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An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples

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ABSTRACT

Predictive maintenance has raised much research interest to improve the system reliability of a wind turbine. This paper presents a new model based approach of integrated fault diagnosis and prognosis for wind turbine remaining useful life estimation, especially the cases with limited degradation data. Firstly, a wavelet transform based fault diagnosis method is investigated to analyze the bearing incipient defect signatures, and the extracted features are then fused by the Health Index algorithm to represent the bearing defect conditions. Taking the empirical physical knowledge and statistical model in a Bayesian framework, the bearing remaining useful life prediction with uncertainty quantification is achieved by particle filter in a recursive manner. The integrated fault diagnosis and prognosis approach is validated using bearing lifetime test data acquired from a wind turbine in field, and the performance comparison with typical data driven technique outlines the significance of the presented method.
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1. Introduction

With the increasing environmental concern and green energy demand, wind farms have gained more and more interest as a source of renewable energy worldwide [1,2]. According to the statistics issued by Global Wind Energy Council (GWEC), the global installed capacity had reached 360,000 MW by the end of 2014, while the installed capacity in China accounted for 114,763 MW. It is envisioned that the scale of the installed capacity will exceed 4×10^5 MW and 10^6 MW by 2030 and 2050, respectively, so as to meet 8.4% and 17% of the electricity demand in China [3]. Similarly in U.S., the percentage of wind energy is envisioned to increase to approximately 20% of the total electricity by 2030, which is only 6.3% at present [4]. To achieve the goal, wind turbines must operate in a highly reliable manner to improve the economic viability of wind energy [5].

Wind turbines are complex electromechanical systems which extract kinetic power of the wind and convert it into electrical power. The wind turbines are usually situated in rural areas, exposed to harsh environment, and consequently subject to high failure rates, especially for offshore ones. It is reported that the operational and maintenance (O&M) costs for offshore wind turbines account for 20%~35% of the total revenues of the generated electricity [6]. As the demand for wind energy continues to grow at the exponential rates, the techniques for effective condition monitoring and fault diagnosis have gained increasing attention to reduce costly downtime and avoid catastrophic damage in wind turbine applications.

Among the various components in a wind turbine as shown in Fig. 1, the gearbox is costly and vulnerable to failure with high downtime per failure [7]. This is mainly due to the complexity of its repair and maintenance procedures, particularly in offshore applications. According to the latest statistics from the NREL gearbox reliability database [8], the majority (about 76.2%) of wind turbine gearbox failures are caused by bearings. The wind turbine gearbox is subject to five major failure modes, including planetary bearing failure, planetary gear failure, intermediate speed shaft (ISS) bearing failure, high speed shaft (HSS) bearing failure, and lubrication system malfunction [9,10]. Most gearbox failures are initiated in bearing locations and migrate to gear teeth as the bearing debris, leading to consequential failures [11,12].

To diagnose incipient defect and predict the remaining useful life of a wind turbine bearing, effective signal processing techniques and prognosis models have been investigated on monitoring sensing measurements [13–15]. In Ref. [16], an integrative

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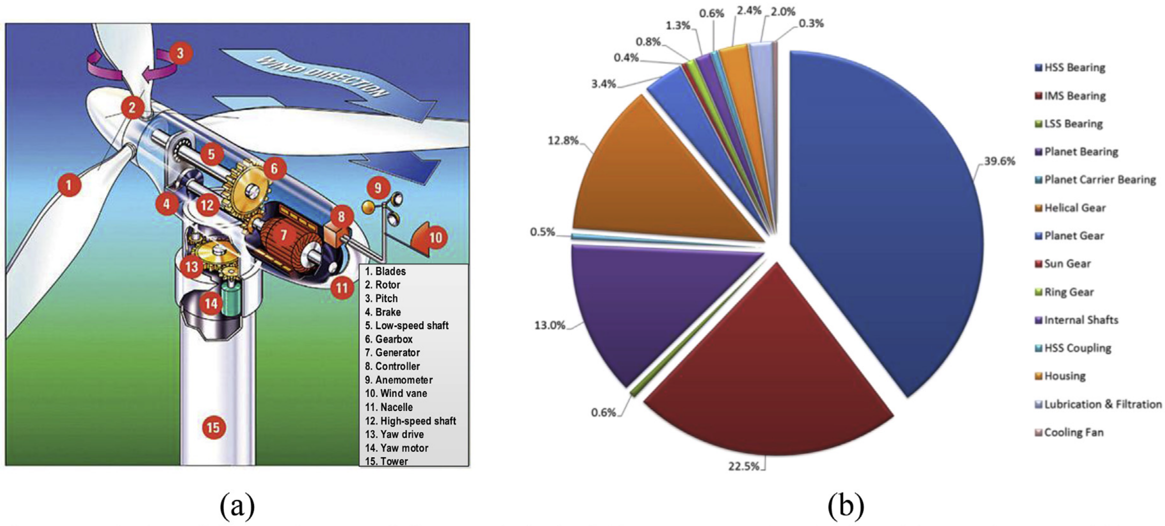

Fig. 1. Wind turbine subassemblies and their failure rates, a) wind turbine subassemblies, and b) the statistics of wind turbine gearbox damage distribution [8].

approach of ensemble empirical mode decomposition and independent component analysis is investigated to separate bearing defect related signals from gear meshing signals for vibration analysis of bearing fault diagnosis. A linear regression analysis approach is presented in Ref. [17] to extract load-independent features for wind turbine bearing diagnosis. A dynamic time-warping algorithm is presented to eliminate the speed fluctuation in vibration fault diagnosis of a wind turbine [18].

