Review of Offshore Wind Turbine Failures and Fault Prognostic Methods

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Abstract—**Wind electricity is a highly promoted energy source all around the world. The number of offshore wind farms, increases gradually because of the high capability of power generation. However, the cost of manufacturing, logistics, installation, grid control and maintenance of offshore wind turbine is high. According to the Condition Monitoring of Offshore Wind Turbine (CONMOW) report of Energy Research Centre in the Netherlands, the investment costs for future offshore wind farms built of larger units are expected to be 1.4 to 2.0 k€/kW. The Operation and Maintenance (O&M) costs 30 to 50 €/kW per year. To enhance a cost effective maintenance strategy and higher quality design, Prognostics and System Health Management (PHM) is applied. In this paper, major failures of wind turbine will be discussed and possible prognostic methods for the failures will be introduced.**

Keywords- Prognostics; Offshore Wind Turbine; Failures; Hidden Markov Model; Neural Networks; Particle Filter

I. INTRODUCTION

Offshore wind power is a popular wind energy source starting from 21st century because of its high energy production. The total power capacity of offshore wind turbines in Europe increased ten-fold during 2001 to 2007 [1]. In China, the 12th Five-Year Plan targeted to build offshore wind farms with newly installed capacity over 70GW [2]. However, people pay less attention to the operation and maintenance cost which may cost 25% to 30 % of the energy generation cost [3]. The accidents of wind turbine also increase year by year. In 2011, there were 13 fatal accidents caused which was the highest year since 1970s [4]. To minimize the O&M cost and the threats to human life, Prognostics and System Health Management (PHM) discipline is integrated with the condition monitoring system of wind farms.

To build up the PHM for the offshore wind turbine, a comprehensive monitoring system with historical database is required. Therefore, the operation condition of the turbine can be captured by the relative sensors or data acquisition system. The data will then be analyzed by the PHM approaches. In this paper, data- driven approaches are discussed because they are more suitable for the pactical remote control and monitoring of offshore wind farm [5]. As the result, the relevant system health management scheme such as emergency alarms, maintanence schedule and grid synchronization strategy will be estimated. The scheme will be recorded to the historical database and will provide a reference to Research and Development (R&D) improvement. So that the product can be improved with better hardware and/or software setup such as sensor reallocation and selection of PHM approaches in different cases. A general data flow diagram of PHM architecture is shown in Figure 1.
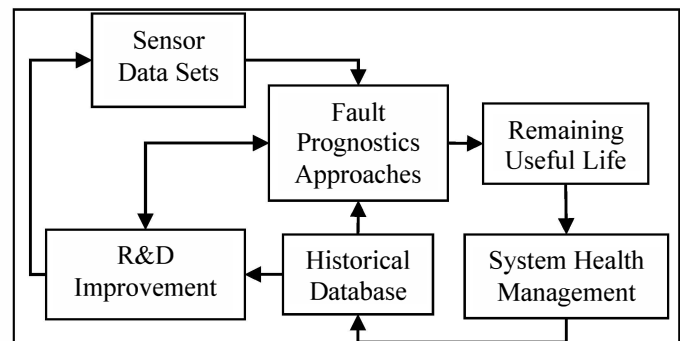

Figure 1. General PHM data flow.

In this paper, we will focus on two major parts of PHM for offshore wind turbines. First, the major hardware failures of offshore wind turbine are discussed in section II. In order to prevent the problems raised in section II, section III will mention 3 popular fault prognostic approaches for the similar machinery failures.

II. FAILURES OF OFFSHORE WIND TURBINE

Electrical control, gearbox, yaw system, generator, hydraulic, grid and blades are rated (60% of the total failures) as the most common failure components of wind turbines (>1.5MW) in the study of Danish turbines [6] (Figure 2). Those challenges cause extra cost on emergency maintenance, component screening, physical designs and so forth. According to the failed components mentioned, a more details are provided in the following with the failure mechanism(s)

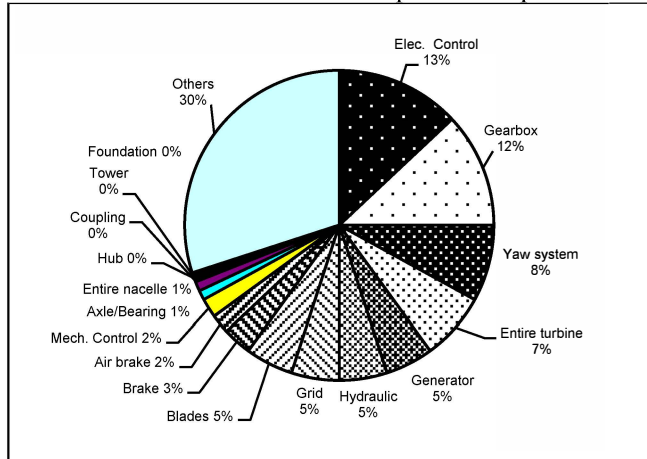and cause(s) of the components. Therefore, prognostic methods can be customized for the specific components.

