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A Data-Driven Maintenance Support System for Wind Energy Conversion Systems

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Abstract: With the rapid growth of wind energy installed capacity, optimized maintenance has gained increasingly attentions from both researchers and wind farm owners. Condition-based maintenance (CBM) has been introduced to the wind energy industry in order to ensure the availability and safety of the wind energy conversion (WEC) system, while minimize the operating and maintenance (O&M) costs. In this paper a maintenance decision support system is introduced. By combining the information delivered by the data-driven WEC condition monitoring system and the economical benefits of each possible corrective maintenance action, the decision support system provides the operators with a choice of the most proper maintenance action for the current situation. The performance of the decision support system is tested with data collected from different WECs in a wind farm.

Keywords: Wind energy conversion system; Condition-based maintenance; Data-driven.

1. INTRODUCTION

With the rapid growth of wind energy installed capacity, optimized maintenance has gained increasingly attentions from both researchers and wind farm owners. However, the O&M cost is rather high, it can take up to 17% of the total life cycle cost (LCC) of a wind turbine [Gasch et al., 2012]. In order to ensure the availability and safety of the WEC system, while minimize the O&M costs, process monitoring methods and technologies have been widely applied on modern WECs [Hameed et al., 2009],[Amirat et al., 2009],[Lu et al., 2009]. Condition based monitoring is one of the most popular technologies, where the information provided by vibration analysis, oil analysis, metal scan, acoustic analysis, thermography, strain measurement etc. are available for the investigation of the current WEC condition [Hameed et al., 2009]. The Supervisory Control and Data Acquisition (SCADA) system collects online all kinds of measurement data from the WEC and record their operation status, which makes it possible to realize the WEC condition monitoring with data-driven multivariate methods (such as artificial intelligence [Kusiak et al., 2012], support vector machine [Laouti et al., 2011] and PCA method [Krueger et al., 2013]). However, as addressed in [Huang, 2008], uncertainties in the practice is unavoidable. A certain fault happened in the system could influence different condition monitoring indices, whilst the root-cause of the same triggered alarms might be due to different faults [Haghani et al., 2013]. These kind of uncertainties, on the one hand, make it difficult to choose a correct maintenance action [Huang, 2008], on the other hand, the operators are overwhelmed by the triggered alarms from different condition monitoring indices. Maintenance management strategies for wind farms have also been studied intensively. In [Amayri et al., 2011], ANN has been applied to predict the failure time distribution of WECs. However, the effectiveness of this method has only been demonstrated with numerical example. Studies have also been carried out based on field data. Maintenance decisions aimed on long-term costs optimization have been investigated with LCC analysis, both on- and offshore wind farms are studied for this maintenance management strategy [Nilsson et al., 2007]. In order to reduce the maintenance actions, costs and component failures, one of the well-established concept, reliability-centered maintenance (RCM) has been implemented in different industries [SAE JA1012 , 2012]. Fischer et al. [2007] has studied the functional failure modes of WEC major components, identified the root causes and suggested possible measures to prevent the failure causes, which forms a basis for the development of an optimized RCM strategy. Nevertheless, it has been pointed out in [Krueger et al., 2013], although the prior knowledge of the abnormality is available, it is still difficult to achieve a correct fault identification since the operating data of different WECs might be slightly influenced by their different operating conditions.

Motivated by the aforementioned observations, in this paper, a data-driven decision support system for WEC maintenance is proposed. Based on the WEC condition monitoring results, this approach combines the historical failure knowledge together with the economical aspect of each possible corrective operation.

The rest of this paper is organized as follows. In section 2, data-driven process monitoring and diagnosis method Fisher Discriminant Analysis is briefly introduced. Section 3 describes the theoretical background of the decision support system. Section 4 provides the implementation results based on real WEC data. Section 5 summarizes this paper with concluding remarks.