To enable automatic fault diagnosis and prognosis, data driven approaches have been widely investigated. In Ref. [19], a multiclass support vector machine is investigated for fault detection and identification of a wind turbine drivetrain gearbox by fusing different time- and frequency-domain features. In Ref. [20], a least squares support vector machine is studied with extracted features by an integral extension load mean decomposition multiscale entropy method for wind turbine fault diagnosis. A spatiotemporal pattern network is investigated to extract spatial and temporal features for unsupervised anomaly detection of a wind turbine [21]. To predict the remaining useful life of a bearing, an artificial neural network is used in Ref. [22] to train the data-driven model for defect prognosis in a wind turbine gearbox. A support vector machine model is trained and tested in Ref. [23] for the prediction of high speed shaft bearing lifetime using the spectral kurtosis derived indices of degradation assessment.

Data driven approaches usually require a large amount of historical data of many degradation sequences from devices of the same type to train the model [24]. Such approaches may not be suitable for fault diagnosis and prognosis of wind turbines with limited degradation data measurements available in practice. Wind turbines are generally complex and large-scale, which are costly and time consuming to gain failure data measurements. The degradation is often affected by many factors (e.g. different failure modes, varying operating conditions, etc.), thus the degradation pattern differs from time to time [25]. The degradation sequence may only contain a few degradation measurements. It brings difficulty to the data-driven model construction. Consequently, fault diagnosis and prognosis based on limited failure data samples are still challenging issues.

In light of the above challenges, this paper presents a new integrated fault diagnosis and prognosis technique for the remaining useful life estimation of a wind turbine bearing with limited failure data measurements available. Firstly, a wavelet based enveloping order spectrum method is performed on the noisy vibration measurements to extract fault-related weak features for early fault diagnosis. Then, the physics behind the degradation process and fault related features representing the degradation status are modeled in a Bayesian framework, and particle filter is employed to estimate the model parameter online and predict the degradation status with uncertainty quantification. The integrated fault diagnosis and prognosis approach is validated using lifetime test data acquired from a wind turbine in field, and the performance comparison with typical data driven technique outlines the significance of the presented method.

The intellectual merits of this paper are outlined. 1) An integrated fault diagnosis and prognosis approach based on wavelet transform and particle filter is proposed for wind turbine bearing defect prognosis with limited data measurements. 2) The explicit failure modes of the bearing are taken into consideration for representative feature extraction and fusion instead of empirical extraction. 3) An experimental study on an in-field wind turbine bearing lifetime test is performed to validate the effectiveness of the presented method. The rest of the paper is structured as follows. The relevant works on predictive analytics are firstly introduced to outline the importance of model based approaches in Section 2. Next, the integrated fault diagnosis and prognosis framework based on wavelet transform and particle filter is formulated in Section 3. The effectiveness of the developed method is then experimentally demonstrated using wind turbine bearing lifetime test data in Section 4. Finally, conclusions are drawn in Section 5.

2. Related work

Predictive analytics refers to forecasting the future progression of a situation, and has been widely investigated in a wide range of applications, including weather forecasting [26], stock market prediction [27], epidemiology prediction [28], and predictive maintenance [29]. With respect to fault prognosis and maintenance strategy, predictive modeling is essential to implementing predictive maintenance. It aims to improve forecasting accuracy as well as guarantee a robust prediction result, which can save considerable production downtime, labour repair resources and economic loss [30].

According to the information utilization and modeling mechanism, the predictive modeling techniques are categorized into three groups: physics-based, data-driven, and model-based. The physics based approach typically describes the physical behaviors of a system using the first principle as a series of ordinary or partial differential equations according to the law of physics [31]. For example, one typical application to crack growth rate is governed by a power law, such as Paris' law [32]. However, the construction of a physics model is usually difficult since it requires detailed and complete knowledge of a complex system. On the other hand, it lacks extensive failure samples to determine the model parameters in practice.

The data driven approach does not rely on physical knowledge, and it constructs a model representing the underlying relationship of a system based on data mining techniques. The data driven approach could be grouped into two categories including statistical and artificial intelligence based models. The typical statistical based models include the autoregressive model and its variations, linear regression, wiener process, and Gamma process, etc. Artificial intelligence based models include artificial neural network [33], clustering classification [34], extreme learning machine [35], fuzzy logic [36], and deep learning model [37], etc. However, the performance of the data driven model is sensitive to the size and quality of the collected dataset. And the constructed model is application specific and lack of generality.

In comparison, the model based approach takes advantage of established physical knowledge and collected data to enhance the prediction performance. It typically involves two steps including model construction and model updating [38]. First, analytical models are built based on the physical or empirical model representing the situation evolution in a quantitative manner. These models are then updated with newly acquired information to predict the future progression of the situation based on Bayesian inference [39]. Comparing with the data driven approach, the model based approach requires less historical data to construct the models. The predicted value is associated with a confidence level, resulting from the uncertainty involved in the prediction process [40].

