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# The adaptive fuzzy - support vector machine for fault detection and isolation in wind turbine

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This paper concerns the problem of fault diagnosis in wind turbines. Motived by SupportVector Machines (SVM) method and Fuzzy Logic algorithm, a novel procedure is derived to provide for the wind turbine diagnosis. Since, the conventional SVM classifier with fixed parameters cannot bring performance of high accuracy and fast reflex. In this work, the proposed FDI strategy has raised the problem of congeal the parameters of classifiers after learning, this novel strategy based on the evaluating of error of classification to adjust the parameters of classifier w and b in real time using the fuzzy logic. This principal allow for achieve a new classifier online, which is able to process the new data comes from measuring sensors. The Different parts of the process were investigated, including actuators, sensors and process faults. With duplicated sensors, have detected sensor faults in blade pitch positions, generator and rotor speeds rapidly, but under specific constraints on the fault. all Process faults mainly concerned friction in the wind turbine, which might cause it damage. The fault could be detected under constraints of high magnitude error. the comparing Our results with the conventional SVM classifier indicate the value of our method

Keywords: Fault Detection and Isolation (FDI), wind turbine, classification, SupportVector Machine (SVM), Fuzzy logic

## 1. INTRODUCTION

Energy is the subject of much global debate today. The aim of the countries is to satisfy the ever increasing demand for energy while respecting the environment and the safety of people. Diversifying energy sources is essential because of the beginning of depletion of natural energy resources such as oil and gas, in order to avoid energy dependence for non-hydrocarbon producing countries, and also to preserve nature [1]. Thus, the focuswas on renewable energies (see fig. 1 and fig. 2).

In recent years, solar energy [2] and the energy produced by wind turbines [3] are part of these trendy energies. Mastering these new energy application progress not only technological but also scientists (See fig. 2).

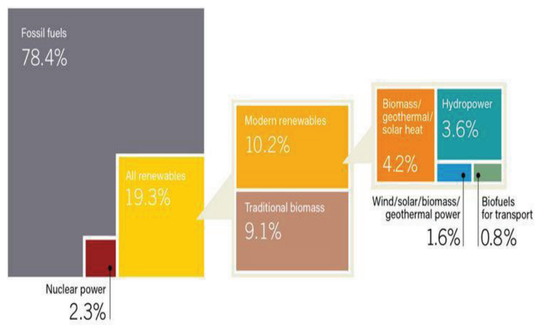


**Figure 1** Estimated Renewable Energy Share of Total final EnergyConsumption, 2016 [25].

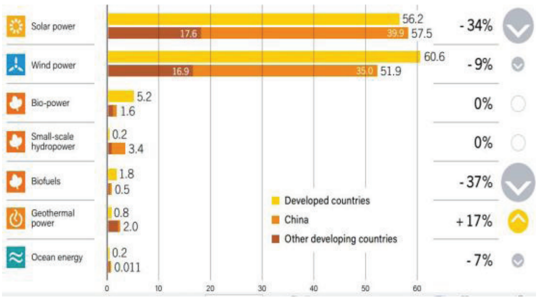


**Figure 2** Global New Investment in Renewable Energy by Technology, Developed and Developing Countries, 2016.

The wind turbine is a renewable energy system that harnesses the wind resource and transforms it into electrical energy. Wind energy is booming today. Several wind farm facilities are offshore. This trend will be confirmed even more in the future to avoid disturbing the citizens in terms of landscape and noise, and also to have a strong wind, frequent and fairly regular.

These floating offshore installations [4] require a thorough study of the wind, aerodynamics, sea currents, hydrodynamics, elasticity, control of the wind turbine, as well as the platform to determine their feasibility. technical and economic. This also requires increasing the availability and reliability of the wind turbine, reducing downtime and maintenance visits that are more difficult and costly compared to the wind turbine's installations on the ground. One way to meet these requirements is to design a fairly efficient fault monitoring and diagnostic system [5]. Monitoring and fault diagnosis of wind turbines can predict and quickly detect any occurrence of a failure before it spreads and lead to the shutdown or even destruction of the wind turbine.

To avoid these problems the researchers offered several of faults detection systems. However, several difficulties and challenges are encountered by the designer of the FDI system as the complex structure and the non-linearity, instability and complexity of the aerodynamics and the wind has a random nature and switching in the control of the wind turbine, which still limits the application of model-based approaches [6-7]. As a matter of fact, Parallel to the research of fault detection techniques based-model, the data-driven methods [8-10] are currently receiving considerable. Since, data-driven methods belong on the datameasured process, such as via exploiting hardware redundancy and based of a bank of robust data-driven detection filters [11], scheme with robust residual generators directly constructed from available process data [12], a Pattern Recognition (PR) approach for fault diagnosis of a wind turbine [13], or based a condition monitoring using Adaptive Neuro-Fuzzy Interference Systems (ANfiS) [14].