2. WEC CONDITION MONITORING

Maintenance actions and trouble shooting results are well recorded in the maintenance documents, which makes it possible to acquire the prior knowledge of the abnormalities taken place in the WEC system. Fisher Discriminant Analysis (FDA) is a powerful pattern classification method [Duda et al., 2001]. For fault diagnosis purpose, the training data are collected from the industrial process. The data are categorized into classes, where each class contains data representing a particular fault [Russell et al., 2000]. By defining a normal operating class, FDA can be applied as an efficient process monitoring tool, because of its discriminant ability among classes of data. Consider a process with p operating classes. The *Off-line training phase* of FDA technique can be formulated as follow:

- *Data collection and normalization:* Collect data from all p operating classes and stack them in matrix $X \in \mathbf{R}^{N\times m}$ with $N = \sum_{j=1}^{p}(n_j)$, where n_j is the number of observations in j^{th} class and m is the number of sensors. Mean value μ_j and standard deviation σ_j are calculated for each class. By scaling all the p classes of data to zero mean and unit variance, we obtain $Z_j \in \mathbf{R}^{n_j\times m}$, $j = 1, \ldots, p$.
- *Computation of within-class-scatter matrix S_w and between-class-scatter matrix S_b:*
$$S_w = \sum_{j=1}^{p} S_j, S_j = \frac{1}{n_j} Z_j^T Z_j \tag{1}$$
$$S_b = \sum_{j=1}^{p} (\mu_j - \mu)(\mu_j - \mu)^T, \tag{2}$$
with $\mu \in \mathbf{R}^m$ is the mean vector of the stacked matrix Z and $\mu_j \in \mathbf{R}^m$ is the mean vector for j^{th} class.
- *Calculation of generalized eigenvalue and the corresponding eigenvector:* Solve the following generalized eigenvalue problem:
$$S_b w_k = \lambda_k S_w w_k. \tag{3}$$
If S_w is invertible, Eq. (3) can be reformulated as:
$$S_w^{-1} S_b w_k = \lambda_k w_k. \tag{4}$$
Since $rank(S_b) \leq p - 1$, there exist maximal $p - 1$ non-zero eigenvalues. Define a as the number of non-zero eigenvalues and save the associated eigenvectors in $W_a = [w_1, \ldots, w_a] \in \mathbf{R}^{m\times a}$
- *Computation of threshold:* With the given significant level α:
$$J_{th,T^2}^{j} = \chi_\alpha^2(a). \tag{5}$$
where $\chi_\alpha^2(a)$ is χ^2 distribution with a degrees of freedom and confidence level $1 - \alpha$.

The *On-line monitoring procedure* is carried out as follows:

- *Data normalization:* Normalize the on-line new measurement sample $x_{new,j} \in \mathbf{R}^{m\times 1}$ as follow:
$$\overline{z}_{new,j} = \frac{(x_{new} - \mu_j)}{\sigma_j} \tag{6}$$
- *Computation of test statistic:* The T^2 test statistic for j^{th} class is defined as follow:
$$T_j^2 = \overline{z}_{new,j}^T W_a (W_a^T S_j W_a)^{-1} W_a^T \overline{z}_{new,j} \tag{7}$$
- *Monitoring logic:* If $T_j^2 < J_{th,T^2}^{j} \Longrightarrow$ data belongs to the j^{th} class.
A fault is considered to be detected when the test statistic T_{normal}^2 exceeds the threshold J_{th,T^2}^{normal}.

3. DECISION SUPPORT SYSTEM

The probability of occurrence of a specific fault or degradation in overall performance of the system, together with loss minimization technique which reflects maintenance operations, forms the basis of this decision support scheme [Haghani et al., 2013]. Given the process measurements and condition monitoring results, the probability of the fault happens in the system is estimated. Together with the maintenance costs and the benefits of the corrective actions, an optimization problem is formed, which is solved by maximum *a posteriori* probability (MAP) criterion. Consider a process is subject to i different abnormalities $f_1, \cdots, f_i$. These faults influence process measurements $\mathbf{x}$ and the monitoring indices in the system $m_1, \cdots, m_j$. The probability of the fault f_t for $t = 1, \cdots, i$ using the on-line process measurements $\mathbf{x}$, and monitoring indices $m_1, \cdots, m_j$ are calculated, namely the following conditional probability:
$$p(f_t|\mathbf{x}(k), m_1(k), \cdots, m_j(k)) \tag{8}$$
for $t = 1, \cdots, i$.

The *Off-line* training of the designed decision support system is achieved by computing the statistical models for different fault classes from available historical data, namely $p(\mathbf{x}|f_1, \cdots, f_i)$, $p(m_1, \cdots, m_j|f_1, \cdots, f_i)$ and corresponding *a priori* probability $p(f_1, \cdots, f_i)$. Assuming a certain distribution for the data for each class, the off-line training data can be considered as a finite mixture of different components where each of them follows a specific distribution with different parameters. A convenient approximation is to assume that the data follow Gaussian distribution and solve the problem by utilizing the Gaussian mixture modeling tools [McLachlan et al. , 2000].

