Advanced Data Mining Approach for Wind Turbines Fault Prediction

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ABSTRACT

Wind turbine operation and maintenance costs depend on the reliability of its components. Thus, a critical task is to detect and isolate faults, as fast as possible, and restore optimal operating conditions in the shortest time. In this paper, a data mining approach is proposed for fault prediction by detecting the faults inception in the wind turbines, in particular pitch actuators. The role of the latter is to adjust the blade pitch by rotating it according to the current wind speed in order to optimize the wind turbine power production. The fault prediction of pitch actuators is a challenging task because of the high variability of the wind speed, the confusion between faults and noise as well as outliers, the occurrence of pitch actuator faults in power optimization region in which the fault consequences are hidden and the actions of the control feedback which compensate the fault effects. To answer these challenges, the proposed approach monitors a drift from normal operating conditions towards failure condition. To achieve drift detection, two drift indicators are used. The first indicator detects the drift and the second indicator confirms it. Both indicators are based on the observation of changes in the characteristics of normal operating mode over time. A wind turbine simulator is used to validate the performance of the proposed approach.

1. INTRODUCTION

1.1. Basic definitions and motivation

The search for alternative clean energy is undoubtedly becoming more and more important in modern societies. The growing interest in wind energy production has led to the design of sophisticated wind turbines. Like every other complex and heterogeneous system, wind turbines are prone to faults that can affect their performance and increase maintenance costs. In addition, it is very difficult and even dangerous to access the turbines. Thus, it is crucial to design an automated diagnostics system in order to achieve the fault detection and isolation.

In general, fault diagnosis of wind turbines is a challenging task because of the high variability of the wind speed and the confusion between faults and noise as well as outliers. However, the fault diagnosis of pitch actuators is particularly a challenging task because of i) the occurrence of pitch actuator faults in power optimization region in which the fault consequences are hidden and ii) the actions of the control feedback which compensate the fault effects.

Operating conditions of a system may change from normal to faulty either abruptly or gradually. In the case of gradual change, the system begins to malfunction (degraded behavior) until the failure takes over completely. The prediction of the occurrence of a failure prior to its occurrence can help providing a time to achieve appropriate corrective actions leading to decrease the maintenance costs and to increase the availability time. This can be achieved by early diagnosis module. Therefore, early diagnosis of pitch actuators is of particular interest for wind turbines industry due to their operational & maintenance costs as well as their essential role in optimizing the energy production.

1.2. State of the art

Diagnosis approaches can be divided into two main categories: analytical model based and data mining approaches. Analytical model based approaches exploit the physical knowledge about the system dynamics and structure to construct a mathematical or analytical model. The conceptual realization of these models can vary according to the used approach as the parity space (Ozdemir, Seiler & Balas, 2011) (Blesa, Puig, Romera & Saludes, 2011), state estimation (Zhang, Zhang, Zhao Ferrari, Polycarpou & Parisini, 2011), unknown input observer (Odgaard & Stoustrup, 2011), Kalman filters, unknown input Kalman filters (Chen, Ding, Sari, Naik,

Khan & Yin, 2011), parameter identification (Simani,Castaldi & Bonfe, 2011), state-parameter estimation, as extended Kalman filter approaches (LIU, 2011) etc. The application of model-based approaches for the fault diagnosis of wind turbines is difficult due to the wind turbine complexity and to the strong non-stationary of its environment. An alternative to the analytical model-based approaches is data mining approaches. In the latter, the model is built using historical data about the system dynamical behaviors. The model is built by learning from data in order to link the input or observation space to the output or decision space. Examples of these approaches applied to fault diagnosis of wind turbines we can cite, support vector machines (SVM) (Laouti,Sheibat-Othman & Othman, 2011), neural networks (Schlechtingen & Santos, 2011), principal component analysis (Kim, Parthasarathy, Uluyol, Foslien, Shuangwen & Fleming, 2011), auto-adaptive dynamical clustering (AuDyC) (Chammas, Duviella & Lecoeuche, 2013), self-feature organization map (Kim, Parthasarathy, Uluyol, Foslien, Shuangwen & Fleming, 2011), k nearest neighbors (Toubakh, Sayed-Mouchaweh & Duviella ,2013).

Few approaches have been proposed to achieve predictive diagnosis of wind turbines, in particular pitch actuators. This is due to the fact that modeling component degradation in strong nonlinear and complex non-stationary environments is very hard task. Examples of these methods, we can cite genetic programming algorithm (Kusiak & Verma, 2011), neural network, neural network ensemble, the boosting tree algorithm, and SVM (Kusiak & Li, 2010). These methods achieve the fault prediction using the Supervisory Control and Data Acquisition (SCADA) data. The latter have the disadvantage to be of limited size and thus they do not provide enough of information about components operating conditions. Thus, the prediction accuracy of specific faults is not sufficiently accurate.

