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Results of a Wind Turbine FDI Competition

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Abstract: In this paper some newly published methods for fault detection and isolation developed for a wind turbine benchmark model are tested, compared and evaluated. These methods have been presented as a part of an international competition. The tested methods cover different types of fault detection and isolation methods, which include support vector machines, observer based methods, and auto generated methods. All of these methods show interesting potentials for usage in the wind turbine application, but all with different strong and weak sides in relation to the requirements specified in the proposed benchmark model.

Keywords: Wind Turbines, Fault Detection and Isolation.

1. INTRODUCTION

Today wind turbines contribute to a larger and larger part of the world's power production. At the same time the size of the standard turbine increases as well. Turbines in the megawatt size are expensive, and hence their reliability is expected to be high to generate as much energy as possible. The wind turbines are expected to produce with very short downtime. A way to contribute to ensure this consists in introducing advanced fault detection, isolation and accommodation systems on the wind turbines. In the state-of-the-art industrial wind turbines fault detection schemes are simple and are often conservative, which the fault accommodation mechanism is as well. Turbines are turned off even at simple faults to wait for service. (In addition to the FDI systems condition monitoring is used at the rotating parts.) Consequently, there is a need for usage of advanced fault detection, isolation and accommodation schemes in order to improve the on-time of the turbine, even though that might result in production with limited power for some faults. Some work has been performed on fault detection, isolation and accommodation on wind turbines; however these works only cover parts of the wind turbine, and they do not include comparisons of the performance of various schemes for detection of faults in various parts of the wind turbine.

In Wei et al. [2008] 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 the detection of sensor faults around the wind turbine drive train in Odgaard et al. [2009a]. In Sloth et al. [2010] active and passive fault tolerant control schemes are applied to a wind turbine model. More focus have been drawn on the electrical conversion system in the wind turbines. Some relevant examples can be found in Rothenhagen and Fuchs [2007] and Rothenhagen et al. [2007]. In the former, an observer based solution for current sensor fault detection is presented; the latter presents an observer based solution for voltage sensor fault detection. In Poure et al. [2007] a fault detection and reconfiguration solution handling faults in a doubly fed wind turbine converter is presented.

Comparing various detection and accommodation schemes on the wind turbine application is beneficial in the process of finding the best schemes to handle the various faults. In Odgaard et al. [2009b] a benchmark model for fault detection and isolation and fault tolerant control of wind turbines are presented. This benchmark model can be used as a platform for such a comparison for fault detection and isolation and fault tolerant control of wind turbines. This benchmark model describes a realistic generic three blade horizontal variable speed wind turbine with a full scale converter coupling. This generic turbine has a rated power at 4.8 MW. Since this model works on a system level, the fast control loops of the converters are not considered.

At IFAC World Congress 2011 two invited sessions were formed with different solutions proposed for the FDI part of the mentioned benchmark model. In this paper some of these proposed methods are compared both on test sequences defined in the benchmark, and in addition on a number additional test sets for testing robust of the proposed schemes to operational point of occurrence of the faults. The compared solutions can be seen in Chen et al. [2011], Laouti et al. [2011], Ozdemir et al. [2011], Svard and Nyberg [2011] and Zhang et al. [2011]. A number of other solutions have also been applied to this benchmark model, among these are: Ayalew and Pisu [2011], Blesa et al. [2011], Dong and Verhaegen [2011], Kiasi et al. [2011], Simani et al. [2011a], Simani et al. [2011b] and Stoican et al. [2011].

The paper is organized as follows. In Sec. 2 the wind turbine system and model is introduced. The used test signals are described in Sec. 3. In Sec. 4 the tested schemes are described. The schemes are evaluated in Sec 5, and the conclusion is drawn in Sec. 6.

2. SYSTEM DESCRIPTION

In this paper a generic wind turbine of 4.8 MW, which is described in Odgaard et al. [2009b] is used. It is a three bladed variable speed horizontal wind turbine.