In machine learning, support vector machines are supervised learning modelswith associated learning algorithms that analyze data used for classification and regression analysis [15]. The SVM method was used only for fault diagnosis in the most cases used to classified the input/output signal [16-18], or by combining with some methods to improve the SVM, as artificial neural networks (ANNs) augmented by genetic algorithms to detect faults in rotating machinery for a number of years, the using statistical methods to preprocess the vibration signals as input features in [19], or fault diagnosis of low speed bearing using multi-class relevance vector machine (RVM) and SVM in [20], or using the algorithm genetic to select appropriate free parameters of SVM [21], or using wavelet analysis to optimizing signal decomposition levels in [22]. The other choice in [23] is the optimization of SVM parameters based on the Colony Algorithm. Therefore, these preceded results in this field of study is not enough for achieving the best performances of FDI strategy. This led us to develop a new strategy which is as follows.

This work focuses to achieve a new FDI strategy for wind turbine based on the SVM technic ameliorated by the fuzzy logic. The idea is to design an adaptive classifier to raise the problem of congeal the parameters of SVM classifier. the FDI strategy proposed based on the evaluation of classification output to adjust the parameters of classifier w and b in the real time using the fuzzy logic. the different parts of the process were investigated, including actuators, sensors and process faults. With duplicated sensors, have detected sensor faults in blade pitch positions, generator and rotor speeds rapidly, but under specific constraints on the fault. all Process faults mainly concerned friction in the wind turbine, which might cause it damage. The fault could be detected under constraints of high magnitude error. the comparingOur resultswith SVM classifier [18] indicate the value of our method. To validate our results we have a benchmark model of wind turbine [24] used simulations with Matlab & Simulink.

The remainder of the paper is organized as follows: in section 2, the wind turbine system modeling. The Faults diagnosis architecture is presented in section 3. In section 4, the proposed strategy is presented. Some important simulation results are represented in section 5 to show the effectiveness of our approach. finally, in section 6 a concluding remark and perspective is given.

## 2. WIND TURBINE

A wind turbine captures the wind kinematic energy and transforms it into mechanical energy (rotating shaft) first and then into electrical energy (generator). The main components of the horizontal-axis wind turbines (HAWT) that are visible from the ground are the tower, nacelle, and rotor, as shown in figure 3.

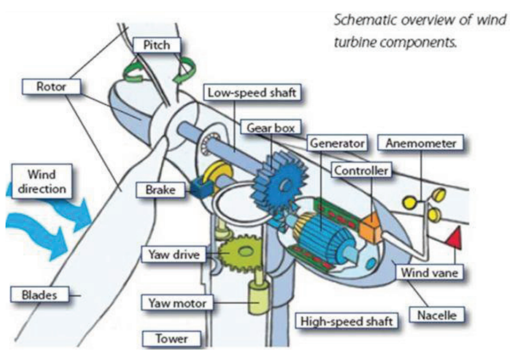


**Figure 3** Wind turbine components.

At first, the wind encounters the rotor on this upwind horizontal-axis turbine and rotates it. The low-speed shaft transfers energy to the gearbox, which steps up in speed and spins the high-speed shaft, which increases the speed and rotates the high-speed shaft. The high-speed shaft causes the generator to spin, producing electricity. In the figure, it is shown that the yaw-actuation mechanism, which is used to turn the nacelle so that the rotor faces into the wind [26].

In this work, the wind turbinemodelwill be used is a three-bladed pitch-controlled variable speed wind turbine with a nominal power of 4.8MW that is the one described in [24]. The description of the model is presented in the following.

## 2.1 Aerodynamic model

The aerodynamics of the wind turbine is modeled as a torque acting on the blades, according to:

$$\tau_r = \sum_{i=1}^{3} \frac{\rho \pi R^3 C_q(\lambda(t), \beta_i(t)) \times v_{\omega,i}(t)^2}{6} \tag{1}$$

where $vw$ is the wind speed, $\rho = 1.225\,\text{kg/m}^3$ is the air density, $R = 57.5$ m is the rotor radius, $\beta_i$ is pitch position, and $\lambda$ is the Tip Speed Ratio, defined as:

$$\lambda = \frac{\omega_r R}{v_w} \tag{2}$$

## 2.2 Pitch system model

For each blade, the hydraulic pitch system is modeled as a closed-loop transfer function between the pitch angle $\beta_i$ and its reference $\beta_{i,ref}$, according to:

$$\frac{\beta_i(s)}{\beta_{i,ref}(s)} = \frac{w_n^2}{s^2 + 2 \cdot \xi \cdot w_n \cdot s + w_n^2} \tag{3}$$

where $\xi = 0.6$ is the damping factor, and $w_n = 11.11$ rad/s is the natural frequency, and $i = 1, 2, 3$ for three blades.