1.3. Our approach

In this paper, a data mining based approach is proposed in order to achieve the prediction of faults that can impact wind turbine pitch actuators. Initial offline modeling allows constructing initial classes based on the historical data set. These classes are represented by restricted zones in the feature space. The latter is formed by sensitive features to pitch actuators' operating conditions in order to distinguish any drift from normal to fault operating conditions. The modeling tool is a dynamical clustering algorithm called AuDyC (Auto-Adaptive Dynamical Clustering) used to initialize the classes that will be dynamically updated. In this work, the faulty class, representing the failure operating conditions of pitch actuator, is considered to be a priori unknown. The only known class in advance is the one representing the pitch actuator normal operating conditions. Gradual degradations in pitch actuator operating conditions

are considered as a drift in the characteristics of normal class, representing the normal operating conditions, over time. This drift is characterized by a change in patterns distribution in the normal class in the feature space. The proposed approach monitors a change in the characteristics of this class in order to detect and confirm a drift, degradation, of pitch actuator normal operating conditions. Detecting and following this drift can help to predict the occurrence of pitch actuator failure. The drift is monitored using two drift indicators: one to detect a drift and the second to confirm it. When the drift is detected by the first indicator, a warning is emitted to human operators. Then, the second drift indicator confirms this drift in order to inform human operators of the necessity to react by taking the adequate correction actions.

The proposed data mining approach is composed of five main steps: processing and data analysis, classifier design, drift monitoring, updating and interpretation steps.

The paper is organized as follows. In section 2, the wind turbine benchmark and the generated fault scenarios are described. In section 3, the proposed approach to achieve fault prediction of pitch actuators is detailed. In section 4, the results based on the use of the wind turbine benchmark are presented. Finally, the conclusion and perspectives are discussed in section 5.

2. WIND TURBINE BENCHMARK DESCRIPTION

A benchmark model for Fault Detection and Isolation (FDI) and fault tolerant control (FTC) of wind turbines was proposed in (Odgaard & Stoustrup, 2009). The benchmark is based on the model of a generic three blade horizontal variable speed wind turbine with a full converter coupling and a rated power of 4.8 MW. The wind turbine model under study is composed of four parts: the blades, the drive train, the generator with the converter, and the controller. More details of the benchmark model can be found in (Odgaard & Stoustrup, 2009).

The controller operates in four zones (see Figure 1). Zone 1 is the start-up of the turbines, zone 2 is power optimization, zone 3 is constant power production and zone 4 is no power production due to a too high wind speed. The focus of this benchmark model is on the operation of wind turbine in zones 2 & 3.

Two control strategies are applied to optimize the energy production and keep it constant at its optimal value: the convertor torque control in zone 2 and the blades angle control in zone 3. In zone 2 (see Fig. 1), the wind turbine is controlled so that it produces as much energy as possible. To do so, the blades angle is maintained equal to 0° and the tip speed ratio is kept constant at its optimal value. The latter is regulated by the rotating speed control by tuning the convertor torque. Once the optimal power production is

achieved, the blades angle control maintains the convertor torque constant and adjusts the rotating speed by controlling the blades angle. The latter modifies the transfer of the aerodynamic power of the wind on the blades.
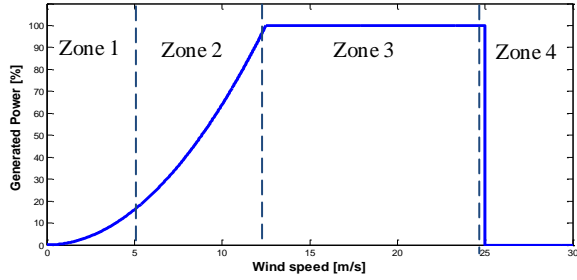

Figure 1. Reference power curve for the wind turbine depending on the wind speed.

Figure 2 shows the overall wind turbine model structure where υ_w denotes the wind speed, τ_r the rotor torque, ω_r the rotor speed, τ_g the generator torque, ω_g the generator speed, β_r the pitch angle control reference, β_m the measured pitch angles, $\omega_{r,m}$ the measured rotor speed, $\tau_{g,m}$ the measured generator torque, $\omega_{g,m}$ the measured generator speed, P_g the measured generated electrical power, $\tau_{g,r}$ the generator torque reference, and P_r the power reference.

The benchmark model permits to simulate the wind turbine behavior in two power zones: 1) zone 2 (power optimization) where τ_g is controlled and β_r is equal to zero and; 2) zone 3 (optimal energy production) where τ_g is kept constant and β_r is controlled. In this paper, we focus on pitch actuator faults as it is discussed in subsection 2.1.
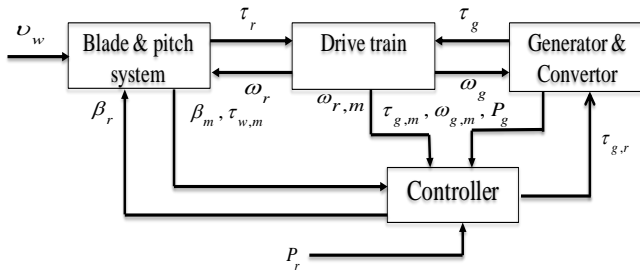

Figure 2. Block diagram of the wind turbine model (Odgaard & Stoustrup, 2009).

