huffel and Lemmerling [2002]) and a proper identification algorithm is used in connection with fuzzy logic descriptions. Secondly, fuzzy prototypes for residual generation are considered instead of using purely nonlinear observer or filters. Moreover, as the purpose of system supervision is to monitor the conditions of the system in different working points, piecewise affine prototypes are successfully proposed (Simani et al. [1999]). Third, the fuzzy identification method enhances the design of the fault diagnosis scheme, and in particular, the development of the residual generator bank for fault isolation. The same methodology was successfully exploited in (Simani [2013]), but applied to real data from a diesel engine process. The benchmark model considered in this paper represents a small wind farm with nine 4.8MW wind turbines, which is described in (Odgaard and Stoustrup [2013]).

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The remainder of this paper is organised as follows. Section 2 describes the wind farm benchmark considered in this paper. Section 3 presents the structure of the fuzzy model, and briefly recalls how to integrate the well–established identification method for the estimation of TS systems within a general procedure for fuzzy identification. Section 4 addresses the design of the diagnostic scheme for FDI of the wind farm. The achieved results summarised in Section 5 seem to demonstrate the effectiveness of the technique proposed. Finally, some concluding remarks are reported in Section 6.

2. WIND FARM BENCHMARK DESCRIPTION

In this benchmark model a simple wind farm with 9 wind turbines is considered, arranged in a square grid layout (Odgaard and Stoustrup [2013]). The distance between the wind turbines in both directions are 7 times the rotor diameter, L. Two measuring masts are located in front of the wind turbines, one in each of the wind directions considered in this benchmark model, *e.g.* 0^o and 45^o. The wind speed is measured by these measuring masts and they are located in a distance of 10 times L in front of the wind farm. The wind turbines of the farm are defined by their row and column indices in the coordinate system illustrated in Fig. 1 (Odgaard and Stoustrup [2013]).

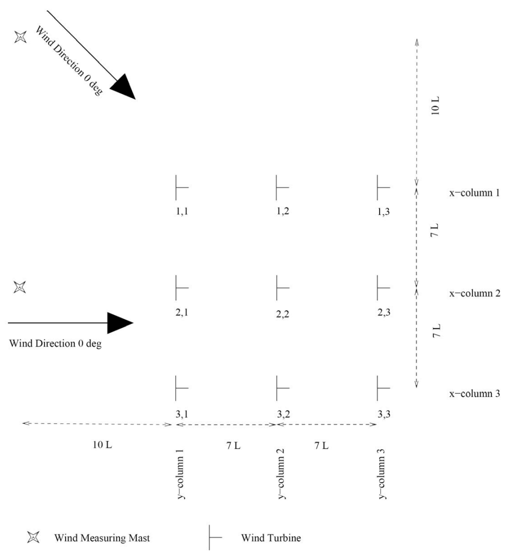

Fig. 1. Layout of the wind farm with 9 turbines of the square grid and the masts along the wind directions.

The farm uses generic 4.8MW wind turbines, which were described in (Odgaard and Stoustrup [2009]). The turbine is a three bladed horizontal axis, pitch controlled variable speed wind turbine. Each of the wind turbines are described by simplified models including control logics, variable parameters and 3 states. The i–th wind turbine model generates the electrical power, $P_{i\,g}(t)$, the collective pitch angle, $\beta_i(t)$, and the generator speed, $\omega_{i\,g}(t)$. Note that only one measured pitch angle is provided since it is assumed that the wind turbine controller regulates the pitch angles in the same way. The two scenarios with different wind directions but driven both by the same wind speed sequence $v_w(t)$ (possibly with a time shift) are considered. The wind sequence contains a wind mean speed increasing from 5 m/s. to 15 m/s, and with a peak value of about 23 m/s. In this benchmark model a very simple wind farm controller is used, which provides the wind turbine controllers with a power reference $P_{i\,ref}(t)$. If the wind farm is requested to generate a power lower than the available one, the references are evenly distributed among the wind turbine controllers. More details on wind farm model considered in this paper can be found in (Odgaard and Stoustrup [2013]). It is worth noting that the wind farm considered here could be seen as simplistic model. However, the work (Odgaard and Stoustrup [2013]) describes how the simulator can fit actual wind farm.