From the above discussion, it can be found that these three approaches have both advantages and disadvantages. The comparison of these predictive modeling techniques is summarized in Table 1. One major factor that needs to be considered for selecting an appropriate prognostic method is the required information input and assumptions for prognostic models. In the case of limited degradation data available, the model based approach is appropriate. Based on the relevant physical mechanisms, state evolution models and measurement models that relate the sensor output to the underlying machine states are established. Subsequently, the machine state can be inferred given new measurements, by means of estimating the posterior probability density function (PDF). Thus, a typical model based approach, named particle filter, is investigated for wind turbine bearing defect prognosis.

3. Integrated fault diagnosis and prognosis framework

In order to enhance the operating reliability and reduce maintenance costs, an integrated fault diagnosis and prognosis framework of wind turbine bearings is presented as shown in Fig. 2. It incorporates the machinery degradation process as a state space model including a system model and a measurement model in a Bayesian framework. The evolving of the system states is described as a system model, while the measurement model relates the sensor output to the underlying system states.

$$x_t = f(x_{t-1}, \theta, u_{t-1}) \tag{1}$$

$$z_t = h(x_t, \theta, v_t) \tag{2}$$

where x_t denotes the hidden defect status, and z_t is the available in-process measurement at the time step t. The parameter θ represents the model parameter.

Considering the complexity and the low signal to noise ratio (SNR) in raw signal measurements, signal processing is conducted by a wavelet based multi-scale enveloping order spectrogram method [41] to detect the fault signature of the wind turbine bearing. The features are extracted and further fused by statistical health index (HI) generation models to obtain the health index, which can represent the degradation state of the wind turbine bearing. The remaining useful life of the wind turbine bearing is adaptively predicted along with the quantified uncertainty using the particle filter based prognostic method.

3.1. Wavelet-based fault representation

The raw signal measurements are usually characterized by large noise and high dimensions. It is difficult to model the relationship between the measurements and machinery defect status. Effective data processing and feature representation techniques are performed to reduce data dimensionality without losing defect signature information. When a surface defect occurs on a certain component in the bearing, it causes the energies increase at the corresponding defect characteristic frequencies (e.g. the ball-pass frequency of the outer ring f_{BPFO}, the ball-pass frequency of the inner ring f_{BPFI}, and the ball-spin frequency f_{BSF}. The ball-pass frequency is the frequency corresponding to the rate at which balls or rollers in a bearing pass a particular location on one of the races, and the ball-spin frequency is the frequency at which the balls or rollers revolve about their own centerline in a bearing). Bearing defect diagnosis is achieved through identifying the existence of defect characteristic frequencies.

Multi-scale enveloping order spectrogram integrates complex wavelet transform with computed order tracking in one framework for effective envelope extraction and speed dependence elimination in bearing defect diagnosis. Based on the rationale of high frequency resonance technique [42], it firstly decomposes the vibration signal into a set of wavelet scales through complex wavelet transform since each wavelet scale is equivalent to narrow band filtering.

$$WT(s,f) = \frac{1}{2\pi\sqrt{s}} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-\tau}{s}\right)dt \right) e^{-j2\pi f\tau} d\tau \tag{3}$$

Table 1
Comparison of different predictive modeling techniques regarding defect prognosis.

Category	Applicable Domain	Typical Models
Physics based approach	Devices of the same type, require abundant failure samples	Paris law, Taylor model
Data driven approach	Devices of the same type, require abundant degradation samples	Neural network, SVM, ELM, RVM, SOM, HMM
	Single device, require single degradation samples	AR model, ARMA, linear regression
Model based approach	Single device, require single degradation samples	Kalman Filter, Particle filter

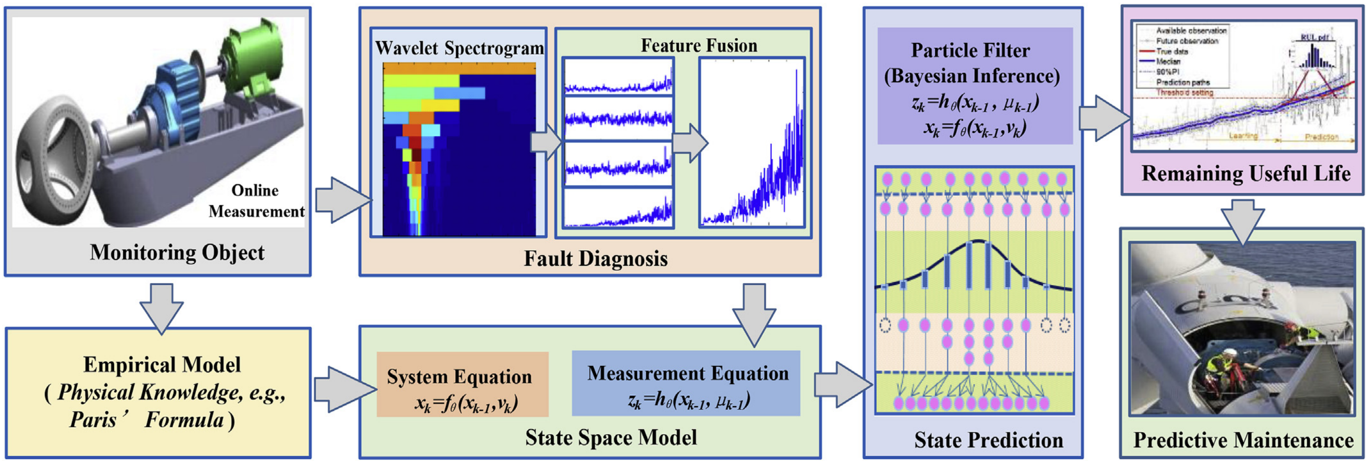

Fig. 2. The framework of the integrated diagnosis and prognosis technique for wind turbines.