2.1. Pitch System Model

The hydraulic pitch system is modeled as a closed loop of dynamic system. The state representation of the nominal pitch system dynamics is:

$$\dot{x}_b = Ax_b + Bu$$
$$y_b = Cx_b$$

$$\begin{bmatrix} \ddot{\beta}_i \\ \dot{\beta}_i \end{bmatrix} = A \begin{bmatrix} \dot{\beta}_i \\ \beta_i \end{bmatrix} + B \begin{bmatrix} \beta_r + \beta_f \end{bmatrix} \tag{1}$$

$$A = \begin{pmatrix} 0 & 1 \\ -\omega_n^2 & -2\zeta\omega_n \end{pmatrix}$$

$$B = \begin{pmatrix} 0 \\ \omega_n^2 \end{pmatrix} \tag{2}$$

$$C = \begin{pmatrix} 0 & 1 \end{pmatrix} \tag{3}$$

The state vector x_b is composed of pitch angular speed $\dot{\beta}_i$, and position β_i for each blade i : $(i = 1, 2, 3)$. y_b is the measured pitch position, β_r is the pitch angle position reference provided by the controller, and β_f is the feedback pitch system (see Figure 3). ω_n, ζ are the parameters of the pitch system where ω_n represent the natural frequencies and ζ is the damping ratio.

The role of the pitch actuator is to adjust the pitch of a blade by rotating it; while the pitch angle of a blade is measured on the cylinder of the pitch actuator.
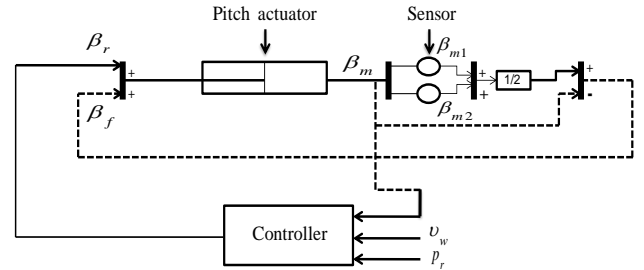

Figure 3. Block diagram of pitch system.

2.2. Fault scenarios

The pitch actuator fault considered in this paper is caused by air content increase in the actuator's oil. This fault is modeled as a gradual change in the parameters ω_n, ζ of pitch actuator n°3 (Odgaard & Stoustrup, 2009). Nine scenarios for this fault are generated in order to simulate slow, moderate and high degradation speeds represented by slow, moderate and high drift speeds. Each drift speed scenario is generated at three different time instances. Thus, parameters ω_n, ζ are changed linearly from ω_{n1}, ζ_1 to ω_{n2}, ζ_2 in a period of 30s, 60s and 90s, corresponding respectively to high, moderate and slow drift speeds. Then, the fault remains active for 100s. Finally the parameters decrease again to return to their initial values (see Figure 4).
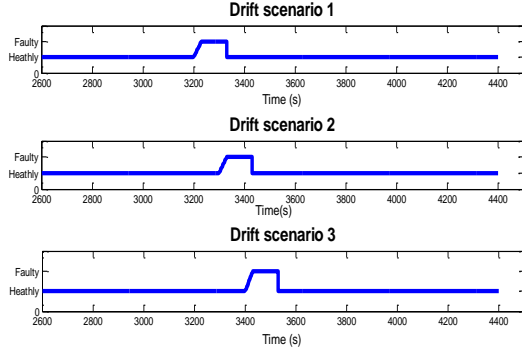
Figure 4. Drift scenarios corresponding to high drift speed in 3 different time instances.

The goal of using three different drift speeds starting in three different instant times is to test the performance, drift detection and confirmation, in the case of slow, moderate and high degradation speeds occurring in different wind speed (zones 2 and 3). Actuator fault scenarios are summarized in Table1.

Table 1. Pitch actuator fault scenarios.

Fault N°	Drift speed	Fault	Period
F_{1h}	30s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3200_s-3330_s
F_{1m}	60s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3200_s-3360_s
F_{1s}	90s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3200_s-3390_s

Fault N°	Drift speed	Fault	Period
F_{2h}	30s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3300_s-3430_s
F_{2m}	60s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3300_s-3460_s
F_{2s}	90s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3300_s-3490_s

Fault N°	Drift speed	Fault	Period
F_{3h}	30s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3400_s-5330_s
F_{3m}	60s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3400_s-5560_s
F_{3s}	90s	$\omega_{n1},\zeta_1 \rightarrow \omega_{n2},\zeta_2$	3400_s-3590_s

3. PROPOSED APPROACH

In this section, a dynamical data mining approach is developed in order to achieve condition monitoring and fault prediction of pitch actuator. It performs this prediction by detecting a drift of the system operating conditions from normal to faulty modes.