With these assumptions, the complete continuous–time description of the wind farm under diagnosis has the following form:

$$\begin{cases} \dot{x}_c(t) = f_c\left(x_c(t), u(t)\right) \\ y(t) \;\; = x_c(t) \end{cases} \qquad (1)$$

where $u(t) = [v_w(t),\, \beta_i(t)]^T$ and $y(t) = x_c(t) = [\omega_{i\,g}(t),\, P_{i\,g}(t)]^T$ are the input and the monitored output measurements, respectively. The subscript i indicates the measurement from the i–th wind turbine of the wind farm ($i = 1, \ldots, 9$). $f_c(\cdot)$ represents the continuous–time nonlinear function that will be approximated with the discrete–time fuzzy prototype from N sampled data of $u(t)$ and $y(t)$, and using the procedure presented in Section 3.

In this benchmark three faults are considered that influence the measured variables from the wind turbine, *i.e.* $\beta_i(t)$, $\omega_{i\,g}(t)$, and $P_{i\,g}(t)$. It is also assumed that the considered faults can be detected at a wind farm level by comparing the performance from other wind turbines in the wind farm, but they are difficult to detect at a wind turbine level. Moreover, these three faults affect different wind turbines at different times, as described in more detail in (Odgaard and Stoustrup [2013]).

The remainder of this section describes the relations among the fault cases considered above, and the monitored measurements acquired from the wind park benchmark, in the presence of uncertainty and measurement errors. In this way, it will be shown that the fault isolation task can be easily solved by using the fuzzy scheme proposed in this work, thus representing one of the main motivations of the suggested approach. In particular, Table 1 shows the fault effect distribution in the case of single fault occurrence, with respect to the acquired inputs and outputs of the wind park simulator.

Table 1. The FMEA results for the wind park benchmark.

Fault affecting wind turbine nr.	Selected measurements after FMEA	Fault case
$i = 2$ $i = 7$	$\{v_w(t),\, \omega_9(t),\, P_{4\,g}\}$	Fault 1
$i = 1$ $i = 5$	$\{v_w(t),\, \beta_2(t),\, P_{6\,g}\}$	Fault 2
$i = 6$ $i = 8$	$\{v_w(t),\, \beta_3(t),\, P_{7\,g}\}$	Fault 3

Table 1 was obtained by performing the so–called fault sensitivity analysis, *i.e.* the *Failure Mode & Effect Analysis* (FMEA) (Stamatis [2003]). In practice, Table 1 is thus built by selecting the most sensitive measurement (u_i or y_j) with respect to the simulated fault conditions. Obviously, when different fault conditions have been considered with respect to the scenario of this work, different measurements will probably be taken into account.

3. FUZZY MODELLING AND IDENTIFICATION

This section addresses the approach exploited for obtaining the mathematical description of the residual generators applied to the wind farm. In particular, the fuzzy identification scheme, which is recalled in Section 3, allows the design of the proposed fault diagnosis scheme shown in Section 4. In this study, TS fuzzy models are exploited (Babuška [1998]). The TS fuzzy model description is able to describe the global behaviour of the nonlinear system.

A large part of fuzzy modelling and identification algorithms (Babuška [1998]) share a common two–step procedure, in which at first, the operating regions are determined using heuristics or data clustering techniques. Then, in the second stage, the identification of the parameters of each submodel is achieved using the identification algorithm in particular already proposed by one of the authors in (Simani et al. [1999]), which can be seen as a generalisation of the classic least–squares. From this perspective, fuzzy identification can be regarded as a search for a decomposition of a nonlinear system, which gives a desired balance between the complexity and the accuracy of the model, effectively exploring the fact that the complexity of systems is usually not uniform. A suitable class of fuzzy clustering algorithms can be thus used for this decomposition purpose, and in particular, the Gustafson–Kessel (GK) fuzzy clustering is exploited in this work, and is available in (Babuška [2000]).