2.1 Wind Turbine Model

The used wind turbine model are from, Odgaard et al. [2009b], and is not described in details in this paper, the details can be found in the mentioned paper. An overview of the model can be seen in Fig. 1.

The objective of the control system in the wind turbine is to follow the power reference; in case the wind speed is too low for the wind turbine to reach the power reference, the wind turbine controller will try to optimize the power production. This power control should keep the mechanical vibrations at an acceptable level. A system overview can be seen in Fig. 1. This figure shows the relations between: Blade & Pitch System, Drive Train, Generator & Converter, and Controller. The variables between these subsystems are defined as: v_w is the wind speed acting on the turbine blades, τ_w, is the torque from the wind acting on the turbine blades, τ_r, is the rotor torque, ω_r is the rotational speed of the rotor, τ_g, is the generator torque, ω_g, is the rotational speed of the generator, β_r, is the reference to the pitch position, β_m, is the measured pitch position, $\tau_{w,m}$, is an estimated wind torque based on a wind speed measurement, $\omega_{r,m}$, is the measured rotational speed of the rotor, $\omega_{g,m}$, is the measured rotational speed of the generator, $\tau_{g,m}$ is the measured generator torque, $\tau_{g,r}$, is the torque reference to the generator, P_r, is the power reference to the wind turbine, and P_g is power produced by the generator. The wind turbine controller provides three pitch references, and all three pitch positions are measured as well with two sensors to ensure physical redundancy of the pitch position measurements. The generator and rotor speeds are also measured with two sensors each for the same reason. These variables are defined as: β_{r1}, β_{r2}, β_{r3} for the pitch reference to Blade 1, 2 and 3. $\beta_{1,m1}$, $\beta_{1,m2}$, are the two pitch measurements for Blade 1, $\beta_{2,m1}$, $\beta_{2,m2}$, are the two pitch measurements for Blade 2, and $\beta_{3,m1}$, $\beta_{3,m2}$ are the two pitch measurement for Blade 3. The two rotor speed measurements are defined as $\omega_{r,m1}$, $\omega_{r,m2}$; the two generator speed measurements are defined as $\omega_{g,m1}$, $\omega_{g,m2}$.

More details on the model can be found in Odgaard et al. [2009b].

3. TEST SIGNALS DEFINITION

In the test signal definition described in Odgaard et al. [2009b] the defined faults are present at a predefined time. In this paper 6 additional test signals sets are defined by time shifting the occurrence of the defined faults, which test the robustness of the fault detection and isolation algorithms towards different operational points of the faults. 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 and can be seen in Fig. 2.

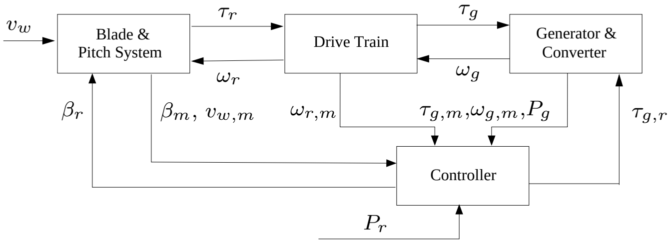

Fig. 1. This figure shows an overview of the benchmark model. It consists of four parts: Blade and Pitch Systems, Drive Train, Generator & Converter and Controller. The variables in the figure are defined as: v_w denotes the wind speed, τ_r is the rotor torque, ω_r is the rotational velocity of the rotor, τ_g is the generator torque, ω_g denotes the rotational velocity of the generator, β_r is the pitch angle reference, β_m denotes pitch position measurement, $v_{w,m}$ is the measured wind speed, $\omega_{r,m}$ denotes the measured rotational velocity of the rotor, $\tau_{g,m}$ denotes the measured generator torque, $\omega_{g,m}$ is the measured rotational velocity of the generator, P_g is the generated power, $\tau_{g,r}$ is the generator torque reference and P_r denotes the power reference to the wind turbine.

