



FAULT DIAGNOSIS OF SENSORS, ACTUATORS AND WIND TURBINE SYSTEM

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Abstract

The production capacity of installed wind power greatly increases in worldwide. Hence the interest is focused on the reliability and efficiency of wind turbines; then to reduce the production cost and increase the yield. The main objective of our research in this work is to diagnose wind system. We presented a state of the art of diagnosis approach applied on wind turbines and various occurred faults which should be detected and isolated in the wind turbine parts. After that, an overview on this proposed solution for wind turbines, which opted for a diagnostic strategy based on support vector machines (SVM). A Benchmark of a wind power of 4.5 MW with faults on sensors, actuators and the systems was presented. Defects of the Benchmark are in the pitch system, the drive system, the generator and the converter. We tested then the effectiveness of the used method by visualizing simulation results of diagnosis in two different scenarios.

Keywords: wind turbine, benchmark, faults, modeling, diagnosis, SVM, FDI.

1. ABBREVIATIONS AND ACRONYMS

<i>FDI</i>	<i>Fault Detection and Isolation</i>	
<i>SVM</i>	<i>Support Vector Machine</i>	
ρ	<i>Density of air</i>	<i>Kg/m²</i>
C_p	<i>power coefficient</i>	
$C_q(\lambda, \beta)$	<i>Coefficient of aerodynamic torque</i>	
λ	$\lambda = w_r R / v_w$ <i>Tip speed ratio</i>	
R	<i>Blade rays</i>	<i>m</i>
v_w	<i>Wind speed</i>	<i>m/s</i>
$\tau_{g,m}$	<i>Real torque of the generator</i>	<i>Nm</i>
β	<i>Pitch angle</i>	<i>deg</i>
$\beta_{k,m}, \beta_{k,d}$	<i>Measured and desired pitch angle</i>	<i>deg</i>
w_n	<i>Natural pulsation</i>	<i>rad/s</i>
ζ	<i>Damping coefficient</i>	
J_r	<i>Moment of inertia of the shaft at low speed</i>	<i>Kg.m²</i>
$\tau_{g,r}$	<i>Desired torque of the generator</i>	<i>Nm</i>
τ	<i>Constant time ($\tau = 0.02$)</i>	<i>s</i>
$w_{p,m}$	<i>($p=g$ or m) Measured speed of the generator and the rotor</i>	<i>rad/s</i>
J_g	<i>Moment of inertia of the shaft at high speed</i>	<i>Kg.m²</i>
K_{dt}	<i>Torsional rigidity of training</i>	<i>Nm/rad</i>
B_{dt}	<i>Coefficient of damped torsion</i>	<i>Nm/(rad/s)</i>
$\theta_{\Delta}(t)$	<i>Angle of torsion</i>	
η_{dt}	<i>Performance of the drive train</i>	
T_e, T_D	<i>Sampling time and detection time</i>	<i>s</i>
N_g	<i>Gear ratio</i>	
B_g	<i>Viscous friction of the shaft at high speed</i>	<i>Nm/(rad/s)</i>
τ_g, τ_r	<i>Generator Rotor torques</i>	<i>Nm</i>
w_r, w_g	<i>Rotational speed of the generator and the rotor</i>	<i>rad/s</i>
P_g	<i>Power produced by the generator</i>	<i>Watt (W)</i>
$\hat{\beta}$	<i>Filtered value of β</i>	<i>deg</i>
\hat{w}	<i>Filtered value of w</i>	<i>rad/s</i>

1. INTRODUCTION AND RELATED WORK

Renewable energies are modes of production of energy using forces or resources whose stocks are unlimited [1]. Mastering these new energies requires progress not only in technology but also in science in order to meet the increased energy demands worldwide [2]. The availability of advanced numerical methods along with improvement in the energy systems capabilities is opening new doors of opportunity for the development of technologies used in condition monitoring of these systems [3].

Various studies on wind turbine failure analysis have shown that the major occurred faults are bearing faults, gear faults, brake failure, generator problem, blade fault, wind tower faults, Blade issues and much more [4], [5]. Faults no matter where they are in wind turbine, cause abnormalities of various subsystems, which are reflected by the appearance of a significant harmonics [4], [6]. Diagnostic approach helps to obtain better operation of these systems to maximize the generation of electricity at a minimal cost while respecting safety conditions [7].