In the TS fuzzy models, the rule consequents are crisp functions of the model inputs:

$$R_i : \quad \textbf{IF } \mathrm{x} \text{ is } A_i \text{ THEN } y_i = f_i(\mathrm{x}) \tag{2}$$

where $i = 1, 2, \cdots, M$, $\mathrm{x} \in \Re^p$ is the input (antecedent) variable and $y_i \in \Re$ is the output (consequent) variable. R_i denotes the i–th rule, and M is the number of rules in the rule base. A_i is the antecedent fuzzy set of the i–th rule, defined by a (multivariate) membership function. The consequent functions f_i are typically chosen as instances of a suitable parameterised function, whose structure remains equal in all the rules and only the parameters vary. A simple and practically useful parameterisation of the function f_i is the affine form:

$$y_i = \mathrm{a}_i \, \mathrm{x} + b_i \tag{3}$$

where a_i is the parameter vector (regressand), and b_i is the scalar offset. $\mathrm{x} = \mathrm{x}(k)$ represents the regressor vector, which can contain delayed samples of $u(t)$ and $y(t)$. This discrete–time model can be written in a polytopic form as (Babuška [1998]):

$$y(k+1) = \frac{\sum_{i=1}^{M} \mu_i \left(\mathrm{x}(k)\right) \, y_i}{\sum_{i=1}^{M} \mu_i \left(\mathrm{x}(k)\right)} \tag{4}$$

where k here indicates the k–th sample. The *antecedent* fuzzy sets μ_i are extracted from the fuzzy partition matrix (Babuška [1998]). The *consequent parameters* a_i and b_i are estimated from the data using the procedure presented in (Simani et al. [1999]). This identification scheme exploited for the estimation of the TS model parameters has been integrated into the FMID toolbox for Matlab® by the author. This approach developed by the author is usually preferred when the TS model should serve as predictor, as it computes the consequent parameters via the Frisch scheme, developed for the Errors–In–Variables (EIV) descriptions (Van Huffel and Lemmerling [2002]). Therefore, after the clustering of the data has been obtained via the GK algorithm (Babuška [1998]), the data subsets are processed according the Frisch scheme identification procedure (Simani et al. [1999]), in order to estimate the TS parameters for each affine submodel.

4. FAULT DIAGNOSIS SCHEME DESIGN

This section addresses the problem of the detection and isolation of the faults affecting the process under diagnosis.

In the following, it is assumed that the monitored system in terms of input–output signals is modelled according to the EIV structure. The term y is the system output vector measurement, and u the control input vector. According to the EIV description, in realistic situations the variables u^* and y^* are measured by means of sensors, whose outputs are affected by noise.

Neglecting sensor dynamics, faults affecting the measured input and output signals u and y are modelled as:

$$\begin{cases} u = u^* + f_u \\ y = y^* + f_y \end{cases} \tag{5}$$

in which, f_u and f_y represent additive signals, which assume values different from zero only in the presence of faults.

There are different approaches to generate the diagnostic signals, *i.e.* the residuals (or symptoms), from which it will be possible to diagnose the considered fault cases. In this work, TS fuzzy prototypes are used as residual generators. The residual signals are generated by the comparison of the measured y and the estimated $\hat{y}$ output. The residual evaluation refers to a logic device which processes the redundant signals generated by the first block in order to detect when a fault occurs, and to univocally identify the unreliable actuator or sensor.

The fault detection task is performed by using the thresholding logic in (6):

$$\begin{cases} \bar{r} - \delta\,\sigma_r \leq r \leq \bar{r} + \delta\,\sigma_r \\ \text{if fault–free} \\ \\ r < \bar{r} - \delta\,\sigma_r \ \text{ or } \ r > \bar{r} + \delta\,\sigma_r \\ \text{if faulty} \end{cases} \tag{6}$$

In practice, the residual signal is represented by the stochastic variable r, whose mean and variance values are estimated from its samples $r(k)$ as follows:

$$\begin{cases} \bar{r} = \dfrac{1}{N} \displaystyle\sum_{k=1}^{N} r(k) \\ \\ \sigma_r^2 = \dfrac{1}{N} \displaystyle\sum_{k=1}^{N} \left[r(k) - \bar{r}\right]^2 \end{cases} \tag{7}$$

$\bar{r}$ and σ_r^2 are the values for the sample mean and variance of the fault–free residual, respectively. N is the number of samples $r(k)$ of the signal r. The values of $\bar{r}$ and σ_r^2 depend on the signal r statistics, which are usually unknown.