## 2.3 Drive train model

The drive train is modeled by a two-mass model:

$$\begin{bmatrix} \dot{\omega}_r(t) \\ \dot{\omega}_g(t) \\ \dot{\theta}_\Delta(t) \end{bmatrix} = \begin{bmatrix} \frac{-B_{dt}-B}{J_r} & \frac{B_{dt}}{N_g J_r} & \frac{-K_{dt}}{J_r} \\ \frac{\eta_{dt} B_{dt}}{N_g J_g} & \frac{\frac{-\eta_{dt} B_{dt}}{N_g^2} - B_g}{J_g} & \frac{\eta_{dt} K_{dt}}{N_g J_g} \\ 1 & \frac{-1}{N_g} & 0 \end{bmatrix} \begin{bmatrix} \omega_r(t) \\ \omega_g(t) \\ \theta_\Delta(t) \end{bmatrix}$$
$$\begin{bmatrix} \frac{1}{J_r} & 0 \\ 0 & \frac{-1}{J_g} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tau_r(t) \\ \tau_g(t) \end{bmatrix} \tag{4}$$

where the generator and rotor torque are $\tau_g(t)$ and $\tau_r(t)$ respectively, the angular velocity of the generator and the rotor are $\omega_g(t)$ (rad/s) and $\omega_r(t)$ (rad/s) (respectively), $J_r = 55 \cdot 10^6$ kg$\cdot$m$^2$ is the moment of inertia of the low-speed shaft, $K_{dt} = 2.7 \cdot 10^9$ Nm/rad is the torsion stiffness of the drive train, $B_{dt} = 775.49$ Nm$\cdot$s/rad is the torsion damping coefficient of the drive train and $Br = 7.11$ Nm$\cdot$s/rad, $B_g = 45.6$ Nm$\cdot$s/rad is the viscous friction of the high-speed shaft, $N_g = 95$ is the gear ratio, $J_g = 390$kg$\cdot$m$^2$ is the moment of the inertia of the high-speed shaft, $\eta dt = 0.97$ is the efficiency of the drive train, and $\Theta\Delta(t)$ is the torsion angle of the drive train.

## 2.4 Generator and Converter model

The generator and converter dynamics can be modeled by a first transfer function:

$$\frac{\tau_g(s)}{\tau_{g,ref}(s)} = \frac{\alpha_{gc}}{s + \alpha_{gc}} \tag{5}$$

The power produced by the generator is given by:

$$P_g(t) = \eta_g \cdot \omega_g(t) \cdot \tau_g(t) \tag{6}$$

where $\alpha_{gc} = 50$ rad/s is the generator and converter model parameter, $\eta_g = 0.98$ is the efficiency of the generator. Besides the generator torque $\tau_g$ is controlled by the reference $\tau_{g,ref}$.

## 2.5 PI control of wind turbine description

Figure 4 shows the different operating ranges of the wind turbine [24].

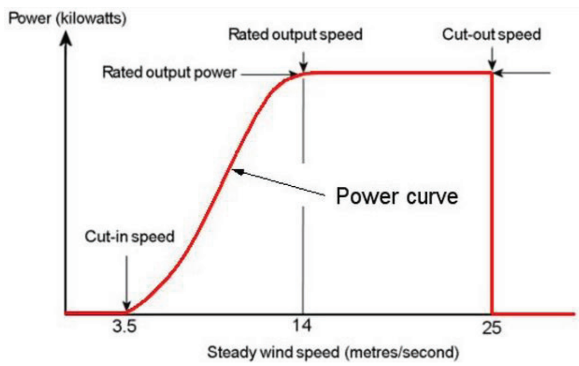


**Figure 4** Illustration of the reference power curve for the wind turbine depending on the wind speed.

The controller has two modes. Mode 1 corresponds to the wind region 2 ([3.5,14]) and mode 2 corresponds to the wind region 3 ([14,25]). Consider ourwind data in figure 5, atmore or less time 2400s, thewind speed goes from region 2 to region 3. Hence, we can assume that from time 0 to 2400s, the PI controller is in mode 1, and after that it goes to mode 2 [24].

The control general objective is tomaximize power absorption while operating in region 2 and to minimize structural loads during operation in the region 3.

