A Novel Degradation Identification Method for Wind Turbine Pitch System

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Abstract. It’s difficult for traditional threshold value method to identify degradation of operating equipment accurately. An novel degradation evaluation method suitable for wind turbine condition maintenance strategy implementation was proposed in this paper. Based on the analysis of typical variable-speed pitch-to-feather control principle and monitoring parameters for pitch system, a multi input multi output (MIMO) regression model was applied to pitch system, where wind speed, power generation regarding as input parameters, wheel rotation speed, pitch angle and motor driving currency for three blades as output parameters. Then, the difference between the on-line measurement and the calculated value from the MIMO regression model applying least square support vector machines (LSSVM) method was defined as the Observed Vector of the system. The Gaussian mixture model (GMM) was applied to fitting the distribution of the multi dimension Observed Vectors. Applying the model established, the Degradation Index was calculated using the SCADA data of a wind turbine damaged its pitch bearing retainer and rolling body, which illustrated the feasibility of the provided method.

1. Introduction

With the large scale of wind turbines and the construction of offshore wind farms, the equipment property loss, power loss and maintenance cost caused by wind turbine accidents will be greatly increased. The Condition Based Maintenance(CBM) of wind turbines can detect hidden troubles in advance, monitoring the development trend of faults, avoid early defects or hidden accidents resulting in more serious failure due to delayed maintenance actions, optimize unit maintenance plan, so as to save the cost of operation and maintenance of the turbines at last.

Condition based maintenance strategy based on Fault Diagnosis and Prognosis (PDF) technology has been extensively studied in the field of traditional power industry. Different with the traditional hydro and thermal power plant, small unit power rate and large number of wind turbines scattered installed in a large geographical area are the characteristics of wind farm. Huge number of sensors is needed to be installed in wind farms, large amount of data needed to be collected and processed, which lead to the cost of condition monitoring of wind turbines increase greatly. Data acquisition and monitoring system, which collects and records 10 min average values of meteorological, mechanical, electrical, temperature and other operating parameter is widely deployed in large wind turbines. The data
acquired by the system contains rich unit status information, which makes it feasible to forecast the health status of unit and its main sub-equipment based on the Supervisory Control and Data Acquisition (SCADA) system. That means the condition based maintenance management of wind turbines can be implemented without adding sensors and wiring in turbines, which is an important significance to reduce the overall cost of operation and maintenance of wind farm [1].

Due to the intermittent wind resource, the output and the rotating speed of wind turbine change stochastically. The main shaft bearing, low speed shaft bearing of gear box, yaw and pitch bearing are low speed or incomplete rotation. These two factors limit the effect of vibration analysis method applied on the status identification of wind turbines. Because the main shaft bearings, yaw and pitch bearings are mostly lubricated by grease or grease and lubricating oil mixed lubrication, it is difficult to on-line monitoring the bearing status. When off-line analysis, it is difficult to ensure that the collected samples are involved in the lubrication work. Therefore, the effect of oil monitoring method for wind turbine status identification is also difficult to guarantee. In addition, threshold evaluation method using one parameter is difficult to adapt to the characteristics of wind turbine operation under variable conditions. Big data [2] and artificial intelligence algorithm has advantages in information correlation analysis, reasoning and optimization decision making, can be effectively applied in the faults detection of complex nonlinear systems [3]. Domestic and foreign scholars have carried out a lot of research on the application of artificial intelligence algorithm in FDP. As noted in [4], Artificial Neural Network (ANN) was applied to predict the wind turbine generation integrating wind speed and direction, air density, geographical location and other factors. Research in [5] indicated, the prediction method based on ANN can send warning information 2 days before the gearbox real fault occurs. Based on the principle of the first law of thermodynamics, a fault prediction model based on gear box temperature change data is established [6]. The application of rule-based expert system in fault diagnosis and prediction of wind turbines is studied in [7]. However, the fault identification sensitivity and accuracy are not enough, because most of the above studies directly use part of the operational data of wind turbines without considering the correlation and coupling within parameters.

An adaptive neuro-fuzzy inference system (ANIFS) was established in [8] to detect the early defect or potential fault for key wind turbine components, and the expert knowledge was used for Fault diagnosis and location. Time series model and Adaptive Neural Network are used to mine the features contained in historical data to achieve rapid detection of device abnormalities[9]. The effectiveness of SVM in fault diagnosis of wind turbine is verified by experiments in [10]. On the basis of principal component analysis (PCA) method to identify the operating condition subspace, health assessment model based on GMM multi state feature fusion was established in [11]. However, these methods can only predict failure a few minutes or one day before it occurs, which is helpless for conduct condition based maintenance strategy.