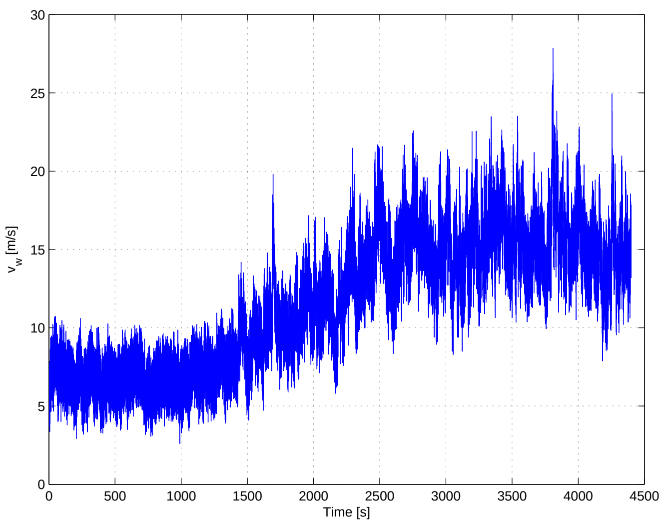

Fig. 2. Illustration of the wind speed sequence used in the benchmark model. It can be seen that the wind speed covers the range from 5 m/s to 20 m/s, with a few spikes at 25 m/s, which is good coverage of normal operational of a wind turbine.

In the listing of the possible faults, a subset is chosen for the benchmark test sequence.

The test includes 5 sensors faults, 3 actuator faults and 1 system fault. In the initial test set (Test Set 1) faults are presented in the same order as in Table 1. The time shift for the different test sets can be seen below.

- Test Set 2: +100s for all faults
- Test Set 3: -100s for all faults
- Test Set 4: -200s for all faults
- Test Set 5: -300s for all faults
- Test Set 6: -400s for all faults
- Test Set 7: -500s for all faults

Table 1. Faults considered in the benchmark model.

Fault No	Fault	Symbols	Type
1a)	Sensor Faults	$\Delta\beta_{1,m1}$, $\Delta\beta_{1,m2}$, $\Delta\beta_{2,m1}$, $\Delta\beta_{2,m2}$, $\Delta\beta_{3,m1}$, $\Delta\beta_{3,m2}$	Fixed Values
1b)	Sensor Faults	$\Delta\beta_{1,m1}$, $\Delta\beta_{1,m2}$, $\Delta\beta_{2,m1}$, $\Delta\beta_{2,m2}$, $\Delta\beta_{3,m1}$, $\Delta\beta_{3,m2}$	Gain Factor
2a)	Sensor Faults	$\Delta\omega_{r,m1}$, $\Delta\omega_{r,m2}$	Fixed Value
2b)	Sensor Faults	$\Delta\omega_{r,m1}$, $\Delta\omega_{r,m2}$	Gain Factor
3a)	Sensor Faults	$\Delta\omega_{g,m1}$, $\Delta\omega_{g,m2}$	Fixed Value
3b)	Sensor Faults	$\Delta\omega_{g,m1}$, $\Delta\omega_{g,m2}$	Gain Factor
4a)	Actuator Fault	$\Delta\tau_g$	Changed Dynamics
4b)	Actuator Fault	$\Delta\tau_g$	Offset
5a)	Actuator Fault	$\Delta\beta_1$, $\Delta\beta_2$, $\Delta\beta_3$ (Hydraulics)	Changed Dynamics
5b)	Actuator Fault	$\Delta\beta_1$, $\Delta\beta_2$, $\Delta\beta_3$ (Air in oil)	Changed Dynamics
6)	System Fault	$\Delta\omega_r$, $\Delta\omega_g$	Changed Dynamics

It should be noticed that the proposed schemes are not designed on the basis of Test Series 2 to 7.

In the following Test Set 1 is defined and the different measurement signals are plotted as well.