## 2.6 Faults scenarios

The following faults are considered in [27] of the wind turbine benchmark model:

**The faults in the pitch systems:** Sensor faults in the pitch position measurements are either electrical or mechanical faults in the position sensors. Fault1 is a fixed value sensor fault on pitch 1 position sensor 1 ($\beta_{1,m1}$); Fault 2 is a scaling error sensor fault on pitch 2 position sensor 2 ($\beta_{2,m2}$); Fault 3 is a fixed value sensor fault on pitch 3 position sensor 3 ($\beta_{3,m3}$). In addition, two actuator faults in the pitch systems

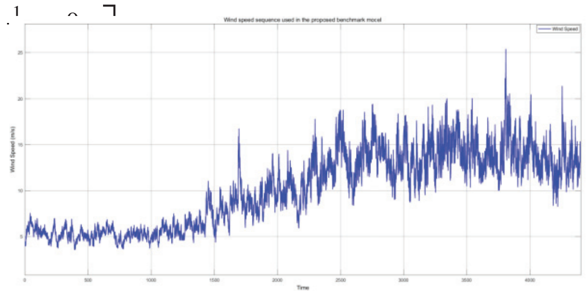

**Figure 5** Wind speed sequence $vw(t)$ used in the proposed benchmarkmodel.

are defined: Fault 6 associated with pitch actuator 2 caused by high air content in oil, and Fault 7 is associated with pitch actuator 3 caused by dropped main line pressure (see Table 4).

**The faults in the drive train system:** Fault 4 is a fixed value sensor fault on rotor speed sensor 1 ($\Omega_{r,m1}$), and Fault 5 is a scaling error sensor affecting both rotor speed sensor 2 and generator speed sensor 2 ($\Omega_{r,m2}$, $\Omega_{g,m2}$) (see Table 4).

The faults in the generator and converter system: Fault 8 is a converter fault, representing an offset in the internal converter control loops (see Table 4).

## 3. FAULT DIAGNOSIS ARCHITECTURE

In this paper, a fault diagnosis method by Fuzzy-SVMis proposed. SVM classification is used to evaluate the generated residuals as well as other features, moreover the fuzzy logic algorithm is used to adjust the SVM classifier parameters in order to conclude on the operating state of the system. It is essential to understand the wind system and how it works before considering a fault diagnosis scheme (figure 6). The idea behind this fault diagnosis scheme for wind turbines is to see the diagnostic problem as a classification problem.

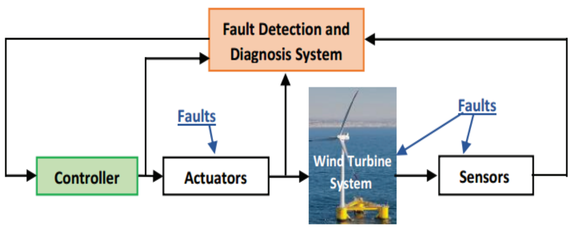


**Figure 6** Fault Diagnostic Scheme for Wind Turbines Systems.

The SVM method has been used for fault diagnosis in the majority of cases by the direct use of input / output signals[16-17-18]. Or by adding a pretreatment phase before applying SVMs: wavelet analysis to optimizing signal decomposition levels in [22], artificial neural networks (ANNs) augmented by genetic algorithms in [19]. The second choice appears the most appropriate because the first scheme may confuse the work of the SVM algorithm that will seek the solution in all directions. In the literature, researchers have tried to combine SVMswith other techniques: ColonyAlgorithmto optimizing the SVMparameters [23],multi-class relevant vectormachine (RVM) [20]. Although this combination somewhat improves the SVM results applied to the raw data, false alerts still remain. This can be understood because Principal Component Analysis (PCA) tries to compress the raw data to a smaller dimension by capturing the maximum variance of the raw data without looking at the symptoms of the defects.

In thiswork, we have proposed the defect detection process in a more general way than that of residue generation by an adaptive classifier. It's about creating features specific to each defect. Among these characteristics is the residue. One can have relevant informative measures of default, combination of measures and filtered measures.

The construction of the characteristics in this work applied to the case of the wind turbines is carried out in a manual way based on the knowledge of the wind system. Subsequently, SVM is used as a first step to evaluate the characteristics of a given defect, and then based on the SVM classifier output as a second step: the presence of the output in an interval shows the state of the system if not by adjusting the parameters of the SVM classifier by the fuzzy logic algorithm according to the rules in Table 1 for the output and Table 2 for the output dynamics to classify this output as shown in figure 7.

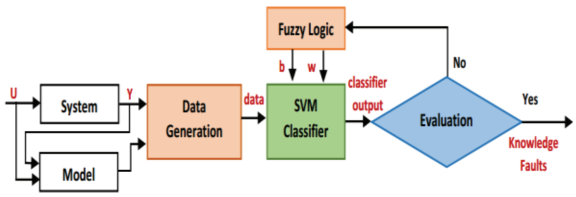


**Figure 7** Proposed Fault Diagnostic Fuzzy-SVM Strategy Scheme.

The proposed Fuzzy-SVMfaults diagnosis is developed in three parts. firstly, 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. in secondly, the obtained models are validated on a new fault scenario, finally, if the classification output is not validated by the evaluation step, the parameters are adjusted using the fuzzy logic.