The proposed approach is based on 5 steps developed in the following subsections (see Fig. 5).
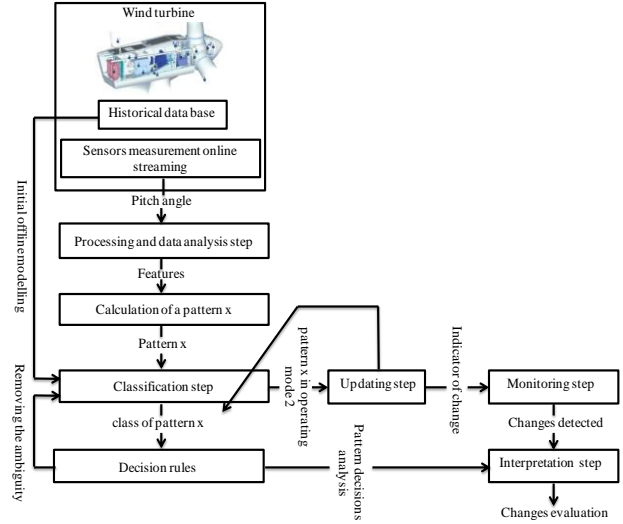

Figure 5. Proposed approach steps.

3.1. Processing and data analysis step

This step aims at finding the features sensitive to the system operating conditions in order to construct the feature space. The position of the pitch actuators is measured by two redundant sensors for each of the three pitch positions $(\beta_{k,mi}\ k =1,\ 2,\ 3,\ i =1,\ 2)$, with the same reference angle β_r provided to each of them. In order to enhance the robustness against noise, the measures are filtered by a first order filter using time constant $\tau = 0.06s$.

The research of sensitive features is based on the signals provided by the pitch sensors as well as the prior knowledge about the system dynamics. These features are chosen in order to maximize the discrimination between operating modes in the feature space. In this work, two-dimensional feature space is constructed for the actuator faults (Toubakh et al., 2013). Both features are residuals $\Delta\beta_A$, $A = 1,2$ computed by (4) and (5). Residuals $\Delta\beta_A$, $A = 1,2$, are generated by the comparison between the pitch angle measurement $\beta_{k,mi}$, $i =1,\ 2,\ k =1,\ 2,\ 3$ and the reference value of the pitch angle β_r (see Figure 3). The strong variability of the wind speed leads to a strong variability of the control pitch command which can increase the residuals

in the normal functioning mode. To overcome this problem which can cause false alarms, the residuals are computed within a time window in order to take into account the control variability $V(\beta_r)$. The size of this time window is determined experimentally to achieve a tradeoff between the delay of drift detection and false drift detection.

$$\Delta\beta_1 = \frac{\left|\beta_r - \beta_{k,m1}\right|^2}{V(\beta_r)} \qquad (4)$$

$$\Delta\beta_2 = \frac{\left|\beta_r - \beta_{k,m2}\right|^2}{V(\beta_r)} \qquad (5)$$

$$V(\beta_r) = \text{variance } (\beta_r) \qquad (6)$$

3.2. Classifier Design step

This step aims at designing a classifier able to assign a new pattern to one of the learnt classes in the feature space. A new pattern characterizes the actual operating conditions (normal or faulty in response to the occurrence of a certain fault) of the system.

Figure 6 shows the classes representing normal and failure operating conditions of pitch actuator in the feature space constituted by the two residuals defined by (4) and (5). Due to the wind turbine non-stationary environments, an overlapping region is created between the normal and failure classes (see Figure 6). In this region, the consequences of the fault are hidden because the actuators are not solicited or are solicited for small angles. In both cases, normal and failure classes overlap because of pitch sensors noises and low wind speed (see Figures 6 and 7).
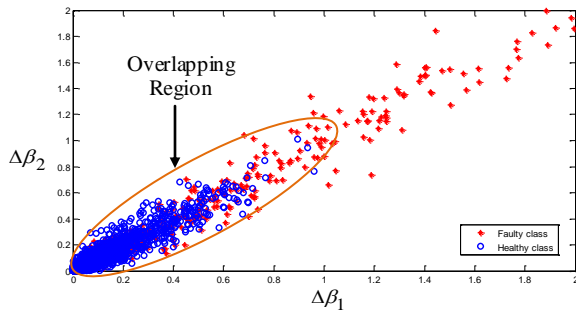

Figure 6. Large view of overlapping region for the third pitch actuator normal and failure operating conditions.
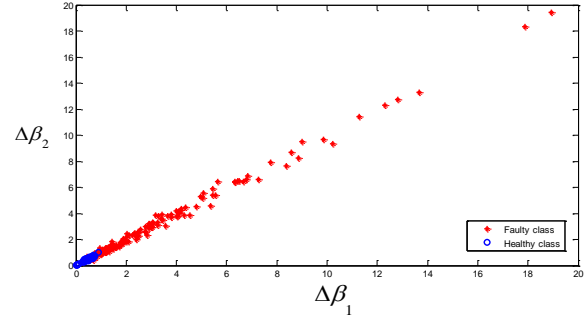

Figure 7. Feature space of the third pitch actuator normal and failure operating conditions.