In recent years there has been some works on the problem of fault diagnosis in wind turbines including observer based on the detection of sensor faults in the wind turbine. In this method an observer based regime is proposed to detect sensor faults in wind turbines. A model of the chain transmission is used to design the observer in which the wind speed is an important input. The regime is applied to a set of sensor faults in terms of gain factor on the measurements [4], [8].

The paper is organized as follows:

- The first part contains the Benchmark modeling of the different subsystems of the wind turbine conversion system;
- The second part focuses on the FDI based on the support vector machine in which details of ten faults are given;
- The third part is dedicated to the results of simulation for two scenarios of detection and isolation of faults.

At last a conclusion was drawn.

2. WIND TURBINE MODELLING

The modeling of the wind turbine mainly represents its aerodynamic, mechanical and electrotechnical characteristics [2], [13]. The model studied is a turbine reference model including sensor, actuator and system faults.

This model describes a specific type of variable speed wind turbine, with a three-axis horizontal axis, a nominal power of 4.8 MW, and a complete converter. The reference model is described by Simulink diagram composed of the different

subsystems of the wind turbine. This turbine model includes the following four blocks as presented in Fig. 1 [14] [15].

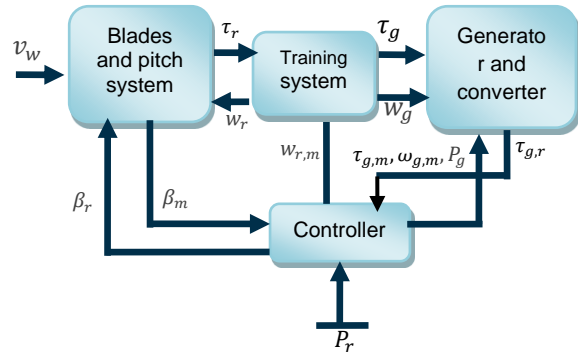


Fig. 1. Simulink scheme of the benchmark model of the wind turbine

2.1. Blades and rigging system

This block is a combination of the aerodynamic model and the blade timing model. The aerodynamic torque acting on the blades is given as follows:

$$\tau_r(t) = \frac{\rho \pi R^3 c_q(\lambda(t), \beta(t), v_w(t)^2)}{2} \quad (1)$$

The hydraulic actuator can be modeled by a 2nd order transfer function with constraints on each blade:

$$\frac{\beta_{k,m}(s)}{\beta_{k,d}(s)} = \frac{w_n^2}{s^2 + 2\zeta w_n s + w_n^2} \quad (2)$$

2.2. The converter and the generator

The dynamics of the converter are modeled by a transfer function of the 1st order :

$$\frac{\tau_{g,m}(s)}{\tau_{g,r}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \quad (3)$$

The produced power by the generator is:

$$P_g(t) = \eta_g w_g(t) \tau_g(t) \quad (4)$$

2.3. Training system

The "drive train" drive system is modeled by a model with three state variables taking into account the inertia of the generator and the rotor. The dynamics of this system are given as follows [16]:

$$\begin{bmatrix} \dot{w}_r(t) \\ w_g(t) \\ \theta_\Delta(t) \end{bmatrix} = A \begin{bmatrix} w_r(t) \\ w_g(t) \\ \theta_\Delta(t) \end{bmatrix} + B \begin{bmatrix} \tau_r(t) \\ \tau_g(t) \end{bmatrix} \quad (5)$$

with :

$$A = \begin{bmatrix} \frac{-Bdt-B}{J_r} & \frac{Bdt}{N_g J_r} & \frac{-Kdt}{J_r} \\ \frac{\eta dt B dt}{N_g J_g} & \frac{-\eta dt B dt}{N_g^2} - B_g & \frac{\eta dt K dt}{N_g J_g} \\ 1 & -\frac{1}{N_g} & 0 \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & -\frac{1}{J_g} \\ 0 & 0 \end{bmatrix}$$

2.4. Controller

The wind speed determines the area of operation of the controller and therefore the wind machine. The controller operates mainly in four areas: the start of the turbine, the optimization of the power, the constant production of the power, the high speed of the wind [5], [14].

In this model, there are different types of faults that can appear in the different subsystems of the reference model. Among these defects we have: sensor faults and actuator faults.