## 4. THE PROPOSED STRATEGY

### 4.1 SVM classification

SVMs are a robust machine learning methodology [28] which has been shown to yield state-of-the-art performance on the classification by finding a hyper plane that separates two classes of data in data space while maximizing the margin between them.

Consider $N$ training vectors $x_i \in R^p$ characterized by a set of $p$ descriptive variables $x_i = \{x_{i1}, x_{i2}, \ldots, x_{ip}\}$ and by the class label $y_i \in \{-1, +1\}$. For nonlinearly separable data $x$, the data can be mapped by some nonlinear function $\theta(x)$ into a high-dimensional feature space where linear classification becomes possible. Rather than fitting, nonlinear curves to the data, SVM handles this by using a kernel function $K(x_i, x) = \prec \varphi(x_i), \varphi(x) \succ$ to map the data into a different space where a hyper plane can be used to do the separation.

The optimization problem is solved using the Lagrange function. The obtained decision function is then:

$$f(x) = \text{sign}\left(\sum_{i=1}^{N} \alpha_i y_i K(x_i, x) + b\right) \tag{7}$$

With the properties:

$$w = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i) \tag{8}$$

SVMs find the hypothesis $w$ and $b$, which defines the separating hyper plane, by minimizing the following objective function over all $n$ training examples:

$$\tau(w, e) = \frac{1}{2}|w|^2 + C \sum_{i=1}^{N} e_i \tag{9}$$

Under the constraints that:

$$\forall i = \{1, \ldots, n\} \;\; y_i(K(x)i, x) + b) \geq 1 - e_i; e_i \geq 0$$

In this objective function, each slack variable $e_i$ shows the amount of error that the classifier makes on a given example $x_i$. Minimizing the sum of the slack variables correspond to minimizing the loss function of the training data, while minimizing the term corresponds to maximizing the margin between the two classes.

Radial Basis Function (or Gaussian kernel) with the variance $\sigma$ was used in this work is follow:

$$K(x_i, x) = \exp\left(-\frac{|x_i - x|}{2\sigma^2}\right) \tag{10}$$

The key idea of learning amodel for fault detection by SVM is the definition of the vector $x$ to be used for classification. This vector should include the most relevant information on the behavior of the system at a given fault. This vector can contain the measured outputs, staggered steps, driveways, instructions, a combination thereof or variations in output over time. To build a useful vector, we must carefully observe the results of the process outputs for each anomaly and propose a combination that ensures high fault impact considered in the vector $x$. In this work, we have proposed the same vectors and the same parameters of the filters in [18].

**Remark 1:** Several vectors are available for different types of defects. Hardware redundancy (duplicate sensors) is used as a feature in most of these vectors. The kernel used for the learning of all faults is theGaussian kernel that is most adapted to noisy actual and disrupted thanks to its great capacity for learning. Most data is filtered by a first order filter with a time constant $\tau$ to reduce sensitivity to process disturbances or measurement noise.

## 4.2 The adaptive Fuzzy-SVM classifier

The disadvantages of the SVM classifier with a fixed parameters open avenue for fuzzy logic utilization in the FDI of wind turbines [18]. Through observing the SVM classifier output and it dynamic to adjusting the kernel parameters of SVM $w$ and $b$ [23]. Therefore, this paper adjusts $w$ and $b$ based on the fuzzy logic. The initial kernel parameters are got from the initial learning by just six samples, then using $\Delta w$ and $\Delta b$ respectively, in order to adjust $w$ and $b$ according to the following equation:

$$\begin{cases} w = w' + \Delta w \\ b = b' + \Delta b \end{cases} \tag{11}$$

This work led us to develop a new strategy to adjustment of the SVM classifier parameters based on the fuzzy logic algorithm, to lift these disadvantages of this classifier presented in [18]. The fuzzy logic algorithm acquire SVM classifier output and it dynamic, as input and $\Delta w$ and $\Delta b$ as output. In accordance with the SVM classifier output value, whether it is us or minus, and it dynamic the fuzzy logic acquire a corresponding decision to adjusting $w$ and $b$ by $\Delta w$ and $\Delta b$ respectively. Then, add $\Delta w$ and $\Delta b$ to the current kernel parameters, and the parameters after modification are obtained. The structure of the adaptive fuzzy-SVM classifier shown in Figure 7.

Algorithm 1: The evaluation Task.

*begin*
*Read the data 'y' come from SVM classifier to decide the fault index 's':*
*If* $y < m$
$s = 0;$
*Else if* $y > M$
$s = 1;$
*Else*
*Go to adjusting the classifier parameters (w and b) according to the equation (11);*
*End*

In this work, the data are assessed in the evaluation task according to the following algorithm 1.