Figure 2. Failure rate of wind turbine components.

A. Electrical Control Failures

Damages of generator windings, short-circuit and over voltage of electronics components, transformers (Figure 3) and wiring damages are the common failures of electrical control [7]. These failures are reported as the results of lightning, poor electrical installation, technical defects and resonances within resistor-capacitor (RC) circuits [8].

Figure 3. Lightning-caused transformer damage.

B. Yaw System Failures

Yaw control system controls the nacelle rotation to place the blades facing the desired angle [9]. It was reported that the cracking of yaw drive shafts, fracture of gear teeth, pitting of the yaw bearing race and failure of the bearing mounting bolts are all categorized as Yaw System Failures [10]. Icing problem in extreme weather [11] and high vibration level during overload [12] are also claimed as the cause of the failures.

C. Gearbox Failures

Gearbox is usually found in the turbines nowadays. However, it was one of the most frequently damaged rotational components in turbine. The failures are usually wearing,

backlash, and tooth breakage (Figure 4). They are claimed as the result of particle contaminations, frequent stoppage and starting and high loaded operation conditions [7].

Figure 4. Tooth breakage caused by frequent stoppage and starting.

D. Grid Failures

The wind speed and direction always change time after time. It is impossible to predict them accurately. If the region is highly dependent on wind power without any backup power storage or other power generation system, wind grid may occur during high power consumption with low wind power generation [13].

E. Hydraulic Failures

Hydraulic components are used in many high pressure connections located in pitch, yaw, braking system and gearbox lubrication system. The leakages of these components are called hydraulic failure. Since the offshore turbines are usually located in extreme environmental conditions, the failure may occur during high/low temperature, corrosion, vibration. The reasons behind are claimed as improper installation, poor system design, poor component quality and system abuse. The improper installation rated as 60% of the total failure causes [14].

F. Blade Failures

Blades are the main rotors of wind turbine and they transfer wind power into up-lifting force by fluid dynamic physical design. Usually, any blade damages, cracks, breakups and bends are said as blade failures. Causes of the blade failures include turbulent wind, out-of-control rotation, lightning [15] and production defects [16]. [4] reported that a broken blade had travelled as far as 1.3km from its tower. Many countries, hence, set up regulations to forbid their civilians to get close to wind farms such as US and Germany [17].

III. PROGNOSTICS AND SYSTEM HEALTH MANAGEMENT

To enhance a high quality of turbine production and minimize the maintenance cost, applying data-driven PHM approaches to the failures mentioned in the previous section is proposed.

A. Hidden Markov Model

Hidden Markov Model (HMM) is a statistical modeling tool which is introduced by Rabiner [18]. It was used in speech recognition [19], fault diagnosis, tool wear detection and prediction [20], electrical fault [21], and fault monitoring [22].

In general, HMM can be defined by the following parameters:

Parameters	Description
C	Number of states/classes
π	C x 1 initial state distribution vector where the ith element is the probability of being in state i at time k = 0. $p(S_0 = i)$.
A	C x C state-transition matrix where the $(i, j)^{th}$ element is the probability of being in state j at time k +1, given that it is in state i at time k, $p(S_{k+1} = j \vert S_k = i)$
B	State-dependent observation density B. Its jth element is the probability of observing O_k at time k given the system is in state j, $bj(O_k) = p(O_k \vert S_k = j)$.

For convenience, the compact notation $\lambda = \{\pi, A, B\}$ is used to indicate the complete parameter set of the model.