In this paper, an online identification model of wind turbine pitch system operating state based on regression model and GMM is established. On the basis of fusing multi-sensor data information of pitch system, the recognition accuracy of the deterioration state and the lead time of fault prediction are improved by the model established.

2. Introduction of wind turbine pitch system

2.1. Wind turbine pitch system structure and fault analysis
Pitch control system is an important part of wind turbine, because it not only ensures the effective utilization of wind energy by wind turbines, but also responsible for ensuring the wind turbine safety, avoid over speeding and falling tower accidents under the extreme bad situation. The pitch system of the wind turbine is installed at a height of tens of meters away from the ground, so it is difficult to maintain after the failure and the maintenance cost is high. Therefore, it is necessary and profitable to apply preventive maintenance on pitch system. The number of observation parameters of pitch system is large, which is convenient for data analysis. Considering the possibility of unit failure caused by failure of each subsystem of wind turbine and technical and economic feasibility of status detection of each subsystem, this paper choose pitch system as the key object of wind turbine condition monitoring.

A single blade pitch device generally includes a controller, servo driver, servo motor, reducer, pitch bearing, sensor, angle limit switch, battery, transformer, power supply, etc. The common faults of pitch system can be divided into three types: executive mechanism failure, sensor fault and control system fault. Some of the faults such as leakage, which can be found by regular manual inspection, are not study in this paper.

2.2. Control strategy and operation characteristics of variable pitch system for wind turbines
The variable pitch variable-speed control strategy of wind turbine control wind energy conversion rate and power output by adjusting blade attack angle and rotating speed. In order to avoid the large power fluctuation and strong instantaneous stress load during the operation transition interval between the optimal blade tip speed ratio tracking control phase to the constant power control phase, Individual Pitch Control (IPC) technology and pitch stress reduction control strategy is widely adopted in wind turbines[12]. The advanced pitch control strategy, which can reduce vibration of blade and tower, improve the power generation efficiency and extend the turbine life simultaneously, require high reliability of pitch system.

The wind turbine actually operated in complex harsh weather environment, which lead to fatigue, overload, internal insulation aging and deterioration of the overall health of the equipment. As a result, the operation parameters of wind turbine have nonlinear relationship, the pattern of pitch system show diversity. Figure 1 shown the SCADA data 3D scattered point diagram for a typical operating wind turbine. Due to the dynamic changes of wind resources and the dynamic characteristics of wind turbines themselves, the distribution of the operating parameters of the pitch system in fig 1 is not completely consistent with the designed power curve.

2.3. SCADA operation data of variable pitch system
Variable pitch system is divided into two types according to different driving modes: hydraulic variable pitch and electric variable propeller. The monitoring parameters of typical electric pitch system include unit operation parameters, pitch motor parameters, pitch converter parameters, standby power parameters, etc. Totally, 9 feature vectors such as wind speed, active power, rotor speed, three blades pitch angle and pitch drive currencies were selected from 47 parameters recorded in SCADA to indicate the pitch system operation status. Despite the obviously inconsistent between actual power curve reflected by wind speed and active power and the designed power curve, which can be find by field operators easily, this paper try to excavate the deep deterioration symptom regarding the pitch system as a Multi Input Multi Output (MIMO) regression model, where wind speed, power generation
regarding as input parameters, wheel rotation speed, pitch angle and motor driving currency for three blades as output parameters. Express characteristic vector of pitch system as formula below:

\[ X_N(M) = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(M) \\ x_2(1) & x_2(2) & \cdots & x_2(M) \\ \vdots & \vdots & \ddots & \vdots \\ x_N(1) & x_N(2) & \cdots & x_N(M) \end{bmatrix} \]  

(1)

Where, \( N \) is for sample size, \( M \) is for dimension of eigenvector.

3. LSSVM regression model of pitch system

Pitch system parameters regression has some difficulties. It is difficult to accurately describe the operation of pitch system through functions. A large amount of data from wind turbine SCADA system is transmitted and accumulated in the form of data stream, so the output of the regression model needs to be quickly obtained.