In the *On-line* implementation phase, the probability in (8) is determined using the current process measurements $\mathbf{x}(k)$ and monitor readings $m_1(k), \cdots, m_j(k)$ together with *a priori* probability $p(f_1, \cdots, f_i)$. To consider the uncertainties in fault detection, diagnosis and prognosis in corrective operation generation and decision making, the probabilities obtained previously can be used.

Associated with each fault there will be a list of corrective operations ranging from doing nothing to the component replacement, with their costs and benefits on improvement of system performance. By combining the probability that a certain fault is happening together with the losses corresponding to the corrective operations respective to that fault, the most proper corrective operation(s) could be found among the list of all operations. A loss due to a corrective operation is defined here as [Camci, 2009]

$$\mathrm{L}(CA_j, f_i) = \mathrm{C}(CA_j) + \mathrm{L}(f_i) - \mathrm{B}(CA_j, f_i) \qquad (9)$$

where L denotes the losses, CA_j represents the corrective operation j associated with the fault i, f_i, C shows the costs of performing a corrective operation and B denotes the benefits of performing the CA_j in the case where f_i occurs in the process. Since $0 \leq \mathrm{B}(CA_j, f_i) \leq \mathrm{L}(f_i)$, (9) can be written as

$$\begin{aligned} \mathrm{L}(CA_j, f_i) &= \mathrm{C}(CA_j) + (1 - \alpha_{i,j})\mathrm{L}(f_i) \\ &= \mathrm{C}(CA_j) + \mathrm{L}(CA_j|f_i) \end{aligned} \qquad (10)$$

where $0 \leq \alpha_{i,j} \leq 1$ is the normalized value of the benefit of CA_j and can be interpreted as the following conditional probability

$$\alpha_{i,j} = p(\mathrm{B}(CA_j, f_i) = \mathrm{high}|f_i, CA_j) \qquad (11)$$

The parameter $\alpha_{i,j}$ can be determined by expert knowledge or historical data.

To determine the proper maintenance operation, the optimization is defined in a probability form and using the MAP criterion, where the most proper corrective operation is the one associated with the highest probability stated below:

$$\begin{aligned} \hat{CA}_{MAP} = \arg\max_j p(\mathrm{B}(CA_j, f_i) = \mathrm{high} \\ , \mathrm{L}(CA_j, f_i) = \mathrm{low}|CA_j) \end{aligned} \qquad (12)$$

The probability in (12) can be written as

$$\begin{aligned} & p(\mathrm{B}(CA_j, f_i) = \mathrm{high}, \mathrm{L}(CA_j, f_i) = \mathrm{low}|CA_j) \\ & = \sum_{f_i} p(\mathrm{B}(CA_j, f_i) = \mathrm{high}|f_i, CA_j) \times \\ & \qquad p(\mathrm{L}(CA_j, f_i) = \mathrm{low}|f_i, CA_j) p(f_i) \end{aligned} \qquad (13)$$

The probability $p(\mathrm{L}(CA_j, f_i) = \mathrm{low}|f_i, CA_j)$ can be formulated as $1 - p(\mathrm{L}(CA_j, f_i) = \mathrm{high}|f_i, CA_j)$, where

$$\begin{aligned} & \mathrm{L}(CA_j, f_i) = \mathrm{high}|f_i, CA_j \\ & \qquad \sim \mathcal{U}\left(\mathrm{C}(CA_j), \mathrm{C}(CA_j) + \mathrm{L}(f_i)\right) \end{aligned} \qquad (14)$$

and its value can be calculated by integrating this uniform distribution up to the current value of $\mathrm{L}(CA_j, f_i)$ (see (9)). For detailed description of the proposed decision support system please refer to [Haghani et al., 2013].

4. IMPLEMENTATION

The approaches introduced in Section 2 and 3 are implemented on WEC field data. Real operation data are collected from different turbines of the same type and produced by the same manufacturer.

Table 1 displays the process measurements that included in this study, which consists of three components: Rotor, Gearbox and Generator. According to the sensor configuration of this type of WEC, the variables considered in this paper are standard available measurements. All the variables are sampled in 10 minutes intervals. According to the gearbox speed, 8 normal operating classes have been defined for the purpose of fault detection.