- Fault 1: fault type 1a) a fixed value on $\beta_{1,m1}$ equal to 5° in the time period from 2000 s to 2100 s.
- Fault 2: fault type 1b) a gain factor on $\beta_{2,m2}$ equal to 1.2 in the time period from 2300 s to 2400 s.
- Fault 3: fault type 1a) a fixed value on $\beta_{3,m1}$ equal to 10° in the time period from 2600 s to 2700 s.
- Fault 4: fault type 2a) a fixed value on $\omega_{r,m1}$ equal to 1.4 rad/s in the time period from 1500 s to 1600 s.
- 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 s to 1100 s.
- Fault 6: fault type 5a) change in the dynamics due to hydraulic pressure drop of the pitch actuator 2, the fault is assumed to be abrupt and it is present in the time period from 2900 s to 3000 s.
- 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; afterwards the fault is active during 40 s, and again decreasing during 30 s. The fault begins at 3500 s and ends at 3600 s.
- Fault 8: fault type 4b) an offset on τ_g of the value 100 Nm, the fault is active from 3800 s to 3900 s.
- Fault 9: fault type 6) and change in the friction in the drive train active from 4100 s to 4300 s.

These faults must be detected and handled according to the requirements given in Odgaard et al. [2009b]. In order to validate the false positive rate of the detection scheme, a set of data simulated on an advanced model of the wind turbine is provided for a fault free run on the same wind speed sequence.

The benchmark model package contains a wind speed sequence, a Simulink model with a parameter file. The package can be obtained at Odgaard [2010].

4. DESCRIPTION OF FDI SOLUTIONS

In this section, five solutions to the Wind Turbine Benchmark model is shortly introduced.

4.1 Gaussian Kernel Support Vector Machine solution (GKSV)

This solution is using a Support Vector Machine based on a Gaussian kernel is presented in Laouti et al. [2011], in which more details of the scheme can be found. In this design a vector x of features is defined for each fault which contains relevant signals obtained directly from measurements, filtered measurements or combinations of these. The number of features used is in the interval from 2 to 4 depending of the fault type.

These vectors are subsequently projected onto the kernel of the Support Vector Machine, which results in a residual for all the defined faults. Different kernels have been tested for the different faults but it was found that Gaussian kernel with different variance values can be used for all faults.

Data with and without faults were used for learning the model for FDI of the specific faults, based on this the vectors, kernel (structure and parameters) were found.

4.2 Estimation Based solution (EB)

The general outline of this scheme is that a fault detection estimator is designed to determine the presence of a fault, and an additional bank of N isolation estimators are designed to isolate the faults, where N is the number of faults considered. As described in Zhang et al. [2011], it is a preliminary and simplified implementation of the general method given in Zhang et al. [2008] and Zhang et al. [2002]. Specifically, the method in Zhang et al. [2011] is designed based on a linear system model and without the use of an adaptive threshold. The estimators used for fault detection and isolation are designed based on the provided models including model parameters. Each isolation estimators is designed based on a particular fault scenario under consideration.

4.3 Up-Down Counter solution (UDC)

In this solution up-down counters are used for decision of fault detection and isolation based on residuals for each of the faults. These residuals are obtained using both physical and analytical redundancy. The details of the solutions can be found in Ozdemir et al. [2011].

The fault detection and isolation residuals are based on residuals obtained by physical redundancy, parity equations, Kalman filters and low pass filters.

The used up-down counters differ from straightforward thresh holding in two ways. First, the decision to declare a fault involves discrete-time dynamics and is not simply a function of the current value of the residual. Second, up-count and down-count parameters introduce a penalty on the residual exceeding threshold.

4.4 Combined Observer and Kalman Filter solution (COK)

Details on this solution can be found in Chen et al. [2011]. This solution uses a diagnostic observer based residual generator for residual generation for the faults in the Drive Train, in which the wind speed also is considered as a disturbance. This diagnostic observer is designed to decouple the disturbance and simultaneously achieve the optimal residual generation in the statistical sense. For the other two subsystems, a Kalman filter based approach has been applied. The second part of the FD system is the residual evaluation. Based on the statistical properties of the residual signals, generalized likelihood ratio test and cumulative variance index are applied. For the fault isolation purpose, a bank of residual generators based on dual sensor redundancy is designed. Based on this, the sensor faults and system faults are isolated by a decision table. Since in the pitch subsystem, the sensor faults will directly influence the system through the feedback, which violates the fault isolation method, a compensation strategy of this influence in the FDI system is proposed.