where $x(t)$ denotes the analyzed signal, $\psi^*(\bullet)$ represents the complex conjugate of the scaled and shifted based wavelet, s represents the scaling parameter, which dilates or contracts the base wavelet, and τ is the shifting parameter that translates the wavelets along the time axis. The envelope corresponding to each scale is then extracted from the modulus of wavelet coefficients. On the other hand, order tracking is performed by incorporating the speed signal measured by a tachometer or an encoder into resampling the wavelet envelope signals at constant angle intervals to eliminate speed dependencies. The resampled wavelet envelope signal is then processed by a spectrum analysis of the bearing defect characteristic frequencies [41].

The energies at bearing defect characteristic frequencies are extracted as the fault features to represent the bearing conditions. Since there is no single feature that is sensitive to every failure mode of a bearing, a proper feature selection/fusion strategy is needed. The Health Index algorithm is an attractive approach for feature fusion by fusing multi-dimensional features into one condition index (CI) [43]. First, a whitening process based on Cholesky decomposition is performed to de-correlate the multi-dimensional features. According to Cholesky decomposition of Hermitian, a positive definite matrix results in:

$$\mathbf{A} = \mathbf{L}\mathbf{L}^* \tag{4}$$

where $\mathbf{L}$ is a lower triangular, and $\mathbf{L}^*$ is its conjugate transpose. The whitened features are obtained as:

$$\mathbf{Y} = \mathbf{L} \times \boldsymbol{CI}^{\boldsymbol{T}} \tag{5}$$

where $\mathbf{Y}$ is a vector of n-dimensional independent features with a unit variance. The correlation of the vector Y is equal to zero. Based on Nakagami and Rayleigh distribution, the condition index can be obtained by fusing the whitened features by Ref. [43]:

$$CI = k\sqrt{\sum_{i=1}^{n} Y_i^2} \tag{6}$$

where k is correlated to the underlying standard deviation of the Rayleigh distribution. The health index in the Health Index algorithm is formulated as:

$$HI = \sqrt{CI^T \sum^{-1} CI} \times 0.7/\nu \tag{7}$$

where Σ denotes the covariance matrix of the sample, and ν is derived from the inverse Nakagami cumulative distribution function (CDF) [43].

3.2. Model construction

A good condition index should present a consistent trend with defect propagation, and is expected to describe the measurement equation using a simple function. The assumption of the linear relationship between the bearing defect status and fused features in the literature [44] is also adopted in this study. The measurement model describes the relationship between the condition index and the defect state as:

$$z_t = x_t + \nu_t \tag{8}$$

where z_t denotes the condition index CI, and ν_t represents the measurement noise.

On the other hand, a system model describes the evolution of the mechanical defect state over time. Regarding to the defect prognosis of a rolling element bearing, the spalling area is a direct indicator of bearing defect severity. An empirical model governing the spalling propagation based on Paris' formula is developed as [45]:

$$\frac{dx}{dt} = cx^m \tag{9}$$

where x represents the spalling area, and the defect growth rate dx/dt is an exponential function of the existing spalling area x. The model parameters c and m are initialized as unknown variables. Take integration operation on both sides after separating variables, it can be rewritten in a state transition form as a system model:

$$x_t = \left[x_{t-1}^{(1-m)} + c(1-m)\right]^{1/(1-m)} + u_{t-1} \tag{10}$$

where t is the time index and u_{t-1} represents the noise in the state evolving process.

3.3. Prediction via bayesian inference

The key idea of defect prognosis is to find the posterior probability distribution $p\ (x_{t+l}|z_t)$ of the future defect status given the present measurements in the state space model. For a nonlinear or non-Gaussian system, particle filter is developed as a recursive numerical method based on the sequential Monte Carlo sampling method to estimate the posterior probability density function of the system state. The posterior probability distribution is recursively computed in two stages: *prediction* and *update*. The prediction stage is to estimate the probability distribution $p\ (x_{t+1}|z_t)$ given the posterior probability distribution $p\ (x_t|z_t)$ at time t, and can be formulated as [46]:

$$\begin{aligned} p(x_{t+1}|z_t) &= \int p(x_{t+1}|x_t)p(x_t|z_t)dx_t \\ &\approx \sum_{i=1}^{M} w_t^i \delta\left(x_t - x_t^i\right)p(x_{t+1}|x_t) = \sum_{i=1}^{M} w_t^i p\left(x_{t+1}\middle|x_t^i\right) \end{aligned} \tag{11}$$

where i is the index of a particle, and M is the total number of particles which affects the accuracy of the represented probability distribution function and the efficiency of computation. $\delta(\bullet)$ is the delta function. In the update step, the weight of each particle is then updated based on the likelihood of the observation z_{t+1} at the time step $t + 1$ as:

$$w_{t+1}^i \propto w_t^i p\left(z_{t+1}\middle|x_{t+1}^i\right) \tag{12}$$

In implementation, resampling is applied in each step to obtain equally weighted samples so as to avoid particle degeneracy issues of particle filter [46].