Support vector machine (SVM), for whom constructing training samples based on historical tag data is needed is a supervised learning method based on statistical learning theory developed in the middle of the 90s. SVM can improve the generalization ability of learning by seeking the minimum empirical risk and confidence risk, and obtain good statistical regularity under the condition of less training samples. If the sample data is linear non separable, SVM can use relaxation variables and kernel function to realize nonlinear classification. This paper applies the Least Squares Support Vector Machine, which transforms the optimization problem into a convex two programming problem with only equality constraints, training MIMO nonlinear model of pitch system.

Assume all training data \( \{x_i, y_i\} \) can be map to high dimensional space using nonlinear mapping \( \phi(\cdot) \), regression of nonlinear functions in an input space can be converted as estimation of linear function in high dimensional space. The form of regression function is  
\[ y(x) = w^T \phi(x) + b, \]  
where \( w \) is weight vector, \( b \) is constant term.
\[
\begin{aligned}
\min \quad & \frac{1}{2} \|w\|^2 + \frac{C}{2} \sum_{i=1}^{n} \zeta_i^2 \\
\text{s.t.} \quad & w^T \varphi(x_i) + b + \zeta_i = y_i
\end{aligned}
\]  
(2)

Where, relaxation variable \( \zeta_i \geq 0, i = 1, \ldots, n \), \( C \) is penalty factor. Lagrangian multiplier \( \lambda \in R^{N \times 1} \).

By KKT rule, equations regarding \([b, \lambda]^T\) are obtained:

\[
\begin{bmatrix}
0 \\
0
\end{bmatrix} = \begin{pmatrix}
0 & e^T \\
e1 & \Omega + \frac{I}{C}
\end{pmatrix}^{-1} \begin{bmatrix}
y \\
0
\end{bmatrix}
\]  
(3)

Where, \( y = [y_1, y_2, \ldots, y_n]^T \), \( e1 = [1, 1, \ldots, 1]^T \), \( \lambda = [\lambda_1, \lambda_2, \ldots, \lambda_n]^T \), \( \Omega_{ij} \in \varphi^T(x_i)\varphi(x_j) = K(x_i, x_j) \), 

\( i, j = 1, \ldots, N \). \( K(x_i, x_j) \) is the kernel function satisfying the Mercer condition. In this paper, we take radial basis function:

\[
K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{\beta^2}\right)
\]  
(4)

solving the equations, achieve;

\[
y(x) = \sum_{i=1}^{n} \lambda_i K(x_i, x) + b
\]  
(5)

The MIMO system is decomposed into several multiple input single output (MISO) subsystems separately trained model by method in [13].

4. Condition identification of pitch system based on GMM

4.1. GMM application

Variable pitch system is divided into Define the deviation between the measured values of the system characteristic vectors and the regression results of the LSSVM as the “Observed Value”, the Observed Vector of pitch system is:

\[
\sigma_j = \left[ \sqrt{(a_i - a_j)^2}, \ldots, \sqrt{(a_m - a_j)^2} \right]
\]  
(6)

Where, \( a_i \) is the measured values of variable \( i \) of vector \( Y \), \( a_j \) is the regression results of the LSSVM, \( m \) is the dimension of the vector. In order to avoid the influence of environmental noise, sensor error containing the collected data, data pre-processing is needed by conventional time series correlation trend analysis. However, the data pre-
processing process will cause loss of data information\(^{[14][15]}\). In this paper, the target detection method named “background subtraction” used in image processing was applied.

Due to its outstanding noise elimination and anti-interference ability, GMM algorithm regarding as an unsupervised learning data classification algorithm is widely used in image processing, pattern recognition. GMM uses Gaussian probability density function describe data space distribution characteristics. Through increasing the number of Gaussian probability density function, GMM can approach any continuous distribution by arbitrary precision. The method does not need to determine the prior probability distribution structure of the object, and can also avoid the difficulty of solving the nonlinear transcendental equations when estimating the parameters of the traditional probability density function. Hence, the Gaussian mixture model (GMM) was applied in this paper to fitting the distribution of the multi dimension Observed Vectors under normal conditions, and regard it as the background of the fault, then perceive the subtle changes in the distribution of observed values when deterioration of the system happened.