In order to separate normal from faulty behaviour, the tolerance parameter δ (normally $\delta \geq 2$) is selected and properly tuned. Hence, by a proper choice of this parameter δ, a good trade–off can be achieved between the maximisation of fault detection probability and the minimisation of false alarm rate. This parameter δ could be fixed with empirical rules or, once the values of $\bar{r}$ and σ_r^2 have been estimated from the r signal, using the 3–sigma rule. On the other hand, less conservative results could be obtained exploiting a procedure borrowed from the aerospace framework (Patton et al. [2010]), which leads to determine via extensive simulations the optimal δ minimising the false alarm rate and maximising the detection/isolation probability. This issue will be briefly considered in Section 5.

Finally, regarding the fault isolation problem, a Dedicated Observer Scheme (DOS) has to be exploited (Patton et al. [1989]). In particular, as described in Section 2, each fault affects different wind turbines, and therefore different measurements β_i, $\omega_{i\,g}$ and $P_{i\,g}$. Therefore, to uniquely isolate these faults concerning one of the inputs u or one of the outputs y of (1), a bank of fuzzy estimators (4) is used, as shown in Fig. 2.

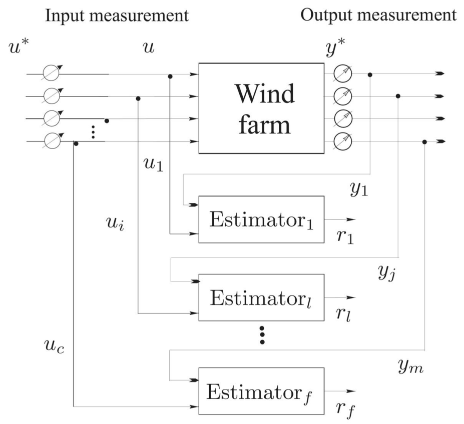

Fig. 2. Fuzzy estimator scheme for fault isolation.

The number of these fuzzy estimators (denoted with f) is equal to the number of residuals r_l required for the correct detection and isolation of the faults f_u and f_y. The number of measured input signals is c, whilst the number of available outputs is m. The l–th fuzzy estimator is driven by the i–th input u_i (or even more inputs, if necessary) and the j–th output y_j of the system, and generates a residual function r_l, which is sensitive to the fault affecting the i–th input u_i or the j–th output y_j. The identification procedure for these output fuzzy estimators follows the procedure described in Section 3. In particular, when the fuzzy estimator insensitive to the i–th input (or even more inputs, if necessary) and the j–th output has to be designed, the corresponding signals are exploited for the identification process. In this way, the fault isolation is possible, since a fault on the i–th input u_i or the j–th output y_j affects the particular residual r_l except that of the device which is insensitive to these signals, u_i and y_j.

5. SIMULATION RESULTS

The proposed methodology was applied to the identification, as well as the fault detection and isolation of the wind farm described in Section 2. The considered process input–output signals are the wind speed $v_w(t)$, the pitch angle $\beta_i(t)$, the generator speed $\omega_{i\,g}(t)$, the generated power $P_{i\,g}(t)$ from the i–th wind turbine of the wind farm. The available data from the measured inputs and outputs consist of 440×10^3 samples from normal operating records acquired with a sampling rate of 100 Hz.

According to Fig. 2, the required fault diagnosis residuals are implemented as a bank of TS fuzzy Multiple–Input Single–Output (MISO) models (4). Thus, by following the scheme of Fig. 2 and the isolation scheme described in Sections 2 and 4, the first fuzzy predictor used for the computation of the residual $r_1(t)$ is fed by the measurements $\{v_w(t),\, \omega_9(t),\, P_{4\,g}\}$, with $M = 5$ and $n = 2$. The second fuzzy estimator generating the residual r_2 is fed by the measurements $\{v_w(t),\, \beta_2(t),\, P_{6\,g}\}$, with $M = 5$ and $n = 2$. Finally, the third fuzzy estimator generating $r_3(t)$ is fed by the measurements $\{v_w(t),\, \beta_3(t),\, P_{7\,g}\}$, with $M = 5$ and $n = 2$. The membership degrees μ_j required by the fuzzy estimators (4) have been modelled with Gaussian functions, whose parameters have been estimated by the fuzzy clustering algorithm (Babuška [2000]).