3. FAULT DETECTION AND ISOLATION

FDI's strategy will be based on Support Vector Machines (SVM) and consists in creating specific characteristics for each defect. Among these characteristics is the residue. SVM classification is used to evaluate generated residues in order to conclude on the system's operating status. SVM defect detection is developed in two parts. First, a set of data with and without defects is used to learn the detection patterns of each defect by using a given wind sequence as input. The obtained models are validated on a new fault scenario] [13], [14].

The key idea in learning a new model for SVM defect detection is the definition of the vector x to be used for classification. For each type of fault, a vector is defined.

Fixed value type (1a): The vector used for detection and isolation is:

$$x = \begin{bmatrix} |\hat{\beta}_{k,m1}(t_j) - \hat{\beta}_{k,m2}(t_{j-1})| \\ |\hat{\beta}_{k,m1}(t_j) - \hat{\beta}_{k,m1}(t_{j-1})| \\ |\hat{\beta}_{k,m2}(t_j) - \hat{\beta}_{k,m2}(t_{j-1})| \end{bmatrix} \quad (6)$$

Where t_j and t_{j-1} are respectively the instants of time j and $j-1$ and $\hat{\beta}$ is the filtered value of β .
Gain type (1b): This fault is detected and isolated in two steps. First the defect is detected using the vector:

$$x = \begin{bmatrix} |\hat{\beta}_{k,m1}(t_j) - \hat{\beta}_{k,m2}(t_j)| \\ |\hat{\beta}_{k,m1}(t_j) - \hat{\beta}_{k,m1}(t_{j-1})| \\ |\hat{\beta}_{k,m2}(t_j) - \hat{\beta}_{k,m2}(t_{j-1})| \end{bmatrix} \quad (7)$$

The second and third lines exclude type 1a defects. If the type b fault is detected, it is isolated between the sensors 1 and 2 by the vector:

$$x = \begin{bmatrix} |\hat{\beta}_{k,d}(t_j) - \hat{\beta}_{k,m1}(t_j)| \\ |\hat{\beta}_{k,d}(t_j) - \hat{\beta}_{k,m2}(t_j)| \end{bmatrix} \quad (8)$$

Where $\beta_{k,d}$ is the desired value of pitch angle β_k .

Fixed Value Types 2a and 3a: The following vector is used for detection and isolation:

$$x = \begin{bmatrix} |\hat{w}_{p,m1}(t_j) - \hat{w}_{p,m2}(t_j)| \\ |w_{p,m1}(t_j) - w_{p,m1}(t_{j-1})| \\ |w_{p,m2}(t_j) - w_{p,m2}(t_{j-1})| \end{bmatrix}, p = g, r \quad (9)$$

For defects 4 and 6, the following vector is used:
 $x =$

$$\begin{bmatrix} |w_{g,m1}(t_j) - w_{g,m2}(t_j)| \\ |\tau_{g,r}(t_j) - \tau_{g,m}(t_j)| \\ \lambda_2 |w_g^d(t_j) - (w_{g,m1}(t_j) + w_{g,m2}(t_j))/2| \end{bmatrix} \quad (10)$$

Where $w_g^d = \frac{P_r}{\tau_{g,r}}$ is the speed of the desired generator. The factor $\lambda_2 = 10^{-10} * v_w^6$ is used to account for wind speed and for normalization.

For defects 5a and 5b, the following vector is used for detection and isolation:

$$x = \begin{bmatrix} |w_{g,m1}(t_j) - w_{g,m2}(t_j)| \\ |\beta_{k,m1}(t_j) - \beta_{k,m2}(t_j)| \\ |\beta_{k,m1}(t_j) - \beta_{k,m1}(t_{j-1})| \\ |\beta_{k,m2}(t_j) - \beta_{k,m2}(t_{j-1})| \end{bmatrix} \quad (11)$$