4.5 General Fault Model solution (GFM)

This is an automatic generated solution for FDI; the details can be seen in Svard and Nyberg [2011]. The design method is composed of three main steps. In the first step, a large set of potential residual generators are generated. In the second step, the residual generators most suitable to be included in the final FDI-system are selected and then constructed by use of the algorithms presented in Svard and Nyberg [2010]. The selection is done by means of a greedy selection algorithm. In the third and final step, diagnostic tests for the selected set of residual generators are designed. The diagnostic tests are based on a comparison between the estimated probability distributions of residuals, evaluated with current and no-fault data.

5. EVALUATION OF SOLUTIONS

In this section the five solutions presented in Sec. 4 are compared on simulations with all 7 Test Series. The mean, minimum and maximum values of T_d, F_D and MD for the different methods are computed for all faults are computed. This means that these variables are computed for a given fault taking all simulations in all Test Series into account.

The following notation is used. $\overline{T}_d$ denotes the mean value of the detection time, $T_{d,min}$ denotes the minimum value of the detection time, $T_{d,max}$ denotes the maximum value of the detection time, $\overline{F}_D$ denotes the mean value of the number of false positive detections, $F_{D,min}$ denotes the minimum value of the number of false positive detections, $F_{D,max}$ denotes the maximum value of the number of false positive detections,$\overline{T}_d$ denotes the mean percent of missed detection in a Test Series, $T_{d,min}$ denotes the minimum percent of missed detections in a Test Series, Md_{max} denotes the maximum percent of missed detections in a Test Series. The results of the evaluation are shown in Table 2 for Fault #1-4 and in Table 3 for Fault #5-8, and if a given fault is detected in all simulations the missed detection values are not included in the able. None of the proposed schemes were designed for the detection and isolation of Fault # 9, so these are not included in the Table.

Some general points can be seen from these tests. All schemes only detect Fault # 8 in Test Series 1, (which they are designed for). The reason for this is the ratio between the offset and the torque reference is relatively large at the time of the fault, compared with the other time locations of the fault. All of the schemes have problems detecting and isolating Fault # 2 for the higher Test Series numbers. This fault is a gain factor on one of the pitch sensors and the mentioned Test Series include a low level of pitch values since the wind speed is low. Actually an active fault tolerant scheme would be better for these faults as proposed in Sloth et al. [2010].

Some more method specific observations are made based on the evaluations in the following.

GKSV only detects and isolates the sensor faults Fault 1-5. Faults # 1,3 and 4 are detected within the requirements in all Test Series without any false positive detections. For those faults this scheme is independent on the time location of the faults and thereby the point of operation at which the faults occurs. This scheme seems to robust towards change operational points of the wind turbine, and also only shown to work on sensor faults.

EB in general detects and isolates the faults fast for the original Test Series and slower as the fault time locations moves away from the Test Series 1. It also results in a high number of false positive detections for some faults.

UDC detects and isolates almost all faults in all Test Series and for most of the faults relatively fast, but with some false positive detections. This scheme is thereby relatively robust towards the operational point at which the faults occur.

COK detects and isolates most of the faults in all Test Series, however, slowly and for most of the faults slower than required, also a few false positive detections are present for most faults.

GFM detects and isolates all faults, (except Fault # 8), in all Test Series slowly and with some false positive detections. In general this scheme performs relatively better than the others as the faults are shifted longer and longer away from their time locations in Test Series 1. This scheme thereby seems to be robust towards to the point of operation at which the faults occurs.

6. CONCLUSION

This paper present some results of tests of scheme designed for and applied to the Wind Turbine FDI benchmark model, in addition to the original test sequences from the benchmark model, seven additional Test Series with different time locations of the faults, which corresponds to different operating points at which the faults occurs are included to test robustness of the proposed and tested schemes. Five different FDI schemes designed for the benchmark model are evaluated on all these seven Test Series.