To account for the model error and process noise, the model parameters are also taken as unknown. The initial parameters of the model are set as probability distributions. If no prior information is available, a uniform distribution is usually chosen and the probability parameters of the lower and upper bounds are empirically selected. The unknown parameters are taken as the part of a state vector, and are estimated based on Bayesian inference [47]. Then, the defect status of the bearing can be predicted using particle filter, and the remaining useful life (RUL) is defined as the service time until the defect state reaches the threshold.

$$RUL(t) = t_r - t_s \tag{13}$$

where t_s is the present time and t_r is the time when the bearing defect state reaches the threshold.

3.4. Performance index

Uncertainty quantification is an important aspect when quantifying accuracy, precision, and confidence in machinery defect prognosis. Accuracy is a measure for how close the estimation of the failure time compared to the actual one, while precision reveals how close the prediction result is clustered. In comparison, confidence is the probability of the actual RUL falling between the bounds defined by the precision. In order to make an assessment and representation the uncertainty of RUL prognosis, the estimated RUL distribution is used by a-λ accuracy, which determines whether the prediction accuracy is within the desired accuracy levels (specified by a) at a given time point (specified by λ). The desired accuracy levels are expressed as a percentage of the true RUL (specified by β). In this paper, a is set as 0.1 and β is set as 50%, which means the prediction result is accepted if more than half of the estimated RUL distribution falls within $1 \pm a$ of the true RUL.

4. Experimental StudIES

To experimentally validate the effectiveness of the proposed method, a set of vibration signals measured on a wind turbine gearbox in a run-to-failure test is analyzed, and the analysis results are discussed.

4.1. Experimental setup

An experimental study of the wind turbine gearbox was made available in a field test. The tested turbine is a stall-controlled, three-bladed, upwind machine with a rated 2 MW power. The wind turbine gearbox is composed of one low speed planetary stage and two parallel stages. Due to varying speed operating conditions, vibration and speed data were measured at the sampling frequency of 97 kHz in a run-to-failure test. The tested bearing was run for about 107 million revolutions continuously to the end of its service life (approximate 65 days).

4.2. Data preprocesing

The measured vibration signals under different operating cycles are illustrated in Fig. 3. The time series signal is stable at the initial phase, and then the pulse train signal appears in the middle phase, and becomes severe in the near-end phase. However, the spectrum analysis of these signal measurements do not reveal much difference. Next, the wavelet transform based multi-scale enveloping order spectrogram is performed for bearing fault diagnosis. The bearing characteristic frequencies are calculated as listed in Table 2, and the energies at bearing characteristic frequencies are extracted as the representative of the bearing defect conditions. Fig. 4 shows the extracted energies at the bearing defect characteristic frequencies as the condition indicators of the bearing in the run-to-failure test. These features increase with the defect growth of the bearing, and thus are selected as the representative features of the bearing conditions. It is found that the tested bearing has experienced a defect on the inner raceway since the energies at the ball pass frequency on the inner raceway f_{BPFI} shows a clearly increasing trend. The defect may also propagate into the cage and the outer raceway since the energies at f_{FTF} and f_{BPFO} also show an increasing trend.

Since each feature contains partial information of the bearing status, the extracted features are fused comprehensively as the health indicator of the bearing status. The fused feature is obtained as shown in Fig. 5 which describes a clear trend representing how bearing defect grows. Based on statistical information (e.g., probability distribution of feature), the fused feature is scaled to represent the defect severity. Based on the rule that has been successfully implemented in aerospace condition monitoring [48], the amplitude in the range of [0 0.5] is set as normal or healthy condition, while the range of [0.5 0.75] is set as mild defective condition, and the amplitude above 0.75 is considered as severely defective condition. The values greater than one indicate that the continuous operations may result in collateral damage to other components in the gearbox. Therefore, the threshold is set as one to determine the components remaining useful time. Due to the dominant noise in the fused feature, it is difficult to determine the RUL directly.

4.3. Result analysis

To facilitate the RUL prediction, the fused features from the time steps [300 500] are chosen as the available observations for model construction and parameter learning. In the presented particle filter based defect prognosis model, the initial parameters of the