As equation below indicated, the probability of Observed Vector \( x_j \) at \( j \) time can be described as the weighted sums of probabilities that the value belongs to the \( K \) Gauss distributions:

\[
p(x | \Theta) = \sum_{k=1}^{K} w_{k,j} N_k(x | \mu_k, C_k)
\]

where, \( N_k(x | \mu_k, C_k) \) is number \( k \) Gaussian distribution, \( \mu_k \) is mean value, \( C_k \) is covariance; \( w_{k,j} \) represent the prior probability of \( x_j \) belong to Gaussian distribution \( k \), \( \sum_{k=1}^{K} w_{k,j} = 1 \), \( x = [x_1, x_2, \cdots, x_m]^T \);

\[ \Theta = \{ w_k, \mu_k, C_k \} \]

\[
N_k(x | \mu_k, C_k) = \frac{1}{(2\pi)^{m/2} |C_k|^{1/2}} e^{-\frac{1}{2} (x - \mu_k)^T C_k^{-1} (x - \mu_k)}
\]

4.2. Background model training

Likelihood function \( L(\Theta | X) \) for sample \( X=(x_1, \cdots, x_n) \) is:

\[
\log(L(\Theta | X)) = \log\left[\prod_{j=1}^{N} p(x_j | \Theta)\right] = \sum_{j=1}^{N} \log p(x_j | \Theta) = \sum_{j=1}^{N} \log \left( \sum_{k=1}^{K} w_{k,j} N_k(x_j | \mu_k, C_k) \right)
\]

Since the equation contain logarithm of sums, applying Expectation Maximization Algorithm (EM) for parameter estimation:

1) Initialization

Covariance matrix is unit matrix, \( w_{k,j} = 1/K \), mean value is the first Observed Vector, turn E-step.
2) E-step
The probability of new Observed Vector $x_j$ belonging to the Gauss distribution $k$ is,

$$p(k \mid x_j, \Phi^k) = \frac{w_k N_k(x_j, \Phi^k)}{\sum_{k=1}^{K} w_k N_k(x_j, \Phi^k)}$$  \hspace{1cm} (10)

3) M-step
prior probability, matrixes updating:

$$w_{k,j+1} = \frac{\sum_{j=1}^{t} p(k \mid x_j, \Phi^k)}{t-1}$$  \hspace{1cm} (11)

$$\mu_{k,j+1} = \frac{\sum_{j=1}^{t} x_j p(k \mid x_j, \Phi^k)}{\sum_{j=1}^{t} p(k \mid x_j, \Phi^k)}$$  \hspace{1cm} (12)

$$C_{k,j+1} = \frac{\sum_{j=1}^{t} p(k \mid x_j, \Phi^k)(x_j - \mu_k)(x_j - \mu_k)^T}{\sum_{j=1}^{t} p(k \mid x_j, \Phi^k)}$$  \hspace{1cm} (13)

4) Convergence criterion
Iteration step E and M, until

$$\left| \log(L(X \mid \Phi^k)) - \log(L(X \mid \Phi)) \right| < \varepsilon$$  \hspace{1cm} (14)

Calculate $\log(L(X \mid \Phi^k))$ as equation (10), $\log(L(X \mid \Phi))$ is the result applying the updated $\Phi$.

5) Determine the background distribution
Sort the $k$ distributions by value of $w_k / \|\sigma_k\|$, $\sigma_k$ is standard deviation, the $C$ distributions in front is background:

$$C = \arg \min \left( \sum_{k=t}^{K} w_k > T \right)$$  \hspace{1cm} (15)

4.3. Discrimination of system health status
1) Determine whether the newly acquired observations $x_i$ match with background Gauss distribution:
\[
\begin{align*}
\lambda &\in [2, 3], \\
\begin{cases}
d_{t,i}d_{t,j} < \lambda^2 \\
d_{t,i} = (\sigma_i, I)^{-1}(x_i - \mu_i) 
\end{cases}
\end{align*}
\] (16)

2) If matching, updating the parameters by equation (12), (13), (14).
3) Calculate degradation index (DI)\(^{[16]}\),

\[
\text{DI} = \frac{1}{\alpha} \sum_{t=1}^{\alpha} \text{NLLP}_t
\]

(17)

Where, \(\text{NLLP}_t = -\ln \left[ \sum_{k=1}^{k} w_t N_k(x_t | \mu_k, \sigma_k) \right]\), \(\alpha\) is sliding window, which can suppress the influence of random factors, reduce misjudgement rate.

4) Turn to 1) for next observations \(x_t\).