Where $m$ and $M$ in each faults are summarized in the following table:

**Table 1** Values of $m$ and $M$

| Faults | Parameters Values |
|---|---|
| Fault 1 | m=0<br>M=0.05 |
| Fault 2 | m=0<br>M=0.05 |
| Fault 3 | m=0<br>M=0.05 |
| Fault 4 | m=0<br>M=0.05 |
| Fault 5a | m=0<br>M=0.05 |
| Fault 5b | m=0<br>M=0.05 |
| Fault 6 | m=0.5<br>M=1 |
| Fault 7 | m=0.5<br>M=1 |
| Fault 8 | m=0.6<br>M=0.8 |

According to rules of adjusting kernel parameters:

"IF $A_i$ and $B_i$, then $C_i$"

The fuzzy control rules are expressed in Table 2 and Table 3.

The linguistic terms of output y is negative big (NB), negative small (NS), zero (ZO), positive small (PS), and positive big (PB). The linguistic terms of yc is negative big (NB), negative small (NS), zero (ZO), positive small (PS), and positive big (PB). The linguistic terms of $\Delta w$ and $\Delta b$ are zero (ZO), small (S), and big (B). Subjection functions for input and output variables of the controller take the form of trigonometric functions.

**Table 2** Fuzzy control rules of $\Delta w$.

| $\Delta w$ | | $y$ | | | | |
|---|---|---|---|---|---|---|
| | | NB | NS | ZO | PS | PB |
| $yc$ | NB | L | M | S | M | L |
| | NS | L | S | ZO | S | L |
| | ZO | L | S | ZO | S | L |
| | PS | L | S | ZO | S | L |
| | PB | L | M | S | M | L |

**Table 3** Fuzzy control rules of $\Delta b$.

| $\Delta b$ | | $y$ | | | | |
|---|---|---|---|---|---|---|
| | | NB | NS | ZO | PS | PB |
| $yc$ | NB | L | L | L | L | ZO |
| | NS | L | M | L | M | ZO |
| | ZO | ZO | L | M | L | MO |
| | PS | ZO | M | L | M | ZO |
| | PB | ZO | L | L | L | ZO |

## 5. THE VALIDATION RESULTS

In this work the wind turbine controller regions as presented in section 2. Region 1 is denoted power optimization, and Region 2 is denoted power reference following . The controller is implemented with a sampling frequency at 100 hz. The controller starts in mode 1. Figure.5 and Figure.8 shows respectively the evolution of the speed of the wind (input) and power electrical generated (output) in terms of time. Clearly, appears that there is a strong connection between these two variables. So, the power is maximum if speed wind exceeds a certain value. The all simulations are taken during 4400 s.

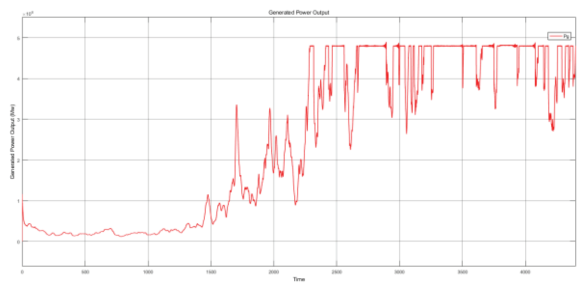

**Figure 8** Generated power output $P_g$.

Since the wind turbine system used in this run is composed of three pitch actuator system, the generator system and the Drive Train system, using this proposed FDI we have got and discuss each fault alone in the following:

*Fault 1:* fixing value sensor fault on pitch 1 position sensor 1 $\beta_{1,m1}$. The Figure.9. shows the results of the detection and isolation of the fixing value sensor fault (Fault1) and the sensor signal $\beta_{1,m1}$.

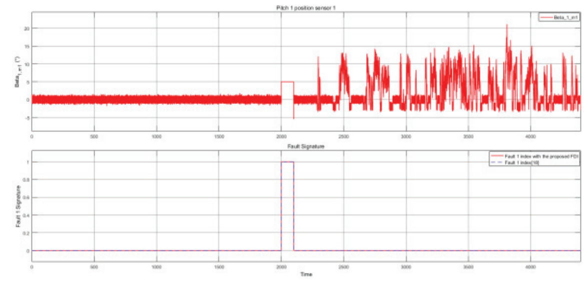

**Figure 9** The FDI of the pitch position $\beta_{1,m1}$.

*Fault 2:* scaling error sensor fault on pitch2 position sensor 2 $\beta_{2,m2}$. The figure.10. shows the results of the detection and isolation of the scaling error sensor fault (Fault2) and the sensor signal $\beta_{2,m2}$.