4.1 Abnormality scenarios and detection results

For this study, three abnormalities taken place in WEC gearbox have been applied for the training phase, namely,

Table 1. Selected Measurements

Variable	Measurement description	Component	Unit
1	Generator Bearing 1 Temperature	Generator	°C
2	Generator Bearing 2 Temperature	Generator	°C
3	Generator Stator Temperature	Generator	°C
4	Gearbox Bearing 1 Temperature	Gearbox	°C
5	Gearbox Bearing 2 Temperature	Gearbox	°C
6	Gearbox Inlet Temperature	Gearbox	°C
7	Gearbox Oil Sump Temperature	Gearbox	°C
8	Gearbox Speed	Gearbox	*rpm*
9	Generator Speed	Generator	*rpm*
10	Rotor Speed	Rotor	*rpm*

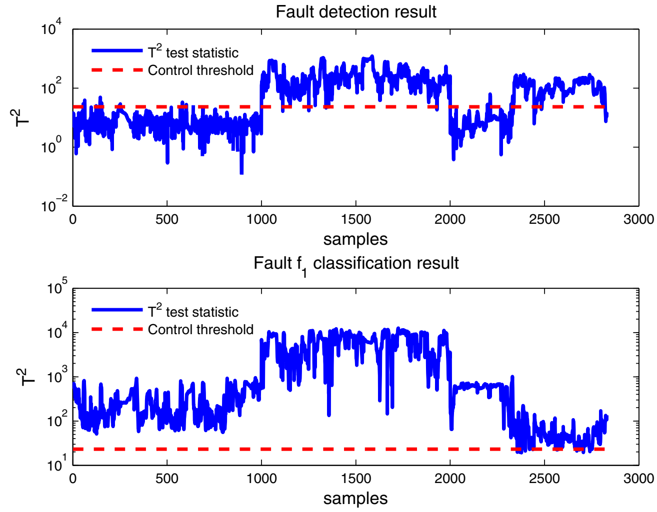

Fig. 1. Fault classification with FDA (1)

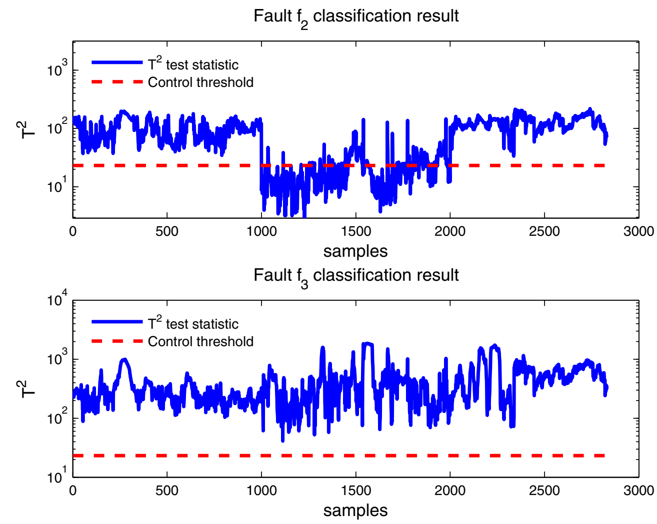

Fig. 2. Fault classification with FDA (2)

fault f_1 is an air cooler malfunction in the cooling system, fault f_2 is an abnormality of the mechanical pump in the lubrication system and fault f_3 refers to a sensor abnormality. For the on-line evaluation, only fault f_1 and f_2 are considered. It is well known that, both cooling

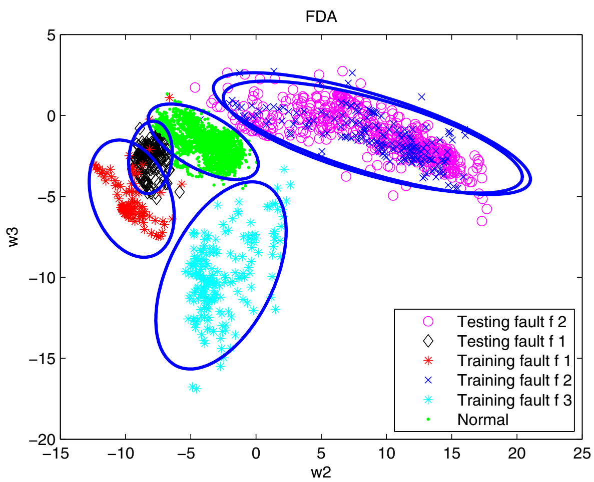

Fig. 3. The projection of WEC data for 4 classes onto the 2nd and 3rd FDA loading vectors