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Table 2. Results of the evaluation Fault 1-4

Fault #	GKSV	EB	UDC	COK	GFM
1	$\overline{T}_d = 0.02[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 0.02[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 0.02[s]$, $T_{d,min} = 0.01[s]$, $T_{d,max} = 0.02[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 3\%$, $MD_{min} = 0\%$, $Md_{max} = 20\%$	$\overline{T}_d = 0.03[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 0.03[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 10.32[s]$, $T_{d,min} = 10.23[s]$, $T_{d,max} = 10.33[s]$, $\overline{F}_D = 0.89$, $F_{D,min} = 0$, $F_{D,max} = 1$	$\overline{T}_d = 0.04[s]$, $T_{d,min} = 0.03[s]$, $T_{d,max} = 0.04[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$
2	$\overline{T}_d = 47.24[s]$, $T_{d,min} = 3.23[s]$, $T_{d,max} = 95.09[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 56\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 44.65[s]$, $T_{d,min} = 0.63[s]$, $T_{d,max} = 95.82[s]$, $\overline{F}_D = 22$, $F_{D,min} = 16$, $F_{D,max} = 28$, $\overline{MD}_D = 56\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 69.12[s]$, $T_{d,min} = 7.60[s]$, $T_{d,max} = 95.72[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 67\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 19.24[s]$, $T_{d,min} = 3.43[s]$, $T_{d,max} = 49.93[s]$, $\overline{F}_D = 0.97$, $F_{D,min} = 0$, $F_{D,max} = 5$	$\overline{T}_d = 13.70[s]$, $T_{d,min} = 0.38[s]$, $T_{d,max} = 25.32[s]$, $\overline{F}_D = 3.08$, $F_{D,min} = 1$, $F_{D,max} = 18$
3	$\overline{T}_d = 0.02[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 0.02[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 0.54[s]$, $T_{d,min} = 0.51[s]$, $T_{d,max} = 0.76[s]$, $\overline{F}_D = 4$, $F_{D,min} = 1$, $F_{D,max} = 11$, $\overline{MD}_D = 3\%$, $MD_{min} = 0\%$, $Md_{max} = 20\%$	$\overline{T}_d = 0.04[s]$, $T_{d,min} = 0.03[s]$, $T_{d,max} = 0.10[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 3\%$, $MD_{min} = 0\%$, $Md_{max} = 20\%$	$\overline{T}_d = 10.35[s]$, $T_{d,min} = 1.54[s]$, $T_{d,max} = 10.61[s]$, $\overline{F}_D = 1.42$, $F_{D,min} = 1$, $F_{D,max} = 4$	$\overline{T}_d = 0.05[s]$, $T_{d,min} = 0.03[s]$, $T_{d,max} = 0.06[s]$, $\overline{F}_D = 1.61$, $F_{D,min} = 1$, $F_{D,max} = 5$
4	$\overline{T}_d = 0.11[s]$, $T_{d,min} = 0.09[s]$, $T_{d,max} = 0.18[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 0.33[s]$, $T_{d,min} = 0.27[s]$, $T_{d,max} = 0.44[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 0.02[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 0.02[s]$, $\overline{F}_D = 1$, $F_{D,min} = 1$, $F_{D,max} = 8$	$\overline{T}_d = 17.67[s]$, $T_{d,min} = 0.03[s]$, $T_{d,max} = 0.46[s]$, $\overline{F}_D = 2.31$, $F_{D,min} = 0$, $F_{D,max} = 5$	$\overline{T}_d = 0.10[s]$, $T_{d,min} = 0.03[s]$, $T_{d,max} = 0.34[s]$, $\overline{F}_D = 3.36$, $F_{D,min} = 1$, $F_{D,max} = 18$

