A Method for Performance Degradation Assessment of Wind Turbine Bearings Based on Hidden Markov Model and Fuzzy C-means Model

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Abstract—**Bearings used in the wind turbine generators (WTGs) will subject to different degrees of damage during operation, including all kinds of vibration and shock. In this paper, a vibration-based performance degradation assessment method for high-speed shaft wind turbine bearings is proposed using fusion of Hidden Markov Model (HMM) and Fuzzy C-means Model (FCM). The wavelet packet decomposition is used to extract the energy of the wavelet packet nodes of the whole life cycle vibration signal. The autoregressive model (AR) extracts the coefficients and residual of the wavelet packet nodes, and takes the two features as the combined features. The FCM is established using the normal and failure samples and the HMM is established using the normal samples. The two degradation indicators which was obtained by imputing the under test data to FCM and HMM model are input to the FCM model as the input characteristic. Then the performance degradation curve is obtained. Finally, Mahalanobis distance (MD) and FCM models are combined to compare and illustrate. The method combines the advantages of spatial statistical distance model and probabilistic statistical model. Then the WTG bearing's experimental data are used and the experimental results of AR model combined with FCM model are compared to verify the conclusions of this paper. The experimental analysis shows that the method is consistent with the performance degradation trend of rolling bearings and has certain adaptability.**

Keywords- Wind turbine bearings; Hidden markov model; Fuzzy c-means model; Mahalanobis distance; AR model; The WTG bearing's experimental.

I. INTRODUCTION

Rolling bearings are one of the most vulnerable parts of rotating machinery and no exception in wind turbine generators. In the actual use of wind turbines, bearing's life is often lower than life expectancy, which is due to the impact of different wind speeds and the influence of weather [1-3]. Many experts and scholars have carried out related research on this issue [4, 5].

The autoregressive parameters and residues of AR model are sensitive to the law of state change, and the autoregressive coefficient and residues of AR model can be used as the characteristic matrix of bearing state recognition to represent important information of system state change [6]. H Albugharbee et al [7]. studied the AR modeling process and the relationship between various parameters and bearing vibration characteristics and states, and the feature vectors extracted from AR model are pattern recognized to distinguish the size and category of faults. Li J et al [8]. built a time-varying autoregressive parameter model for vibration signal, extracted its mean value as characteristic parameter, and then input the support vector machine for fault identification and classification to realize bearing fault diagnosis. Yu D et al [9]. used the variance of the AR model coefficient and the residue combination feature as the feature vector to establish the Mahalanobis distance discriminant function, so as to judge the working state and fault type of the rolling bearing.

There may be learning or overflow problems in the HMM learning process, and the number of hidden states of the model needs to be agreed in advance. Li Z et al [10]. proposed an infinite hidden markov model (iHMM) for the above problems, which could be adaptive to the number of hidden states and mathematical structure of the model and realize the judgment of fault types. Purushotham V et al [11]. used discrete wavelet analysis to extract features of rolling bearings, and then used HMM model to conduct fault diagnosis for bearings, achieving the effect of bearing fault classification. Tobon-Mejia D A et al [12]. combined Gauss Mixture Model (GMM) with HMM to predict slow-varying faults in complex systems. However, both the GMM and the HMM model require a large number of training samples, and their probabilistic similarity values will be over-learned or pre-saturated when the bearing does not fail, so the degradation state of the bearing cannot be accurately determined [13]. Pan Y et al.[14] proposed a method which based on the lifting wavelet packet decomposition and fuzzy c-means in 2016. The indicator of the method can reflect effectively performance degradation of bearing. But the FCM method has the problem of membership constraint [15, 16].

Among the above mentioned methods, there are certain defects in both the distance model and the probability model. Aiming at the above problems, a method combining FCM and HMM model is proposed, which is applied to the performance degradation assessment of wind turbine bearings. It combines the advantages of distance and probability models.

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II. Rolling Bearing Performance Degradation Assessment using the Proposed Method

A. A brief introduction to AR model

AR model is a time series model developed on the basis of linear regression. It describes a stationary random process, which meets the mean value of zero and it is normally distributed. As the most basic modeling method, modeling least-squares is the most frequently used method because of its high accuracy. The mathematical formula of AR model is shown as follows.

$$A(q)y(t)=e(t) \tag{1}$$

where $y(t)$ represents the output of the system, $e(t)$ denotes the white noise input signal, q is the translation operator and its formula $A(q)$ is expressed as follows.

$$A(q)=1+a_1q^{-1}+a_2q^{-2}+\cdots+a_nq^{-na} \tag{2}$$

where $A(q)$ represents the autoregressive coefficient of the model.