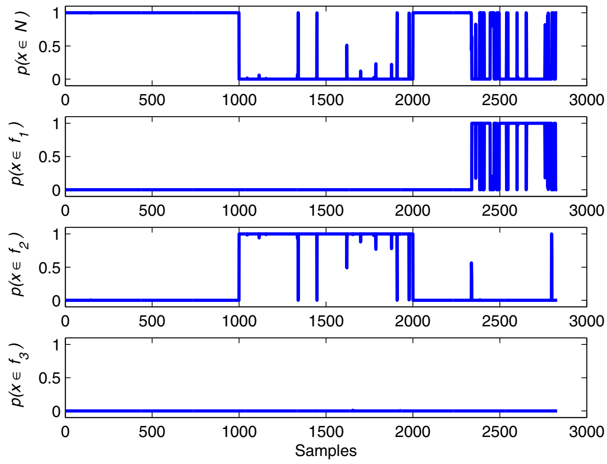

Fig. 4. Probability of the faults

and lubrication system in the gearbox play vital roles in ensuring the performance, effectiveness, safety and lifetime of WECs. Fig. 1 and Fig. 2 are plotted in semi-log coordinate system, where the fault detection and classification results are shown based on FDA method. The test fault f_2 began at sample 1000 ended at sample 2000 and the test fault f_1 took place after sample 2238. It can be seen that both test abnormalities have been detected. On the one hand, for f_2 the fault detection rate is about 99.1%, where the fault detection rate of f_1 is 95.7%. On the other hand, comparing with the fault detection rate, the fault classification rate is rather low, for f_2 is 76.8% whilst for fault f_1 is only 4.7%. As demonstrated in Fig. 3, it is obvious that the test f_2 can be well identified based on the off-line trained fault class. However, for the classification of test f_1, it is difficult to identify it correctly due to the slightly different operating conditions (environment, sensor installation position and so on) between the training WEC data and the testing WEC data.

4.2 Decision support system for WEC

From the maintenance reports and expert knowledge, a list of maintenance operations is defined for each fault. The losses due to the faults and maintenance actions related to each fault is shown in Table 2. Due to the confidentiality of the involved information, only normalized data are listed in this paper. Moreover, the fixed costs of each maintenance operation and the parameters α_{ij}, which are basically the benefit of performing CA_j in case of fault i, are listed in Table 3. The parameter α_{ij} is obtained from expert knowledge and maintenance reports. It is assumed that the value of the power generation until the next scheduled maintenance is 5 units, where the power generation is considered to be constant at the historical average value. It should be pointed out that the losses of f_1 and f_2 will increase with the time due to fault propagation to other components and the threats brought by those malfunctions to the operation safety.

Table 2. Maintenance operations with respect to each fault and losses due to each fault

Fault	Losses	Maintenance operation
f_1	2	Reduce power generation
		Replace/repair air cooler motor
		Do nothing
f_2	8	Reduce power generation
		Replace/repair the mechanical pump
		Do nothing
f_3	0.4	Adjust the sensor
		Replace the sensor
		Do nothing

Consider that the data follows Gaussian distribution, the statistical models for different faults $p(\mathbf{x}|f_1, \cdots, f_i)$ can be obtained: $\mathbf{x} \sim \mathcal{N}(m_{f_i}, \Sigma_{f_i})$. The probabilities that the WEC is operating under different scenarios are shown in Fig. 4. The considered scenarios are as follow: WEC operation is normal $(p(\mathbf{x} \in N))$; WEC is subject to fault f_1 $(p(\mathbf{x} \in f_1))$; WEC is subject to fault f_2 $(p(\mathbf{x} \in f_2))$; WEC is subject to fault f_3 $(p(\mathbf{x} \in f_3))$; As shown in Fig. 5, at the beginning the WEC is working under normal operation class, where the fault detection index is under the threshold (see Fig. 1) and the probability of normal operation is high (see Fig.4), the recommended maintenance action is doing nothing. After the probability of fault f_2 changed to almost 1, the decision support system suggests to carry out maintenance action CA_1 which is reducing the power generation. By reduced power generation, it would not be necessary for the lubrication system to work with full power. Normally, the gearbox lubrication system consists of two pumps, one mechanical pump one electrical pump. The mechanical pump is working all the time as long as the wind turbine is operating. The electrical pump