Table. Parameters and requirements of faults handled by the FDI

Nr of fault	Type of fault	Parameters	Time period
1	1a	$\beta_{1,m1} = 5^\circ$	2000 s – 2100 s
2	1b	$\beta_{2,m2} = 1.2\beta_{2,m2}$	2300 s – 2400 s
3	1a	$\beta_{3,m1} = 10^\circ$	2600 s – 2700 s
4	2a	$w_{r,m1} = 1.4rad/s$	1500 s – 1600 s
5	2b and 3b	$w_{r,m2} = 1.1w_{r,m2}$ and $w_{g,m1} = 0.9w_{g,m1}$	1000 s – 1100 s
6	5a	Sudden change (actuator of pitch 2)	2900 s – 3000 s
7	5b	Slow change (actuator of pitch 3)	Faults start at 3500 s and finish at 3600 s
8	4a	$\tau_g = \Delta\tau_g + 2000 Nm$	3800 s – 3900 s

3. SIMULATION RESULTS

The benchmark model of wind energy we use is the model developed by kk-electronic. Afterwards, we will apply our diagnostic system to this model. The nominal operating case corresponds to the reference parameters of the benchmark given in appendix A [15].

Fig. 1 and Fig. 2 show respectively the evolution as a function of time of the wind speed (the input) and the electric power generated (the output). It is clear that there is a great relationship between the wind speed and the generated electric power. The power is maximum when the wind speed reaches a certain value [17].

$$v_w[m/s] = f(t[s])$$

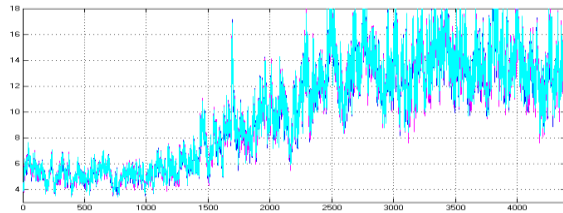


Fig. 1. Wind speed

$$P_g[W] = f(t[s])$$

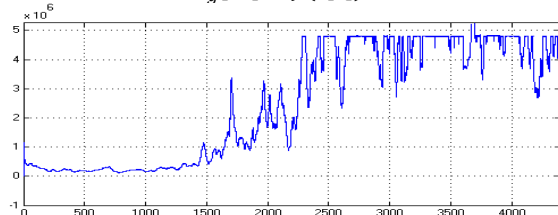


Fig. 2. Generated electric power in nominal operating

Two fault scenarios were used, in which we vary the reference parameters and the requirements in terms of detection and isolation time as shown in the appendix B.

3.1. Scenario 1

Five faults were detected and isolated simultaneously in this scenario. Fig. 3 shows the electrical power generated in this scenario. We find that the production of energy is influenced by the command. We observe a fault between the instants 2000 s and 2200 s. This is due to a fault in the drive system.

$$P_g[W] = f(t[s])$$

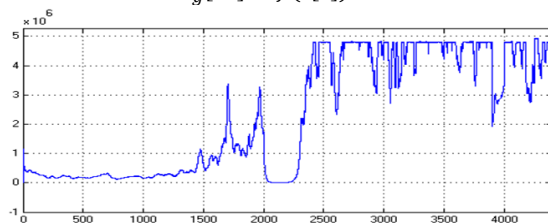
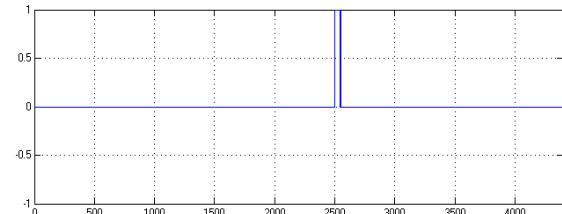


Fig. 3. Electrical power generated in scenario 1

There is no fault coming from the sensor $\beta_{2,m1}$ so the measurement error on pitch 2 comes from the sensor $\beta_{2,m2}$. Fig. 4 shows the decision result of fault 2 in the sensor $\beta_{2,m2}$ as well as the measurement of the sensor $\beta_{2,m2}$. We notice that the fault appears between the instants 2500s and 2600s. It is detected at the moment 2500.03 s and well isolated [16], [17].