In prognostic application of HMM, Learning Phase and Exploitation Phase are included. In Learning Phase, the feature(s) from normal condition to failure situations are transformed into HMMs by Baum-Welch algorithm [23]. The HMMs then construct historical database for each failure. In Exploitation Phase, the on-line data are input to the model database to evaluate the health status of the current product or component by computing the probability $P(O \mid \lambda)$ where O is defined as the observation sequence and λ is the online extracted features. Once the specific HMM is selected, Viterbi Algorithm [24] is used to find the state sequence $(s_1, s_2, ..., s_t)$ and the last states sequence $(s_{t-l}, ..., s_{t-2}, s_{t-1}, s_t)$ where l is the past observation factor and t is current time. Then, Chapman – Kolmogorov equation (1) is applied to estimate the health state after n iterations [25]. The Remaining Useful Life (RUL) is calculated when the predicted probability of being in the last state reaches a predefined limit ε in equation (2) [26].

$$\hat{P}(n) = \pi_t A^n \tag{1}$$

$$RUL = n \Leftrightarrow \hat{P}(s = s_N \mid n) = \varepsilon \tag{2}$$

B. Neural Network

Neural Network (NN) is a mathematical model based on interconnected brain neuron structure. It can compose a large number of highly interconnected elements (neurons) working together to provide output(s) for problem solving. Besides PHM application, it was widely used in medical, marketing, electronic chip development, speech and vision recognition.

In the theory of NN, the neurons have 2 operation modes, training mode and using mode which are for 'learning' purpose and 'decision making' purpose, respectively. In using mode, if there are any inputs that are have not been learnt before, the 'decision making' will follow the firing rules such as Hamming distance technique. NN is divided into 2 working principles. Feed-forward Network only allows signals travel in one way from inputs to outputs. It is extensively used in pattern recognition. Feedback networks enable feedbacks between neurons communications. The networks are dynamic which change continuously until the equilibrium state is reached. It can be extremely complicated but powerful.

Practically, NN is used in fault prognostic of axle gear [27]. Vibration signal of the axle gear is preprocessed by feature extraction and then used as the precursor for prediction system. There are 3 layers contained by Feed-forward network (Figure 5). The prediction is estimated by the previous outputs of the network. For example, the network takes $y_{t-k+1}, y_{t-k+2}, ..., y_t$ as input to predict $\hat{y}_{t+1}$ at time instant t by Radial Basis Function (RBF) Networks [28] [29] (Figure 6).
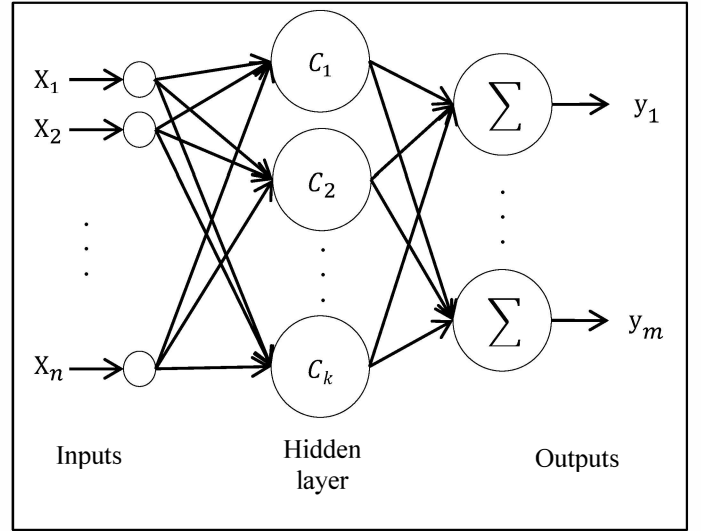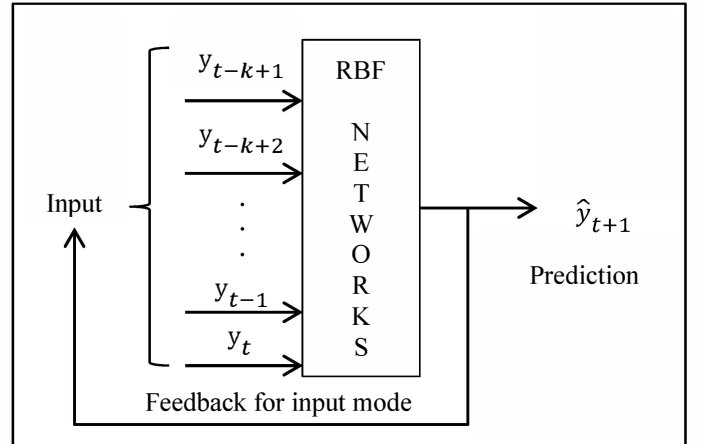

Figure 5. Feed-forward network layers.