Table 3. Maintenance operations, their costs and benefits

Sig.	Maintenance action	Fix costs	α_{ij}		
			f_1	f_2	f_3
CA_1	Reduce power generation	0.5	0.6	0.4	0
CA_2	Replace/repair the air cooler motor	1	1	0	0
CA_3	Replace/repair the mechanical pump	3	0	1	0
CA_4	Adjust the sensor	0.2	0	0	0.3
CA_5	Replace the sensor	0.3	0	0	1
CA_6	Do nothing	0	0	0	0

will be switched on to strengthen the lubrication system. Therefore the WEC that suffers from the mechanical pump malfunction could be firstly treated with CA_1 in order to avoid unscheduled maintenance. However, this situation could not last too long. If the mechanical pump is not working correctly, or even suffers from a total malfunction, the electrical pump will be overloaded. After a while it may become faulty as well. A replacement of electrical pump could be expensive. At the same time, a lubrication system malfunction could affect directly the safety of WECs. Therefore, it can be seen that, after the test f_2 has been detected for a short period, the system suggests for a shut down and replacement of the mechanical pump.

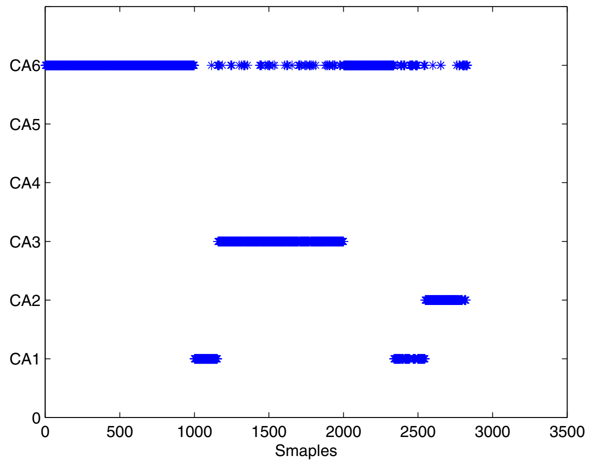

Fig. 5. Results of decision support system

In the second period of the samples, from sample 2001 to 2238, the WEC is under normal operation condition, where the suggestion from the decision support system is to do nothing. Furthermore, as an abnormality has been detected, the probability of the WEC operates normally is changing rapidly from 1 to 0 and back to 1. The same phenomenon could be observed from the probability of the WEC suffers from f_1. The decision support system recommended to perform CA_1, where the power generation will be reduced so that the cooling system would not be that heavily loaded. Since the probability of f_1 stays around 1, the suggested maintenance action is to replace the air cooler.

It should be pointed out that, as f_1 and f_2 are detected, there are still suggestions from the decision support system recommending doing nothing as the best maintenance choice. A possible reason could be that the cooling system and lubrication system are both highly related to the WEC operating speed. If the WEC is working around a low speed, both systems are not required to work fully loaded. As the result, it would be difficult to detect the considered abnormalities under low wind speed, which leads to the suggestion that no maintenance should be performed.

5. CONCLUSION

In this paper, the decision support system has been implemented for the purpose of WEC condition based maintenance. The recommendations from the system combined the condition monitoring results provided by the data-driven WEC monitoring system with the financial benefits of possible maintenance actions. Furthermore, the operation safety and the consequences of fault propagation have been taken into consideration. Real WEC data has been applied for the validation of the introduced decision support system, where the results are reasonable and easy for the operator to understand. One constraint of this method is that the decision support system requires pre-knowledge of the possible faults for the training phase. In order to improve the performance of the decision support system and optimize the maintenance schedule, detailed information of fault propagation should be studied in relationship with operation safety. Moreover, the wind speed forecast could also be integrated in the decision support system so that the maintenance could be rescheduled according to the weather. Further tests should be carried out on other abnormalities and components as well so that the system could learn or relearn parameters, such as: the fault models and the benefits of performing a certain corrective action.

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