Fault



$$\beta_{2,m2}[deg] = f(t[s])$$

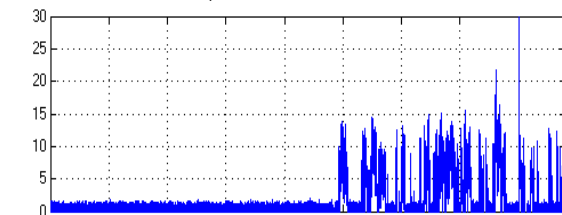
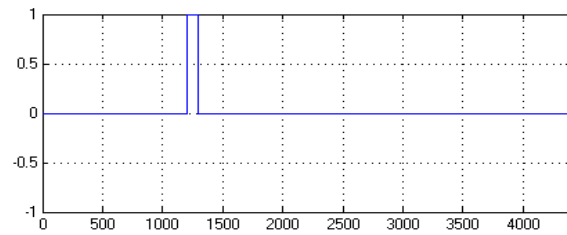


Fig. 4. Detection et isolation of fault 2 on the sensor $\beta_{2,m2}$

Fig. 5 shows the sensor measurement $\omega_{r,m1}$ and the result of the fault decision. We note the existence of a fault between the times 1200 s and 1300 s. It is a fixed value defect. This is the fault 4. It is instantly detected at the instant 1200.02 s. Note that the detection signals on other faults display a value of zero [13].

Fault



$$\omega_{r,m1}[rad/s] = f(t[s])$$

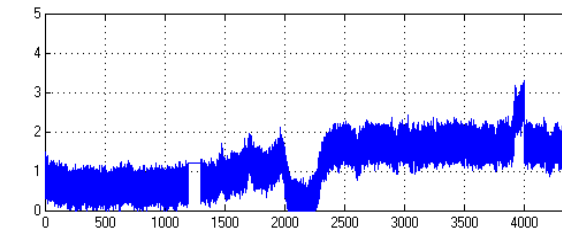


Fig. 5. Detection et isolation of fault 4 on the of the rotor speed sensor $\omega_{r,m1}$

Fig. 6. shows the sensor measurements $\omega_{r,m2}$ and the result of the fault decision. We notice the existence of a defect, of type gain. It is the fault 5. It appears between the instants 1700s and 1800s. The measurement of $\omega_{g,m1}$ which is also influenced

by disturbances and other types of faults which makes the isolation task more complicated. However the defect was detected and isolated between the instants 1700.03s and 1800.06 s [13].

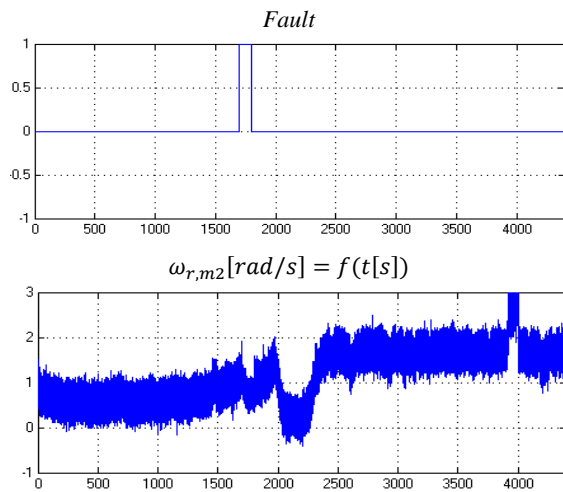


Fig. 6. Detection and isolation of the fault 5 (2b) on the rotor speed sensor $\omega_{r,m2}$

Fig. 7 measures the rotational speed sensor of the generator $\omega_{g,m1}$ as well as the fault decision result. We note the existence of a gain-type defect that appears between the times 1700 s and 1800 s. This is the fault 5 (3b). It is detected and isolated during the same time interval [17].

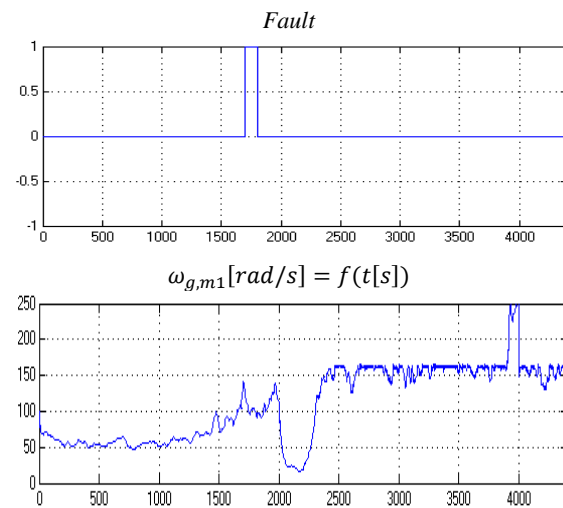


Fig. 7. Detection and isolation of fault 5 (3b) on the sensor $\omega_{g,m1}$

Fig. 8 shows the measurements of the torque τ_g and the decision of fault. We find the existence of a defect. This is the fault 8. The detection is performed instantly at 4200.02 s instant.