Figure 6. Prediction framework of RBF Networks.

C. Particle Filter

Particle Filter (PF) is another method for fault prognostics applications. 'Particle' means the unknown sample. The method aims to approximate the relevant distributions with particles and their associated weights. The state of Probability Density Function (PDF) is estimated which is used to predict the evolution in time of the fault indicator. It is useful to solve difficult nonlinear and/or non-Gaussian problems because of the use of Bayesian theory. Moreover, fewer samples are required to approximate the trend with acceptable accuracy. The short computation speed is also the advantage of the method. All these benefit in fault diagnostics and prognostics of complex dynamic systems like engines, gearboxes and bearings [30].

For the application of fault prognostics, there should be at least one parameter data set providing the health condition of

product/ component. If there are 2 or more parameters available, they are always combined to generate a single signal. The evolution in time of failure condition is described through the following nonlinear state equation.

$$\begin{cases} x_1(t+1) = x_1(t) + x_2(t) \cdot F(x(t), t, U) + w_1(t), \\ x_2(t+1) = x_2(t) + w_2(t) \end{cases} \quad (3)$$

where $x_1(t)$ is state representing the quantized fault scale under analysis, $x_2(t)$ is a state associated with an unknown model parameter, U are external inputs to the system, $F(x(t), t, U)$ is a general time-varying nonlinear function, w_1 and w_2 are white noises represented by vectors or scalars. $F(x(t), t, U)$ may represent a model based on a neural network or fuzzy system.

According to the equation (3), long term predictions can be calculated using kernel function to reconstruct the stated PDF in future time instants:

$$\hat{p}(x_{t+k} \mid \hat{x}_{1:t+k-1})$$

$$\approx \sum_{i=1}^{N} w_{t+k-1}^{(i)} K\left(x_{t+k} - E\left[x_{t+k}^{(i)} \mid \hat{x}_{t+k-1}^{(i)}\right]\right) \quad (4)$$

where $K\left(x_{t+k} - E\left[x_{t+k}^{(i)} \mid \hat{x}_{t+k-1}^{(i)}\right]\right)$ is the kernel density function, which may correspond to the process noise PDF, Gaussian kernel or a rescaled version of Epanechnikov kernel.

The upper and lower bound of the predicted PDF can be used as a fault indicator to determinate hazard zones based on historical failure data. Hazard zone specifies the probability of failure and the weights $\left\{w_{t+k}^{(i)}\right\}_{i=1,2,\ldots,N}$ represent the predicted probability for the predicted path. Then, RUL of the system can be estimated by applying the law of total probabilities as follows:

$$\hat{p}_{RUL}(t) = \sum_{i=1}^{N} Pr\left(Failure \mid X = \hat{x}_t^{(i)}, H_{lb}, H_{ub}\right) \cdot w_t^{(i)} \quad (5)$$

where H_{lb} is the lower bound of PDF, H_{ub} is the upper bound of PDF [31].

D. Summary

According to the characteristics of the fault prognostic methods and their practical examples mentioned above, the turbine failures in section II are matched and summarized in the following table [20-22, 27, 30].

TABLE II. MATCHING OF FAULT PROGNOSTIC METHOD AND TURBINE FAILURES

Failures	Prognostic Method(s)
Electric Control	Hidden Markov Model
Grid	
Blades	
Coupling	
Hub	
Tower	
Foundation	
Hydraulic	Particle Filter
Entire nacelle	
Entire turbine	
Brake	Hidden Markov Model and Neural Network

Air brake	
Mech. Control	Hidden Markov Model and Particle Filter
Generator	Neural Network and Particle Filter
Gearbox	
Yaw system	Both 3 methods
Axle/Bearing	

IV. CONCLUSION

Offshore wind farm is a high cost investment project with high O&M expenses and it is expected for 10 years or longer operation period. PHM implementation to offshore wind turbines is necessary in order to optimize the turbine R&D for component reliability, minimize the construction cost, O&M cost and catastrophes and fatalities. In this paper, a brief introduction to PHM is shown. Then, the popular offshore wind turbine failures are evaluated such as electrical control failures, yaw system failures, gearbox failures, grid failures, hydraulic failures and blade failure. Furthermore, 3 relative fault prognostic methodologies, Hidden Markov Model, Neural Networks and Particle Filter are reviewed. Finally, a summery with matching table showed the connection between the turbine failures and the fault prognostics methods.

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