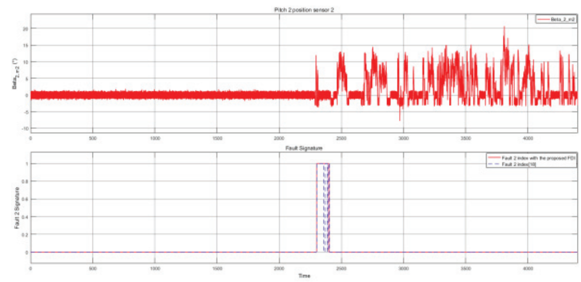

**Figure 10** The FDI of the pitch position $\beta_{2,m2}$.

*Fault 3:* fixing value sensor fault on pitch 3 position sensor 3 $\beta_{3,m1}$. The Figure.10 shows the results of the detection and isolation of the fixing value sensor fault (Fault3) and the sensor signal $\beta_{3,m1}$.

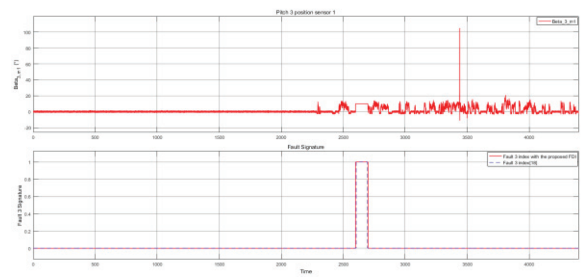

**Figure 11** The FDI of the pitch position $\beta_{3,m1}$.

*Fault 4:* Fault 4 is a fixed value sensor fault on rotor speed sensor 1 $\omega_{r,m1}$. The Figure 12. shows the results of the detection and isolation of the fixing value sensor fault (Fault 4) and the sensor signal $\omega_{r,m1}$.

*Fault 5:* Fault 5 is a scaling error sensor affecting both rotor speed sensor 2 and generator speed sensor2 ($\omega_{r,m2}$, $\omega_{g,m2}$).

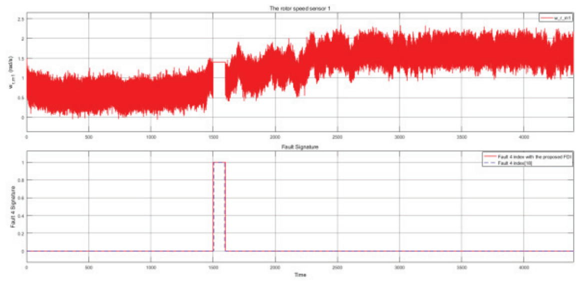

**Figure 12** The FDI of the rotor speed $\omega_{r,m1}$.

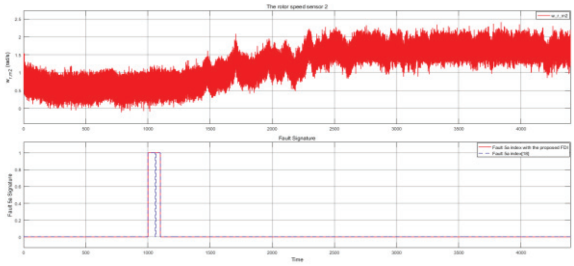

**Figure 13** The FDI of the rotor speed $\omega_{r,m2}$.

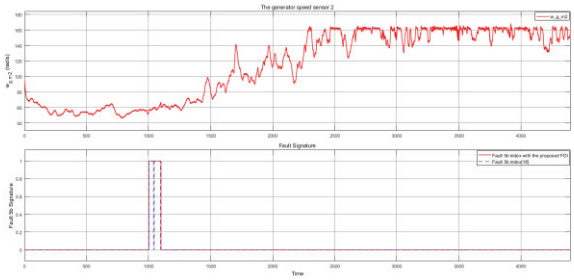

**Figure 14** The FDI of the generator speed $\omega_{g,m2}$.

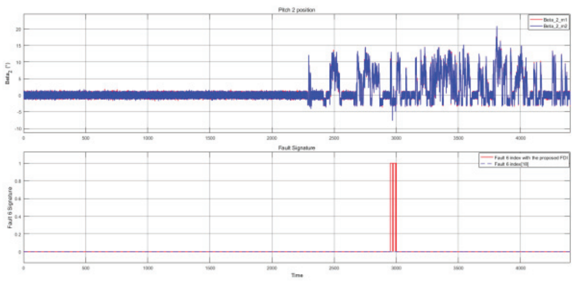

**Figure 15** The FDI of the pitch position $\beta_2$.

The Figure 13 and Figure 14. shows the results of the detection and isolation of the scaling error sensor (Fault 5) and the each sensor signal.

*Fault 6:* associated with pitch actuator 2 caused by high air content in oil. The Figure 15 shows the results of the detection and isolation of the changing pitch actuator 2 parameters fault (Fault 6).

*Fault 7:* Fault 7 is associated with pitch actuator 3 caused by dropped main line pressure. The Figure 16 shows the results of the detection and isolation of the changing pitch actuator 3 parameters fault (Fault 7).