3.2. Scenario 2

In this scenario, three defects were detected simultaneously. Fig. 9 shows the electrical power generated in this scenario. We find that the generator took a long time to actually start producing [16].

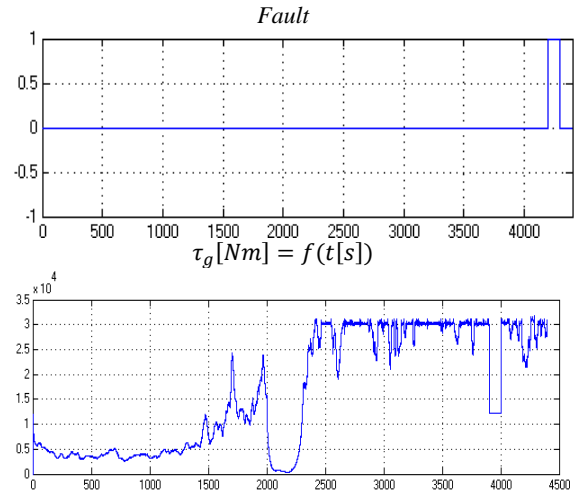


Fig. 8. Detection and isolation of fault 8 on the converter actuator

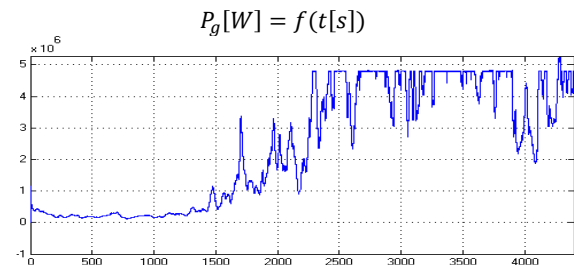


Fig. 9. Electrical power generated in scenario 2

Fig. 10 shows the sensor measurements $\beta_{1,m1}$ and the fault result. We notice the presence of a fixed value defect. This is the fault 1, it is detected and isolated between the instants 245s and 345s [17].

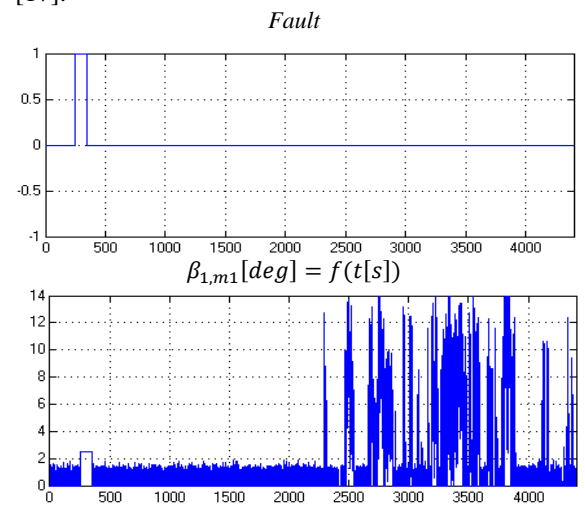


Fig. 10. Detection and isolation of fault 1 on the sensor $\beta_{1,m1}$ in scenario 2

Fig. 11 shows the rotational speed sensor $\omega_{m,1}$ measurements of the rotor. We notice the existence of a fixed value defect. It is fault 4, which is detected and isolated between times 800 s and 900 s [17].

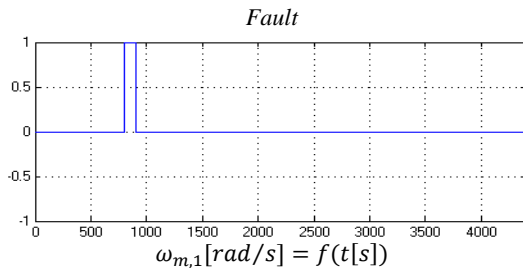


Fig. 11. Detection and isolation of fault 4 on the rotational speed of the rotor in scenario 2

Fig. 12 shows the sensor measurements $\omega_{r,m2}$ of the rotational speed of the rotor and the result of the fault decision. We note that a gain-type defect appears between the instant 2200 s and 2300 s. This is the fault 5 (2b), it is detected and isolated during the same time interval [13], [17].