B. Mahalanobis distance（MD）model introduction

The Mahalanobis distance, a method that can effectively calculate the similarity of two unknown sample sets, was proposed by the Indian statistician P. C. Mahalanobis in 1936 [17]. What is special about the MD is that it allows for the information connection between the various properties in the sample, and it doesn't depend on the dimensionality between the sample variables. When dealing with vibration signals, it can eliminate the interference of correlation between sample variables, and it has a certain effect processing noise interference.

Suppose there is a set of vibration signals, m represents the dimension of this set of data and n represents the number of columns of each one-dimensional data in this set of data. Then its MD can be expressed by the following formula.

$$MD(i)=\sqrt{(x_i-\mu)\sum^{-1}(x_i-\mu)^T} \tag{3}$$

$$\mu=\frac{1}{n}\sum_{i=1}^{n}x_i \tag{4}$$

$$\sum=\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(x_i-\mu_i)(x_j-\mu_j)}{n-1} \tag{5}$$

where $i=1,2,\cdots,n$, $j=1,2,\cdots,m$, and μ , Σ are used to represent the mean and covariance matrices of the sample population.

In the performance degradation assessment models, the models we often used can be divided into distance statistical model and probability similarity model. In the distance statistical models, it is generally based on the Euclidean distance. Although the Euclidean distance calculated simply, it depends on the dimension of sample variables. The Mahalanobis distance does not take dimension into account, so it can eliminate the interference between samples.

C. HMM model introduction

HMM is a time series probabilistic model that Hidden Markov chains randomly generate unobservable state random sequences, and then generate observation random sequences from each observation state [12].

The HMM with N states (denoted as $S_1,S_2\ldots S_N$) can be described by the formula $\lambda=(N,M,\pi,A,B)$. Where the M represents the number of possible observations for each state. The state of time t is $b_t\in\{S_1,S_2\ldots S_N\}$ and the observed value at time t is $o_t\epsilon(V_1,V_2\cdots V_M)$ .Where the π indicates the probability of the initial state, where $\pi_i=P(q_i=S_i)$, $1\le i\le N$ and π_i must satisfy the normalization condition $\sum_{i=1}^{N}\pi_i=1$. There are also A and B in the formula, where A represents the state transition probability matrix and B represents the probability matrix of the observed values. They are denoted as $A=(a_{ij})_{N\times N}$ and $B=(b_{jk})_{N\times M}$ respectively. The parameters j and k satisfy the range $1\le j\le N, 1\le k\le M$ and it has to satisfied with the formula $\sum_{j=1}^{N}a_{ij}=1$, $\sum_{k=1}^{N}b_{jk}=1$.

D. Introduction to FCM model

The Fuzzy c-means model, was proposed by Bezdek in 1973 [18], is a clustering algorithm that determines the degree of membership of each sample point by membership function, and then realizes classification. The FCM model divides the data into fuzzy subsets of class c and finds the clustering centers of each class, minimize the target function (6).

$$J(U,c_1,\cdots,c_c)=\sum_{i=1}^{c}J_i=\sum_{i=1}^{c}\sum_{j}^{n}u_{ij}^m d_{ij}^2 \tag{6}$$

where U represents the membership matrix, and c_c represents the clustering centers that it can be determined by the following steps.

(1) The membership matrix U is initialized with random numbers between intervals (0, 1), and the total membership degree of the sample set is 1.

$$\sum_{i=1}^{c}u_{ij}=1,\forall j=1,\cdots,n \tag{7}$$

(2) The clustering center of each sample subset is determined by (8).

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{8}$$

where $i = 1, \cdots, c$.

(3) According to (6), the objective function is calculated. If the value we obtained is less than the set threshold or the change relative to the previous one is less than the set threshold, the calculation is stopped.