Therefore, the complete fuzzy estimator strategy is obtained by following Table 2, as these estimators, organised into a bank structure, after the fault detection, allow to perform also the required fault isolation task, as described in Section 4 and Table 1.

Table 2. Wind farm measurement selection.

Residual signals for fault isolation	Fuzzy generator inputs	Fault case
$r_1(t)$	$\{v_w(t),\, \omega_9(t),\, P_{4\,g}\}$	Fault 1
$r_2(t)$	$\{v_w(t),\, \beta_2(t),\, P_{6\,g}\}$	Fault 2
$r_3(t)$	$\{v_w(t),\, \beta_3(t),\, P_{7\,g}\}$	Fault 3

In particular, the measurement selection is summarised in Table 2 and was obtained by considering the fault scenario described in Section 2. In practice, Table 2 is obtained by selecting the measurement (u_j and y_l) affected by the simulated fault conditions (fault 1, fault 2, and fault 3). Note also that, since each fault affects 2 different turbines of the wind farm, each fault is diagnosed by using the residual generator $r_h(t)$ depending on a set of input–output measurements from i–th wind turbine, as highlighted in Table 2.

The considered faults cause the alteration of the signals $u_i(t)$ and $y_j(t)$, and therefore of the residual $r_k(t)$ given by the predictive model (4). These residuals indicate the fault occurrence according to the logic (6), whether their values are lower or higher than the thresholds fixed in fault–free conditions.

By considering different test data sequences generated by the wind farm simulator, Table 3 reports the achieved Predicted Per Cent Reconstruction Error ($PPCRE$). These reconstruction errors for $r_k(t)$ in fault–free conditions are computed as the difference between the measurement and the corresponding output from the k–th fuzzy predictor. Since this error is normalised with respect to the output standard deviation, the $PPCRE$ index can be also seen as the percentage of data that are not correctly explained by the identified TS models. The values summarised in Table 3 indicate that the fuzzy prototypes are able to generate reliable residual signals for the wind farm fault diagnosis. Note that Table 3 highlights how the $PPCRE$ values in general increase when sequences different from the estimation data are used, *e.g.* the so–called validation and test sets.

Table 3. TS fuzzy model errors.

Data Set	PPCRE		
	r_1	r_2	r_3
Estim. data	0.90%	0.87%	0.92%
Valid. data	2.80%	1.80%	2.10%
Test data	4.20%	3.50%	4.00%

These identified TS fuzzy prototypes organised into the residual generator bank structure of Fig. 2 have led to the results summarised in Fig. 3.

In particular, Fig. 3 shows the residual $r_1(t)$ affected by the fault 1. The fault detection thresholds, which are highlighted in Fig. 3 with dashed lines, have been settled according (6) with $\delta = 3.1$.

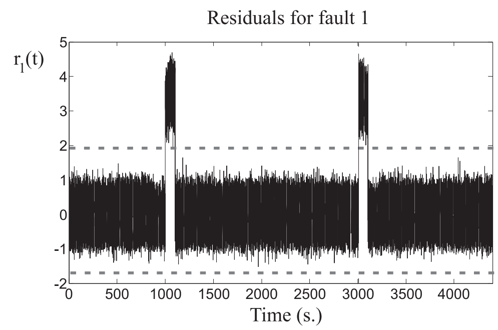

Fig. 3. (Solid black line) faulty residuals for fault 1 and (dashed grey line) detection thresholds.

As highlighted in Figs. 3 and 4, the fault 1 can be detected and isolated by the residual r_2 between 1000s. and 1100s., and by the signal r_1 from 3000s. to 3100s. On the other hand, Fig. 4 depicts the residual signal $r_2(t)$ for the FDI of the fault 2. Similar results have been obtained for the residual signal $r_3(t)$, but they will not be reported here for lack of space.