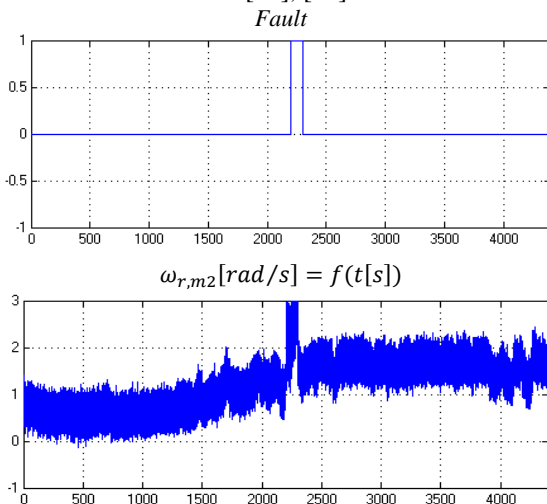


Fig. 12. Detection and isolation of fault 5 (2b) on the rotational speed of the rotor in scenario 2

CONCLUSION

The research work deals with the problem of fault diagnosis in wind systems. The previously defined goal of this work was to model a fault diagnosis system for a wind energy system and propose sophisticated technique which provides much diagnostic information. A wind Benchmark with defined parameters was simulated and so affected by sensor, actuator and system faults which were used to perform the tests. We used the support vector machine method for fault detection and isolation. This allowed us to easily manipulate noise, disturbances and outliers.

The performance of the developed method was evaluated using two fault scenarios with different parameters considered in the wind energy

Benchmark. Satisfactory results have been obtained when all defects could be detected and then isolated as soon as possible and in different operating points at which the faults are occurred. As a perspective for future research work, we suggest the study of wind energy Benchmarks with simultaneous faults then we will design fault tolerant control. This will test the robustness of the proposed solution.

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Appendix A: *Parameters of the wind turbine system Benchmark model*

Parameters of the models of blade pitch angle	Parameters of the train system	Parameters of the models of the converter and the generator	Reference power
R	B_{dt}	α_{gc}	$4.5 * 10^6$
57.5	775.49		
ρ	B_r		
1.225	7.11		
ζ	B_g	50	
0.6	45.6		
w_n	N_g		
11.11	95	η_{gc}	
ζ_2	K_{dt}		
0.45	$2.7 * 10^9$		
w_{n2}	η_{dt}	0.98	
5.73	0.97		
ζ_3	η_{dt2}		
0.9	0.92		
w_{n3}	J_g		
	390		
3.42	J_r		
	$55 * 10^6$		

Appendix B : *Parameters of scenario 1 and scenario 2*

Scenario 1				
$\beta_{1,m1}$	$\beta_{2,m2}$	$\beta_{3,m1}$	$\omega_{r,m1}$	$\omega_{r,m2}$
4	41.8	12	1.2	$0.7\omega_{r,m2}$
τ_{gc}	$\omega_{g,m2}$		η_{dt2}	$\omega_{g,m1}$
700	$1.7\omega_{g,m2}$		0.3	100
Scenario 2				
$\beta_{1,m1}$	$\beta_{2,m2}$	$\beta_{3,m1}$	$\omega_{r,m1}$	$\omega_{r,m2}$
2.5	$4\beta_{2,m2}$	13	1.7	$1.7\omega_{r,m2}$
τ_{gc}	$\omega_{g,m2}$		η_{dt2}	$\omega_{g,m1}$
-500	$0.7\omega_{g,m2}$		0.6	150



Messaouda AZZOUZI was born in Djelfa (Algeria), she had got her Engineering diploma in electronics from Ziane Achour University of Djelfa (Algeria) in 2002. She had finished her PhD thesis in automatic control form Politehnica University of Bucharest (Romania) in 2008.

Actually she is an associate professor at the Ziane Achour University of Djelfa (Algeria) and she is the head of the LMD Electronics specialty.

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