(4) The membership matrix U is updated by (9) and return to step (2).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} (\frac{d_{ij}}{d_{kj}})^{2/(m-1)}} \tag{9}$$

E. Model establishment and index extraction

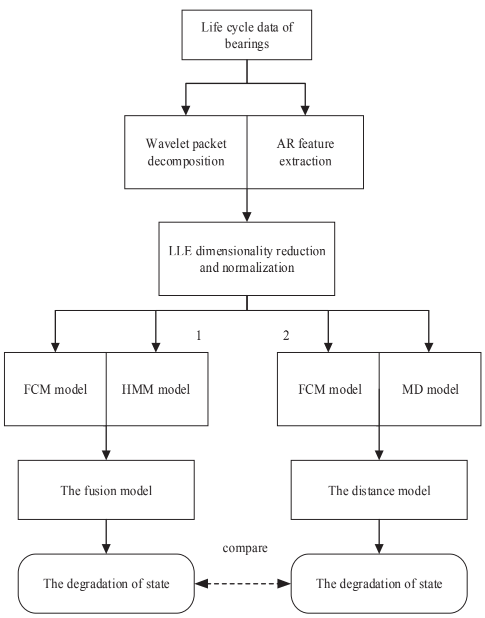

Figure1. The flow chart of bearing performance degradation assessment for wind turbines generators

Firstly, the wavelet packet and AR feature extraction are performed on the whole life cycle data. After the dimension reduction and standardization processing, the FCM and HMM models are built by using the feature data, and in order to get the final degradation indicator, we enter the combined features into the FCM model. Then describe the degradation performance curve and determine the bearing status. In the same way, Mahalanobis distance model combined with FCM model is compared with the proposed method.

III. EXPERIMENTS AND DISCUSSION

A. Data description

The data signal was collected from a 2.2MW wind turbine. The experiments test conditions are shown in figure 3. The real word high speed shaft bearing form a WTG provided by the Green Power Monitoring Systems in the USA [1, 19]. The type of the bearings is SKF 32222 J2. And the outer diameter of the bearing is 200mm, the inner diameter is 110mm, the number of rolling bodies is 20, and taper angle is 16°, bearings weight about 20 pounds. The tested bearing measures the force on the bearing through a force sensor. The maximum test load of the bearing fixed by the two bearing seats is 50% of the rated power, which can effectively reduce the failure rate of the transmission. The experiment obtained the original vibration data of 50 days, and the data was collected once a day at a high sampling rate, with a time of 6s and a sampling frequency of about 100kHz.

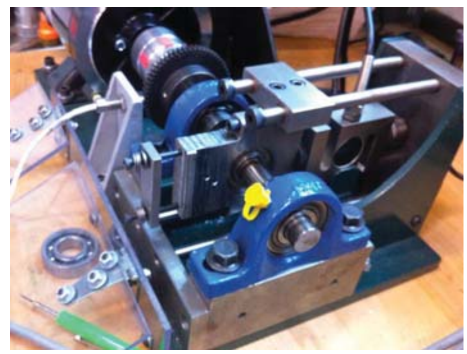

Figure2. The vibration data acquisition equipment of bearings

B. Establishment and discussion of the proposed model

The vibration signal processing software we used is Matlab 2016b. The data used in this article is the bearing life cycle data collected over 50 days. Firstly, wavelet packet decomposition and AR feature extraction are used to process the vibration data. The node energy of three-layer wavelet packet decomposition and the coefficients and residuals of AR model are extracted as eigenvectors. Then local linear embedding is used to reduce the dimension of eigenvectors, and the eigenvector matrix of 50*8 is obtained. Parameter initialization for HMM model and FCM model. According to the vibration test data set $M = 8$, fuzzy weighted index $q = 2$, clustering number off for $c = 2$ and the iterative threshold is $\varepsilon_1 = 10^{-4}$. Input the first 10 groups of fault-free data after initialization to establish HMM model. And then put the test sample data into the established HMM model, and the performance degradation index P of rolling bearings is obtained. The degradation curve is shown in Figure 3.

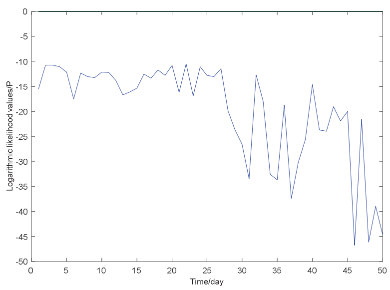

Figure3. The performance degradation assessment results of HMM model

The experiment used the first 10 sets of bearing data without failure and the 5 sets of data with the complete failure at the end to establish the FCM model. And then put the test sample data into the established FCM model, and the performance degradation index DI0 of rolling bearings is obtained. The curve of the rolling bearing is shown in Fig. 4.