*Fault 8:* representing an offset in the internal converter control loops. The Figure 17 shows the results of the detection

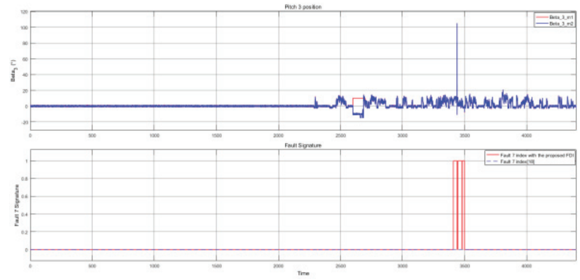

**Figure 16** The FDI of the pitch position $\beta_3$.

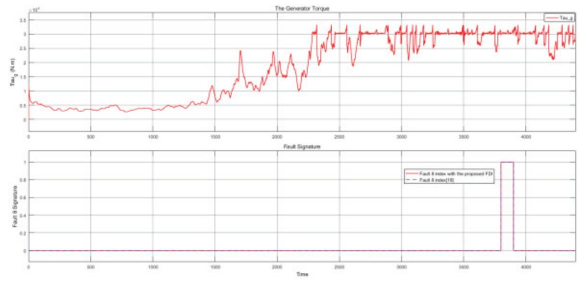

**Figure 17** The FDI of the generator torque $\tau_2$.

and isolation of the converter fault (Fault 8) and the it sensor signal.

The Table 4 summarized all defects, its description, its types, its occurrence periods, its decision compared by the SVM classifier [18] (detected or not) and the time of detection to demonstrate the efficiency of this proposed approach.

*Remark 2:* The proposed SVM-based approach provides a useful generalization ability even with a reduced number of training samples, and also to easily manipulate the nonlinearity of the wind turbine system. So having an objective of solving the same problem with the same data where everyone faces the same requirements and to respect, allow me to say objectively that my approach has proved effective, and its superiority flexibility in resolving the fault diagnosis problem in the wind compared to other methods used in the literature.

## 6. CONCLUSION

The fault diagnostic strategy proposed in this paper involves several disciplines ranging from signal processing, physics, machine learning, automatic electricity. allows to eliminate the disadvantages to fixed of kernel parameters ofSVMclassifiers and the FDI off-line, the fuzzy algorithmandSVMclassifier are integrated together to design this novel strategy of FDI online in wind turbines , adjusting the proportion and integration parameters in the real time. Set the feature vector and the adjustment of themodel parameters are essential to detect and isolate these defects. A compromise done manually between detection sensitivity to noise and fault must be determined. The proposed approach based on adaptive Fuzzy-SVM provides a useful generalization ability even with a small number of training samples, and also to easily handle the nonlinearity of the wind system.

**Table 4** Faults detection results.

| N | Fault | Fault site | Period (s) | Faults values | FDI SVM [18] | FDI Fuzzy-SVM | $T_D$ |
|---|---|---|---|---|---|---|---|
| **F1** | Fixed value | Sensor fault Blade 1 positions | [2000,2100] | $\beta_{1,m1} = 5°$ | Yes | Yes | 2000.00 |
| F2 | Gain factor | Sensor fault Blade 2 positions | [2300,2400] | $\beta_{2,m2} = 1.2 * \beta_{2,m2}$ | Yes | Yes | 2301.33 |
| F3 | Fixed value | Sensor fault Blade 3 positions | [2600,2700] | $\beta_{3,m1} = 10°$ | Yes | Yes | 2600.51 |
| F4 | Fixed value | Sensor fault rotor speed | [1500,1600] | $W_{r,m1} = 1.4$ rad/s | Yes | Yes | 1500.35 |
| F5 | F5a Gain factor | Sensor fault rotor speed | [1000,1100] | $W_{r,m2} = 1.1 * W_{r,m2}$ | Yes | Yes | 1000.01 |
| | F5b Gain factor | Sensor fault generator speed | [1000,1100] | $W_{g,m2} = 0.9 * W_{g,m2}$ | Yes | Yes | 1000.01 |
| F6 | Changed dynamic | Actuator fault, pitch system 2 | [2900,3000] | $\zeta_2 \rightarrow \zeta_2 = 0.45$ $W_{n2} \rightarrow W_{n2} = 5.73$ | NO | Yes | 2951.00 |
| F7 | Changed dynamic | Actuator fault, pitch system 3 | [3400,3500] | $\zeta_2 \rightarrow \zeta_2 = 0.9$ $W_{n3} \rightarrow W_{n3} = 3.42$ | NO | Yes | 3409.68 |
| F8 | Offset | Actuator fault convertor system | [3800,3900] | $\tau_g \rightarrow \tau_g + 2000$ | Yes | Yes | 3800.01 |

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