Table 3. Results of the evaluation Fault 5-8

Fault #	GKSV	EB	UDC	COK	GFM
5	$\overline{T}_d = 25.90[s]$, $T_{d,min} = 1.24[s]$, $T_{d,max} = 87.49[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 3\%$, $MD_{min} = 0\%$, $Md_{max} = 20\%$	$\overline{T}_d = 0.01[s]$, $T_{d,min} = 0.01[s]$, $T_{d,max} = 0.01[s]$, $\overline{F}_D = 117$, $F_{D,min} = 95$, $F_{D,max} = 142$	$\overline{T}_d = 2.96[s]$, $T_{d,min} = 0.38[s]$, $T_{d,max} = 21.08[s]$, $\overline{F}_D = 0.75$, $F_{D,min} = 0$, $F_{D,max} = 3$	$\overline{T}_d = 31.32[s]$, $T_{d,min} = 1.54[s]$, $T_{d,max} = 91.13[s]$, $\overline{F}_D = 0.26$, $F_{D,min} = 0$, $F_{D,max} = 2$, $\overline{MD}_D = 14\%$, $MD_{min} = 0\%$, $Md_{max} = 40\%$	$\overline{T}_d = 9.49[s]$, $T_{d,min} = 0.56[s]$, $T_{d,max} = 17.18[s]$, $\overline{F}_D = 2.42$, $F_{D,min} = 1$, $F_{D,max} = 18$
6	$\overline{MD}_D = 100\%$, $MD_{min} = 100\%$, $Md_{max} = 100\%$	$\overline{T}_d = 11.31[s]$, $T_{d,min} = 0.06[s]$, $T_{d,max} = 55.27[s]$, $\overline{F}_D = 2$, $F_{D,min} = 0$, $F_{D,max} = 20$	$\overline{T}_d = 11.81[s]$, $T_{d,min} = 0.53[s]$, $T_{d,max} = 55.72[s]$, $\overline{F}_D = 22$, $F_{D,min} = 15$, $F_{D,max} = 25$	$\overline{T}_d = 23.80[s]$, $T_{d,min} = 0.33[s]$, $T_{d,max} = 64.95[s]$, $\overline{F}_D = 0.03$, $F_{D,min} = 0$, $F_{D,max} = 3$	$\overline{T}_d = 15.52[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 61.13[s]$, $\overline{F}_D = 3.67$, $F_{D,min} = 1$, $F_{D,max} = 37$
7	$\overline{MD}_D = 100\%$, $MD_{min} = 100\%$, $Md_{max} = 100\%$	$\overline{T}_d = 26.07[s]$, $T_{d,min} = 3.33[s]$, $T_{d,max} = 52.66[s]$, $\overline{F}_D = .36$, $F_{D,min} = 1$, $F_{D,max} = 5$	$\overline{T}_d = 12.93[s]$, $T_{d,min} = 2.86[s]$, $T_{d,max} = 51.08[s]$, $\overline{F}_D = 2$, $F_{D,min} = 1$, $F_{D,max} = 4$	$\overline{T}_d = 34.00[s]$, $T_{d,min} = 17.22[s]$, $T_{d,max} = 52.93[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$	$\overline{T}_d = 31.70[s]$, $T_{d,min} = 0.61[s]$, $T_{d,max} = 180.70[s]$, $\overline{F}_D = 1.25$, $F_{D,min} = 1$, $F_{D,max} = 5$
8	$\overline{T}_d = 0.01[s]$, $T_{d,min} = 0.01[s]$, $T_{d,max} = 0.01[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 97\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 0.01[s]$, $T_{d,min} = 0.01[s]$, $T_{d,max} = 0.01[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 97\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 0.02[s]$, $T_{d,min} = 0.02[s]$, $T_{d,max} = 0.02[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 97\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 0.00[s]$, $T_{d,min} = 0.00[s]$, $T_{d,max} = 0.00[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 97\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$	$\overline{T}_d = 7.92[s]$, $T_{d,min} = 7.92[s]$, $T_{d,max} = 7.92[s]$, $\overline{F}_D = 0$, $F_{D,min} = 0$, $F_{D,max} = 0$, $\overline{MD}_D = 97\%$, $MD_{min} = 0\%$, $Md_{max} = 100\%$