In order to distinguish as much as possible the operating conditions (normal/faulty) and to improve the misclassification rate of the classifier, the normal and failure classes are split into three classes 1, 2 and 3 and the pitch actuator dynamics are represented by two different operating modes. The first one corresponds to the case of big pitch angles and high wind speed; while the second operating mode represents the case of small pitch angles and low wind speed (see Figure 8). Class 1 is the ambiguity class. It gathers the patterns processing pitch actuator normal or faulty operating conditions. This class represents the operating mode 1 (small angle and low wind speed). Class 2 represents the normal operating conditions class in operating mode 2 (large angle and high wind speed). Class 3 represents pitch actuator failure class in operating mode 2.
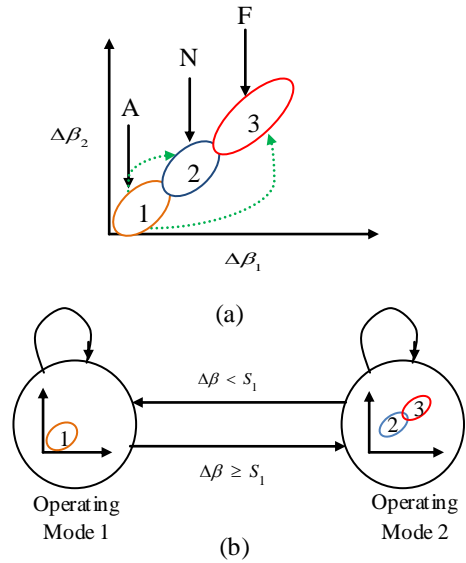

Figure 8. (a) Actuator decision space. (b) Operating modes 1 and 2 modeled by a finite state automaton containing two states.

3.2.1. Pattern decisions analysis

When a new pattern is classified in the ambiguity class, assigning it to normal or failure operating conditions is a risky decision since normal and failure classes are overlapped in this region of the feature space. In order to reduce this risk of misclassification, the decision about the status (normal or faulty) of any pattern classified in this region is delayed by assigning the label 'A' (ambiguity decision). Then, this ambiguity can be removed by analyzing the past and future decisions of this pattern. This pattern decisions analysis is achieved by using a set of decision rules allowing assigning to ambiguity patterns label 'N' or label 'F' (normal or faulty) as follows. Let us suppose that $X_A = \{x_t, x_{t+1}, \ldots, x_{t+n}\}$ is a set of patterns associated with the decision 'A'. Let x_{t-1} be the previous pattern arrived just before x_t, $D(x_{t-1})$ be the decision of this pattern, x_{t+n+1} be the pattern arrived just after x_{t+n}, $D(x_{t+n+1})$ be the decision for this pattern. Then, decision $D(x), \forall x \in X_A$ can be updated as follows:

$$D(x_{t-1}) = N \wedge D(x_{t+n+1}) = N \Rightarrow D(x) = N, \forall x \in X_A \qquad (7)$$

$$D(x_{t-1}) = F \wedge D(x_{t+n+1}) = F \Rightarrow D(x) = F, \forall x \in X_A \qquad (8)$$

$$D(x_{t-1}) = N \wedge D(x_{t+n+1}) = F \Rightarrow D(x) = A, \forall x \in X_A \qquad (9)$$

$$D(x_{t-1}) = F \wedge D(x_{t+n+1}) = N \Rightarrow D(x) = A, \forall x \in X_A \qquad (10)$$

where $\wedge$ refers to 'And' logical operation.

3. 2.2. Classification approach

Auto-adaptive Dynamical Clustering Algorithm (AuDyC) is used as a classification method in order to design the classifier. AuDyC was chosen because it is -) dynamical, -) unsupervised classification method and -) able to model streams of patterns since it reflects always the final distribution of patterns in the features space. It uses a technique that is inspired from the Gaussian mixture model (Lecoeuche & Lurette, 2003), (Traore, Duviella & Lecoeuche, 2009). Let E^d be a d-dimensional feature space. Each feature vector $x \in E^d$ is called a pattern. The patterns are used to model Gaussian prototypes P^j characterized by a center $\mu_{p^j} \in R^{d \times 1}$ and a covariance matrix $\Sigma_{p^j} \in R^{d \times d}$. Each gaussian prototype characterizes a class. A minimum number of N_{win} patterns are necessary to define one prototype, where N_{win} is a user-defined threshold. A class models an operating mode and groups patterns that are similar one to each other. The similarity criterion that is used is the Gaussian membership degree. Faults will affect directly this distribution and this will be seen on the continuously updated parameters. AuDyC will be associated with decision rules in order to design the classifier able to analyze the trajectory.