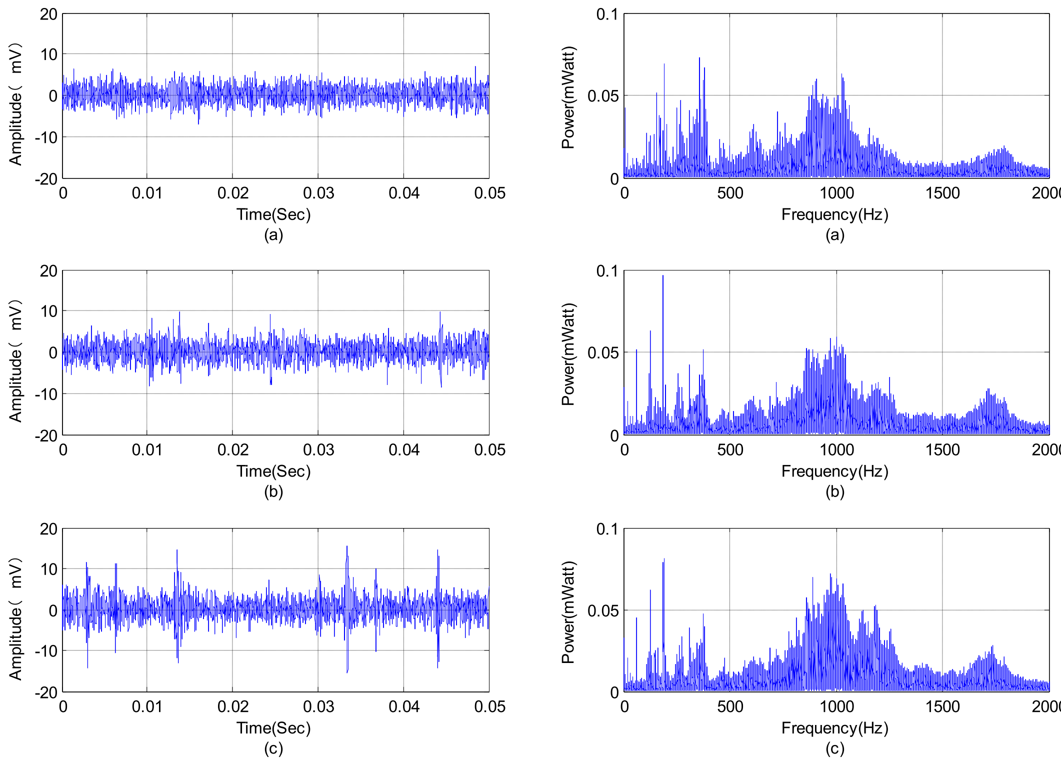

Fig. 3. The exemplified vibration signal measurements and their spectrums under different operating periods, a) initial phase, b) middle phase, and c) near-end phase.

Table 2
The defect characteristic frequencies of the wind turbine bearing.

Bearing defect characteristic frequency	Expression	Value
Cage frequency	$f_{FTF} = \frac{f_r}{2}\left(1 - \frac{d}{D}\right)$	$f_{FTF} = 0.42 \times f_r$
Ball spin frequency	$f_{BSF} = \frac{Df_r}{2d}\left(1 - \frac{d^2}{D^2}\right)$	$f_{BSF} = 2.87 \times f_r$
Ball pass frequency on Outer raceway	$f_{BPFO} = \frac{nf_r}{2}\left(1 - \frac{d}{D}\right)$	$f_{BPFO} = 6.72 \times f_r$
Ball pass frequency on Inner raceway	$f_{BPFI} = \frac{nf_r}{2}\left(1 + \frac{d}{D}\right)$	$f_{BPFI} = 9.46 \times f_r$

Note: f_r is the shaft speed. The parameters d, D, and n are the diameter of rolling element, the pitch diameter, and the number of rolling element, respectively.

model are set as probability distributions. If no prior information is available, a uniform distribution is chosen and the probability parameters of the lower and upper bounds are empirically selected according to empirical knowledge. With prior knowledge about parameters estimated using the EM algorithm, the uniform distributions of parameters are determined as:

$$\overline{\theta} = [\overline{m} \sim (0.7,\ 1),\ \overline{c} \sim (0.003,\ 0.0006)] \tag{14}$$

Here, the terms $\overline{m}$ and $\overline{c}$ represent the parameters in the system equation. The process noise u and the measurement noise v are ignored since they can be handled through the uncertainty associated with the model parameters. With the available measurement information, model parameters could be updated based on Bayesian estimation as shown in Fig. 6.

With the learned model parameters, the state space model is determined in the prediction stage and particle filter is used for bearing defect prognosis. It is found that the probability distribution of the model parameters fluctuates continuously during the learning stage while remains constant in the prediction stage owing to the lack of available measurement to update. Fig. 7 shows the prediction results of the bearing defect state in the next 100 steps. It is found that the median of the predicted bearing defect state closely follows the trend of the observation. Because of the defect accumulating effect in the system model, the predicted bearing defect status grows monotonically since mechanical defect cannot heal itself. It can facilitate the RUL calculation of the bearing by comparing the predicted defect states with the threshold setting as shown in Fig. 8, and the uncertainty of the prediction results is well quantified through the 90% confidence interval.

Next, the defect prognosis under different steps-ahead prediction is performed to evaluate the robustness of the presented method, and the results are shown in Fig. 9. It can be found that the shorter are the predictive steps, the smaller is the distribution internal of the bearing defective state. From another perspective, the length of the prediction steps determines the amount of prior information. Therefore, the longer are the prediction steps, the greater is the uncertainty of the RUL prediction. According to the

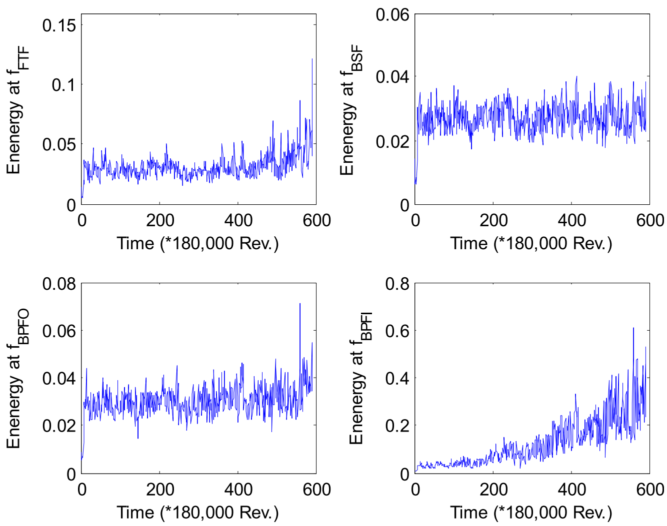

Fig. 4. The extracted energies at bearing defect characteristic frequencies.