5. example analysis

5.1. Parameter identification of regression model
In order to avoid the influence of power curtain due to transmission line limitation, the wind farm connected to East China Power Grid and close to the load centre was studied by this paper. There are totally 24 sets of 2MW variable speed pitch unit installed in the farm. The unit happened a 191# fault, which is that 2# blade pitch is not synchronized with the other two blades, at 19:25 November 20, 2014 was studied. Maintenance personnel found blade pitch bearing cage and rolling body damage, needed to replace the variable pitch bearing. Totally, 60 354 history data from SCADA was applied to train the model. Excluding data during period of maintenance, commissioning, manual start and stop, and all active power less than or equal to zero data, the rest data almost represented all operating conditions of the wind power generation. The fluctuation range of wind speed is 2.9-23.3m/s (rated wind speed is 12.5m/s), and the power fluctuation range is 0.1-1997kW.

Firstly, data normalization was conducted using a linear transformation function, and unified mapping to \([0,1]\) interval:

\[
\overline{x}_t = \frac{(x_t - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})}
\]

(18)

Where, \(x_t, x_{\text{min}}, x_{\text{max}}, \overline{x}_t\) are measurement variable, the maximum input sample, the minimum input sample and the normalized value respectively.

Through parameter optimization, the parameters of the LSSVM model are \(C = 35, \beta^2 = 10\). Observed Vector consisted of rotor speed, Pitch angle and current of pitch motor for 1#, 2# and 3# blade, consists of 7 dimensions, \(m = 7\).

5.2. GMM background recognition
The prior probability $T$ used to determine the background distribution in GMM model is difficult to be deduced by theory, the influence of different $T$ values on the identification effect is evaluated by experimental method in this paper. Maintaining $K$ constant as 16, changing $T$ values as 0.5, 0.6, 0.7, 0.8 for test. As the test results shown in table 1, when $T$ is 0.5 or 0.6, misjudgement occurred due to the selected background distribution can’t cover the whole normal operation conditions. Detection time with $T$ value of 0.7 is earlier than the time with $T$ value of 0.8, since sensitivity of recognition is reduced when $T$ value is 0.8, and there are too many Gauss distributions in the background model.

| Number | $T$ value | Date of detection | Time of detection | Judgment result |
|--------|-----------|-------------------|-------------------|-----------------|
| 1      | 0.5       | 2014/8/21         | 10:30             | Error detection |
| 2      | 0.6       | 2014/8/30         | 23:10             | Error detection |
| 3      | 0.7       | 2014/11/11        | 8:20              | Correct         |
| 4      | 0.8       | 2014/11/13        | 7:40              | Correct         |

5.3. Evaluation of identification results of deterioration
Calculating the DI applying the method in 4.3 section. A large sliding window $\alpha$ would decrease sensitivity and the actual deterioration would not be confirmed in time. When $\alpha$ is 20, the time of Deterioration Index appeared obvious change is 8:20 November 11, 2014. When $\alpha$ is 10, the time of Deterioration Index appeared obvious change is 17:10 on November 9, 2014, which indicated the deterioration of the pitch system. Hence, $\alpha$ is 10 in this paper.

![Figure 2. Degradation Index calculation result of wind turbine pitch control system.](image)

As the DI curve in figure 2 indicated, Deterioration Index of the turbine began to increase on November 9, 2014, around 11 days ahead of the time when fault happened. Comparison between actual health state and model calculation results of wind turbines proved that this method has higher sensitivity to this kind of fault. The effectiveness of the method based on GMM proposed in this paper for the identification of the deterioration of the pitch control system is verified.
6. conclusion
Finding signs of potential failure in advance is the key to conduct CBM or kind of preventive maintenance for wind turbines, and improve economic benefits of the in-service wind farm. This paper proposed a novel method to identify the deterioration status of pitch system based on SCADA data.
1) The LSSVM regression model was established to solve the problem that the traditional pre-set threshold method could not adapt to the variable operating conditions of wind turbine.
2) The GMM model is used to fit the distribution law of the multi-dimensional observation values during normal operation of the unit, which avoids the shortcoming of information loss caused by the single parameter or the reduced dimension evaluation method.
3) The model application on a 2MW wind turbine with pitch bearing retainer and roller damage is presented in this paper. Compared with the traditional threshold method, the provided method can find the early characteristics of equipment degradation and significantly improve the lead time of fault prediction.
In order to facilitate the implementation of the preventive maintenance strategy for wind turbines, it is important to study the method of fault location and fault severity evaluation in the future works.

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