For more details on the functionalities of AuDyC, then adaptation like merging classes, splitting classes etc. The rules of recursive adaptation and the similarity criteria in AuDyC, can be found in (Lecoeuche & Lurette, 2003), (Traore et al., 2009).

3.3. Updating step

The updating step aims at reacting to the changes in the feature space. AuDyC is dynamic since it continuously updates the parameters by using the recursive adaptation rules (11), (12). In such a way, its validity and performance over time is preserved.

$$\mu_{p^j}(t) = \mu_{p^j}(t-1) + f\ (\mu_{p^j}(t-1), x^{new}, x^{old}, N_{win}) \qquad (11)$$

$$\Sigma_{p^j}(t) = \Sigma_{p^j}(t-1) + g\ (\Sigma_{p^j}(t-1), \mu_{p^j}(t-1), x^{new}, x^{old}, N_{win}) \qquad (12)$$

Where x^{new} and x^{old} are the newest arrived pattern and the oldest pattern in the time window N_{win} respectively.

Initial offline modeling allows the construction of initial classes that characterize knowledge from historical data. The historical data are usually sensor data that are saved. The modeling tool AuDyC used to initialize the feature spaces is based on extracted features from historical data, that will be online dynamically updated. Knowledge of failure modes given from (labeled) historical data can help building a classification scheme for fault diagnosis. However, in reality, these data are hard to obtain.

In this work, we suppose that only data corresponding to normal operating conditions (normal class) are known in advance. The training of the process by applying AuDyC is made based on features that are extracted from historical sensor data once finished; the class corresponding to normal operating mode is retained. We denote this class by $C_N = (\mu_N, \Sigma_N)$.

In online functioning, the parameters of C_N are dynamically updated by AuDyC for each new pattern arrives in operating mode 2. This yields changes in the class parameters which continuously reflect the distribution of the newest arriving patterns. We denote by $C_e = (\mu_e, \Sigma_e)$ the

evolving classes in the feature space. We have $C_e(t=0)=(\mu_e,\Sigma_e)=C_N$.

In operating mode 1, normal and faulty behaviors cannot be distinguished. Thus, in the proposed approach, the decisions about the status (normal/faulty) of patterns located in this region are delayed. Therefore in this case, the classifier will not be updated in order to avoid integrating in the drift time window useless patterns. In order to detect the drift as soon as possible, AuDyC updates the class parameters by using a window that contains only the patterns belonging to operating mode 2. AuDyC is dynamic by nature in the sense that it continuously updates the parameters of the classes as new patterns arrive.

3.4. Drift Monitoring step

The key problem of drift monitoring is to distinguish between variations due to stochastic perturbations and variations caused by unexpected changes in a system's state. If the sequence of observations is noisy, it may contain some inconsistent observations or measurements errors (outliers) that are random and may never appear again. Therefore, it is reasonable to monitor a system and to process observations within time windows in order to average and reduce the noise influence. Moreover, the information about possible structural changes within time windows can be interpreted and processed more easily. As a result, a more reliable classifier update can be achieved by monitoring within time windows. The latter must include enough of patterns representing the drift. To distinguish the useful patterns, the pitch actuator dynamics are represented by two different operating modes. In the operating mode 2, the degradation consequences of pitch actuator can be observed. Therefore, all patterns in this mode are useful to be analyzed and to be included in the drift time window. In the operating mode 1, the degradation consequences are masked. Patterns representing normal operating conditions cannot be distinguished from patterns representing pitch actuator degradations. Therefore in this case, no decision (normal/drift) will be taken in order to avoid integrating in the drift time window useless patterns.

The proposed methodology makes use of class parameters which are dynamically updated at each time but only with the patterns belonging to operating mode 2. Drift indicators are extracted from these parameters and detection of faults inception will be made based on their values. We define $I_{h1}(x), I_{h2}(x)$ as:

$$I_{h1}(x)=d_{Mah}\left((\mu_N,\Sigma_N),\mu_e\right) \tag{13}$$

$$I_{h2}(x)=d_E(\mu_N,\mu_e) \tag{14}$$

Where d_E, d_{Mah} are, respectively, the Mahalanobis and Euclidean metrics. Euclidean metric computes the distance between center of the normal class μ_N and the center of evolving class μ_e; on the other side Mahalanobis metric computes the distance between the normal class C_N and evolving class center μ_e.

$$d_{Mah}(C_N,\mu_e)=\sqrt{(\mu_N-\mu_e)\ \Sigma_N^{-1}\ (\mu_N-\mu_e)^T} \tag{15}$$

$$d_E(\mu_N,\mu_e)=\sqrt{(\mu_N-\mu_e)\times(\mu_N-\mu_e)^T} \tag{16}$$

3.5. Interpretation step

This step aims at interpreting the detected changes within the classifier parameters and structure. This interpretation is then used as a prediction about the tendency of the future development of the wind turbine current situation. This prediction is useful to formulate a control or maintenance action.