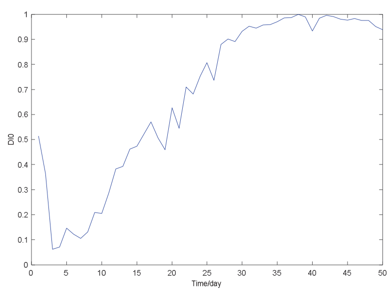

Figure4. The performance degradation assessment results of FCM model

It can be seen from figure 3 that the degradation curve of bearings has a small fluctuation in the first 25 days or so, but it maintains a relatively stable trend. Within 26-45 days, the evaluation curve fluctuated sharply up and down. After 45 days, the evaluation curve declined, and the evaluation curve was inconsistent with the overall degradation trend. From the above figure, we could get that the evaluation curve has a sharp downward trend in the first three days, and maintained a relatively stable upward trend in the fourth to the 41st days. However, after the 41st day, the evaluation curve showed a downward trend. Compared to the performance degradation trend of the bearing itself, the resulting curve does not reflect the performance degradation process of the bearing.

Using the same data processing method as before, the two degradation indicators P and DI0 are input into the established FCM model as eigenvectors, and the degradation indicator DI is obtained. Figure 6 shows the evaluation results of the fusion model based on the anomaly detection algorithm. Using the same method of vibration data processing, the HMM model is replaced by AR model and combined with the FCM model, the final degradation results of rolling bearings are shown in Figure 5.

It can be seen from Figure 5 that the overall degradation result of this combined method is the same as that of the FCM method, and it cannot represent the degradation result of wind turbine bearing. From Figure 6, it can be seen that the degradation curve of rolling bearings maintained a relatively stable trend in the first 25 days. During the 26th to 46th days, the rolling bearing is in the running-in period evaluation curve, and the evaluation curve shows a rapid rise until the failure after 46 days. The resulting evaluation curve is the same as the full life cycle degradation trend of the bearing. Compared with the previous methods, the fusion method can better describe the performance degradation trend of rolling bearings, highlighting its practicability and applicability.

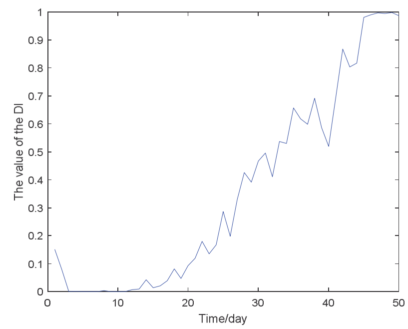

Figure5. The performance degradation assessment results based on MD and FCM models

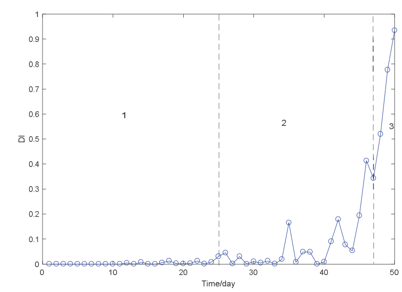

Figure6. The performance degradation assessment results based on HMM and FCM models

IV. Conclusions and Prospects

A fusion performance degradation assessment method of FCM-HMM is proposed based on Hidden Markov Model. For the case that probability similarity will be saturated ahead of time, AR model is used to extract the coefficients and residuals of signals. The test sample data is input into the model to obtain the values of P and DI, and a 50*2 vector feature matrix is formed. To get the Euclidean distance between the normal and failed sample points to the cluster center, input the feature matrix into the established FCM model. The degree of degradation is used as the degradation index to obtain the degradation information.

The degradation curves obtained by HHM, AR and FCM models are compared with those obtained by fusion methods. The fusion anomaly detection algorithm can better describe the performance degradation trend of rolling bearing and has more applicability advantages.

With the rapid development of artificial intelligence, deep learning has been widely used in various fields. In recent years, deep learning has also been applied to the field of prognostics and system health management (PHM) and fault diagnosis. We are currently studying mechanical fault diagnosis with deep learning, hoping to make a breakthrough.

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