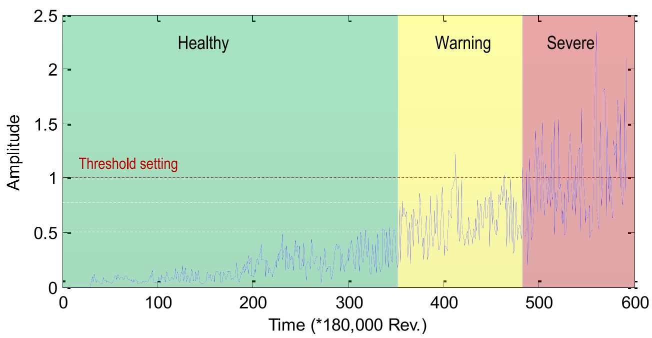

Fig. 5. The fused feature obtained in the health index algorithm.

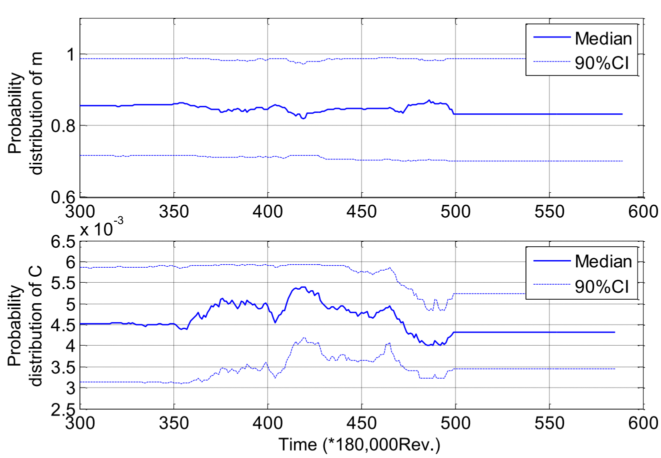

Fig. 6. Distribution of the model parameters using the PF approach.

definition of a-λ accuracy, Fig. 10 indicates that the RUL prediction starting from the 50th hour is all acceptable. It is evidently found that the interquartile range of the estimated RUL distribution indicating the size of uncertainty is much smaller with shorter predictive steps. Furthermore, the median of the RUL distribution representing the accuracy of prediction results is also much closer to the true RUL under long-term prediction.

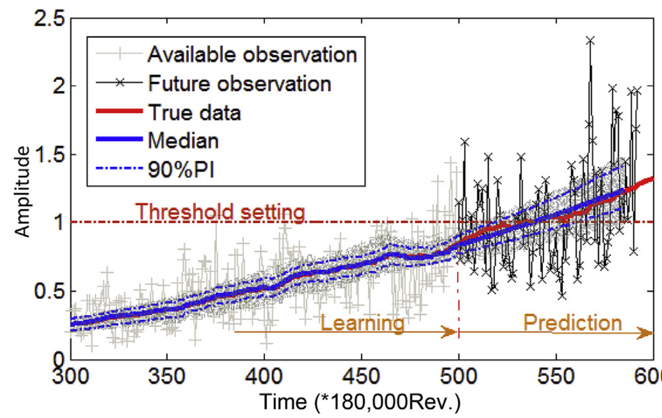

Fig. 7. Uncertainty quantification of the predicted state using the PF approach.

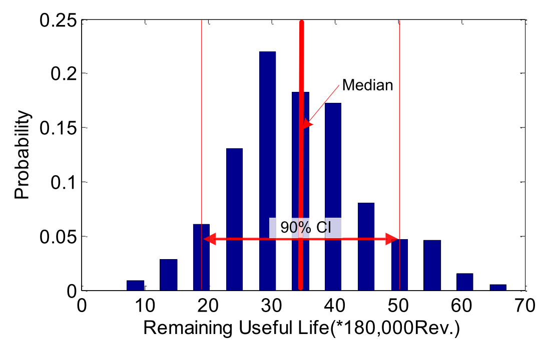

Fig. 8. The probability distribution of the bearing RUL using particle filter.

4.4. Performance comparison

Given the limited number of experimental data sets, an autoregressive moving average (ARMA) model is used to predict the bearing defect growth for comparison, and the results are shown in Fig. 11. It is found that the prediction results of the ARMA model follow the trend closely; however, it cannot quantify the prediction uncertainty. The tendency to go up and down makes it difficult to determine the RUL of the bearing.

From the above analysis, the presented method can incorporate the estimation of the model parameters and the prediction of the hidden defect state in one framework. By taking advantage of physical empirical knowledge, the hidden defect state of the bearing can be inferred from noisy measurement based on Bayesian inference. The estimated defect state with threshold setting can be used to determine the RUL of the bearing. The uncertainty of the RUL prognosis is also quantified in a probabilistic manner. Therefore, the developed method can facilitate the threshold setting with the estimated defect state (reduced variance) instead of noisy measurement to reduce the false alarm rate and improve the maintenance strategy in practice.

5. Conclusions

This paper presents an integrated fault diagnosis and prognosis approach for remaining useful life prediction of a wind turbine gearbox. Based on the results obtained, the following conclusions can be drawn.