In this work we have two indicators of change $I_{h1}(x), I_{h2}(x)$. If one indicator exceeds a certain threshold th, the drift alarm will be launched. This means that the pitch actuators state has been moved (drift) away from the normal class. The second indicator aims at confirming the drift detection. The reason behind the use of two distance metrics (Euclidean and Mahalanobis ones) in the same time is to exploit the complementarily between them. Indeed, the Mahalanobis metric calculates the distance between the gravity center of the evolving class and the initial class. This will give more reactivity in case of change; while the Euclidean metric confirms this change by calculating the distance between the gravity center of the initial class and gravity center evolving class. The selection of th is motivated statically.

4. EXPERIMENTATION AND OBTAINED RESULTS

The failure of pitch actuator is caused by a continuous degradation of its performance over time. This degradation can be seen as a continuous drift of the normal operating conditions characteristics (normal class) of the pitch actuator. Detecting and following this drift can help the prediction of the occurrence of the pitch actuator failure. The two monitoring indicators defined by (13) and (14) are used to detect and to confirm this drift for the nine scenarios defined in section 2.

Figures 10 and 11 show the obtained results using the two drift detection indicators defined by (13) and (14). Table 2 shows the values of these indicators for the nine defined drift scenarios. These values represent the required time

(starting from the drift beginning) to detect and confirm the drift occurrence. Thus, they can be used as an evaluation criterion to measure the time delay to detect a drift before its end.
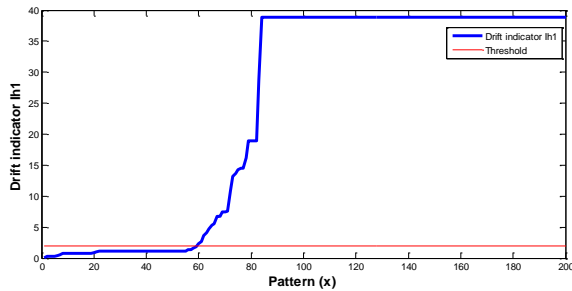

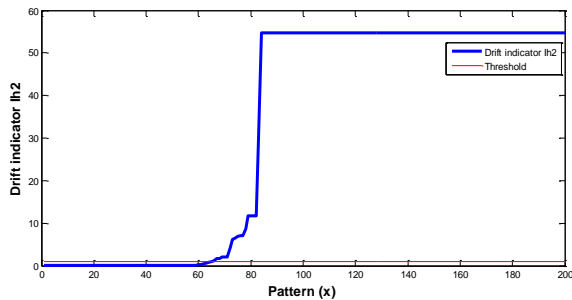Figure 10. Drift indicator based on Mahalanobis distance of the third pitch actuator.

Figure 11. Drift indicator based on Euclidean distance of the third pitch actuator.

Table 2. Results of drift detection and confirmation for the nine drift scenarios.

Fault N°	Drift speed	I_{h1}	I_{h2}	Period
F_{1h}	30s	7_s	11.10_s	3200_s-3330_s
F_{1m}	60s	14.40_s	28.70_s	3200_s-3360_s
F_{1s}	90s	28.70_s	31.40_s	3200_s-3390_s

Fault N°	Drift speed	I_{h1}	I_{h2}	Period
F_{2h}	30s	10.70_s	11.50_s	3300_s-3430_s
F_{2m}	60s	18.50_s	21.40_s	3300_s-3460_s
F_{2s}	90s	21.30_s	31.60_s	3300_s-3490_s

Fault N°	Drift speed	I_{h1}	I_{h2}	Period
F_{3h}	30s	9.90_s	10.70_s	3400_s-5330_s
F_{3m}	60s	13.00_s	20.30_s	3400_s-5560_s
F_{3s}	90s	22.70_s	29.30_s	3400_s-3590_s

5. CONCLUSION AND FUTURE WORK

In this paper, a methodology of condition monitoring and fault prediction was established. It is based on dynamical architecture of fault prediction. It was based on monitoring dynamically updated evolving class parameters. The methodology was tested on a benchmark of a wind turbine. It was shown that under the assumptions developed in this paper, the methodology has given promising results for different scenarios of simulation.

Future work will focus on the fault prediction and prognostics of other wind turbine critical components as the converter and drive train.