The non–zero values of the residuals when the faults are not acting on the wind turbines are due to modelling and measurement errors. A value of $\delta = 4.5$ has been selected, according to the logic of Section 4. Note that the fault detection thresholds reported in the relation (6) are represented as constant grey dashed lines in Fig. 3. Their values were properly settled by selecting δ, which leads to minimise the false alarm and missed fault rates, while maximising the correct detection and isolation rates.

In the remainder of this section, further experimental results have been reported regarding the performance evaluation of the developed FDI scheme with respect to

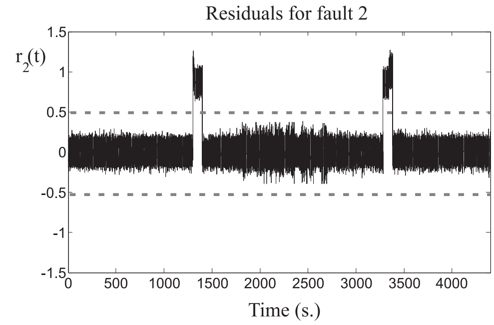

Fig. 4. (Solid black line) faulty residuals for fault 2 and (dashed grey line) detection thresholds.

modelling errors and measurement uncertainty. In particular, the simulation of different fault–free and faulty data sequences has been performed by exploiting the simulator capabilities described in Section 2 and a Matlab® *Monte–Carlo* analysis. In fact, the Monte–Carlo tool is useful at this stage as the FDI performances depend on the wind process, its realisations, and the residual errors. As remarked in Section 2, the wind farm benchmark is able to generate the required signals and the injection of realistic fault cases.

Moreover, it is assumed that the input–output data were affected by measurement errors. Thus, for performance evaluation, robustness and reliability analysis of the FDI scheme, some indices have been used. The performances of the FDI method are thus empirically evaluated on 500 Monte–Carlo runs. These indices are defined as:

False Alarm Rate (r_{fa}): the number of wrongly detected faults divided by total fault cases;

Missed Fault Rate (r_{mf}): for each fault, the total number of undetected faults, divided by the total number of times that the fault case occurs;

True Detection/Isolation Rate (r_{td}, r_{ti}): for a particular fault case, the number of times it is correctly detected/isolated, divided by total number of times that the fault case occurs;

Mean Detection/Isolation Delay (τ_{md}, τ_{mi}): for a particular fault case, the average detection/isolation delay time.

These criteria are computed off–line for each fault case. Table 4 summarises the results obtained by considering the fuzzy residual generators, and with a choice of the threshold parameter δ in (6) leading to achieve optimal results.

Table 4. Monte–Carlo analysis by monitoring residuals via (6) with optimal δ.

Fault	r_{fa}	r_{mf}	r_{td}, r_{ti}	τ_{md}, τ_{mi}	δ
1	0.002	0.003	0.997	0.75s	4.8
2	0.001	0.001	0.999	0.95s	4.5
3	0.002	0.003	0.997	0.60s	4.6

Table 4 shows that with the proper selection of the threshold levels depending on δ it is possible to achieve false alarm and missed fault rates of less than 0.3% and detection and isolation rates larger than 99.7%, with minimal detection and isolation delay times. The results demonstrate also that in this case, the Monte–Carlo analysis is an effective tool for experimentally testing the design robustness of the proposed FDI method with respect to error and uncertainty. This last simulation technique example hence facilitates an assessment of the reliability of the developed and applied FDI method to real test cases, as shown for example in (Simani [2013], Simani and Castaldi [2013b,a]).

6. CONCLUSION

This paper proposed a procedure for the fault detection and isolation of a wind park model using fuzzy prototypes estimated from uncertain input–output measurements. It is assumed that the process under investigation was nonlinear, and the available measurements were normally not very reliable, due to the wind speed uncertain nature. The fault diagnosis strategy considered here for residual generation was based on Takagi–Sugeno fuzzy models, which were able to describe the different operating conditions of the process. The proposed approach was exploited to generate redundant residuals, thus enhancing also the fault isolation task. The effectiveness of these strategies was tested on the data acquired from the wind park benchmark. The robustness and reliability properties were investigated via extensive Monte–Carlo experiments. Future investigations will concern the application of the diagnosis strategy to real wind farm installations.

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