REFERENCES

Blesa, J., Puig, V., Romera, J. & Saludes, J. (2011). *Adaptation of set theoretic methods to the fault detection of wind turbine benchmark*. (8316– 8321), August 28 - September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi: 10.3182/20110828-6-IT-1002.01842

Chammas, A., Duviella, E., & Lecoeuche S. (2013). *Fault Diagnosis of Wind Turbine Drive Train Faults based on Dynamical Clustering*, (5650 - 5655), December 10-13, in Proceedings of CDC Firenze, Italy . doi: 10.1109/CDC.2013.6760779

Chen, W., Ding, S., Sari, A., Naik, A., Khan, A., & Yin, S. (2011), *Observerbased fdi schemes for wind turbine benchmark*. *General Guidelines*. (7073–7078), August 28 - September 2,in Proceedings of IFAC World Congress 2011. Milan, Italy. doi: 10.3182/20110828-6-IT-1002.03469

Laouti, N., Sheibat-Othman, N., & Othman, S. (2011). *Support vector machines for fault detection in wind turbines*. (7067– 7072) ,August 28 - September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi:10.3182/20110828-6-IT-1002.02560

Lecoeuche, S. & Lurette,C. (2003) *Auto-adaptive and dynamical clustering neural network*. (350–358) June 26–29. in ICANN'03 Proceedings, Istanbul, Turkey. doi: 10.1007/3-540-44989-2_42

LIU .W, (1999). *An extended Kalman filter and neural network cascade fault diagnosis strategy for the glutamic acid fermentation process*. Artificial intelligence in engineering A. page 131-140, vol. 13, n° 2, doi.org/10.1016/S0954-1810(98)00007-7

Odgaard, P., & Stoustrup, J. (2009), *Fault tolerant control of wind turbines a benchmark model*.(155–160), June 06-07,in Proceedings of the 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes. Sants Hotel, Spain. IFAC, doi: 10.3182/20090630-4-ES-2003.00026

Odgaard, P., & J. Stoustrup. (2010).*Unknown input observer based detection of sensor faults in a wind turbine.* (310 –315), September 8-10, in Proceedings of Control Applications (CCA), Yokohama , Japan. doi: 10.1109/CCA.2010.5611266

Ozdemir, A., Seiler, P., & Balas, G. (2011). *Wind turbine fault detection using counter-based residual thresholding*. (8289– 8294), August 28 - September 2, in Proceedings of IFAC World Congress. Milan, Italy. doi:10.3182/20110828-6-IT-1002.01758

Kim, K., Parthasarathy, G., Uluyol, O., Foslien , W., Shuangwen, S.,Fleming P. (2011*). Use of SCADA Data for Failure Detection in Wind Turbines.* August 7-10 , ,in Proceedings of the Energy Sustainability Conference and Fuel Cell Conference, Washington, USA. doi: DE-AC36-08GO28308.

Kusiak, A., Li, W. (2011). *The prediction and diagnosis of wind turbine faults*, in Proceedings of Renewable Energy , volume 36, Issue 1Pages 16-23. doi:10.1016/j.renene.2010.05.014

Kusiak, A.,Verma, A. (2011). *A Data-Driven Approach for Monitoring Blade Pitch Faults in Wind Turbines,* Sustainable Energy, page 87-96. doi: 10.1109/TSTE.2010.2066585

Simani, S. , Castaldi, P. , & Bonfe, M. (2011). *Hybrid modelbased fault detection of wind turbine sensors,*(7061– 7066), August 28 - September 2, in Proceedings of IFAC World Congress, Milan, Italy, doi: 10.3182/20110828-6-IT-1002.01311

Schlechtingen, M., & Santos, I. F. (2011) *Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection.*, Mechanical Systems and Signal Processing . Page 1849–1875. doi: org/10.1016/j.ymssp.2010.12.007.

Toubakh; H, Sayed-Mouchaweh, M. ; Duviella, E. (2013) *Advanced Pattern Recognition Approach for Fault Diagnosis of Wind Turbines.* (368 - 373) Decembre 4-7. in Proceedings of 12th ICMLA, Miami, USA. doi: 10.1109/ICMLA.2013.150

Traore, M. , Duviella, E., & Lecoeuche, S. (2009) *Comparison of two prognosis methods based on neuro fuzzy inference system and clustering neural network*. (1468-1473) June 06-07. in 7th IFAC symposium on Fault Detection, Supervision and Safety of Technical Processes, Sants Hotel, Spain. doi: 10.3182/20090630-4-ES-2003.00239

Zhang, X., Zhang, Q., Zhao, S., Ferrari, R. M., Polycarpou, M. M. & T. Parisini (2011). *Fault detection and isolation of the wind turbine benchmark: An estimation-based approach*, (8295– 8300), August 28 - September 2, in Proceedings of IFAC World Congress 2011. Milan, Italy. doi:10.3182/20110828-6-IT-1002.02808

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