1) The presented method takes advantage of physical knowledge and statistical models in one approach, and the accurate

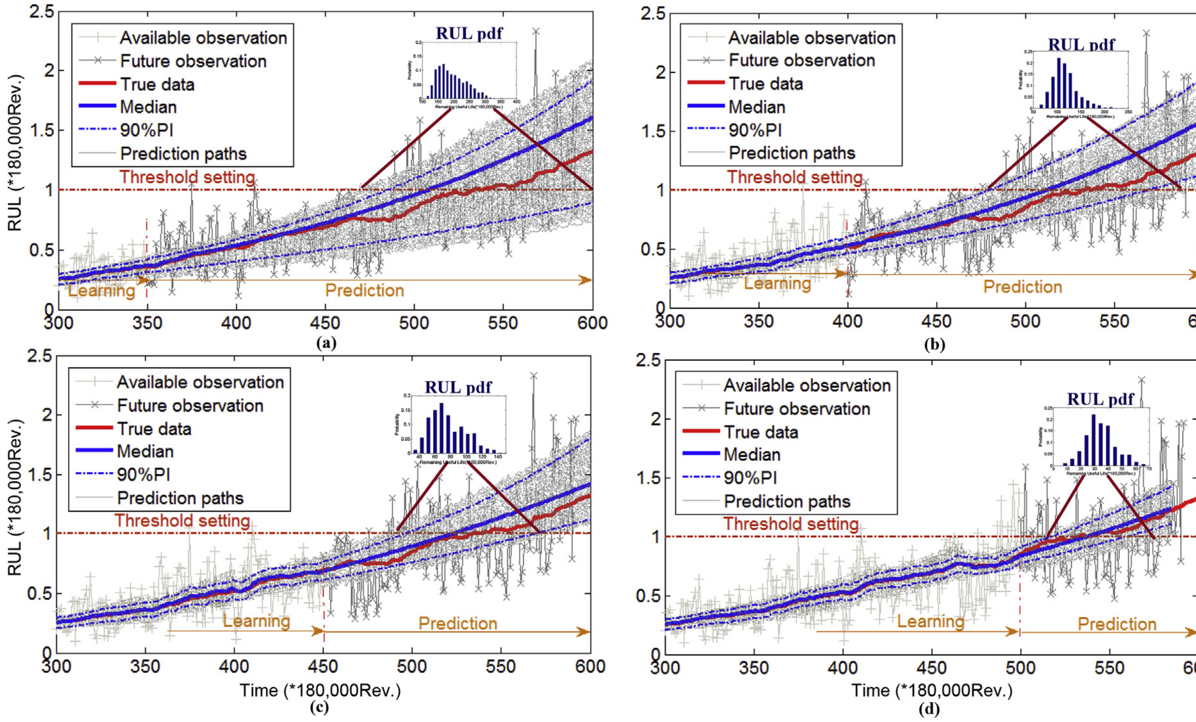

Fig. 9. Predicted bearing defect state and RUL under different steps-ahead prediction.

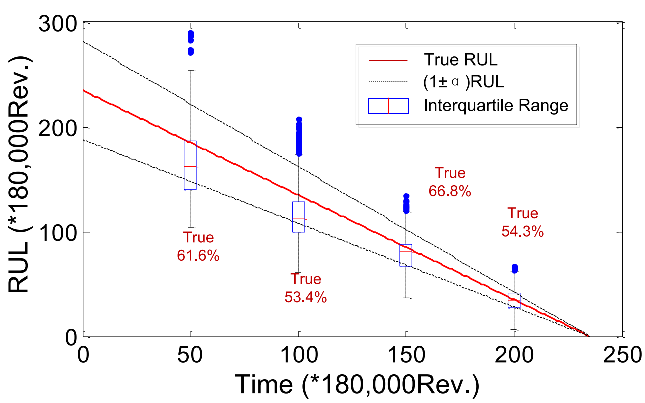

Fig. 10. Uncertainty quantification of RUL under different steps-ahead prediction.

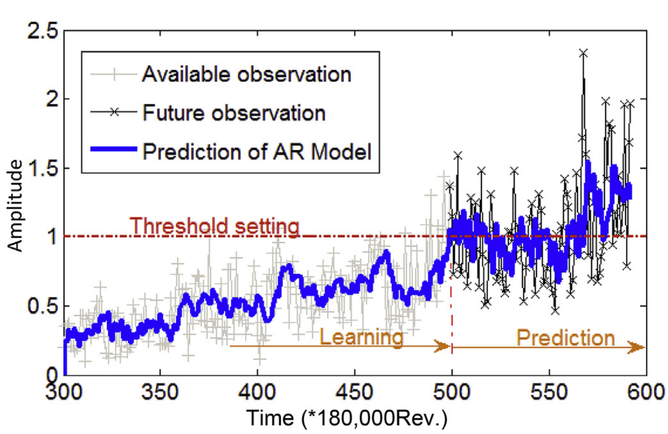

Fig. 11. Predicted bearing defect growth using the ARMA model.

prediction is achieved by Bayesian inference with uncertainty quantification.

2) The extracted features based on wavelet transform manifest the incipient defects, and the fused feature shows a good representation of bearing defect conditions.
3) The presented method can adaptively learn from the noisy data measurements, and it is robust to different steps-ahead predictions with limited set of degradation samples.

The performance of the developed method has been demonstrated using an experimental study in a wind turbine bearing run-to-failure test. It can also be applicable for the other bearing fault diagnosis and prognosis, such as the bearings in wind turbine generator. A wide range of experiments will be performed to investigate the robustness of the developed method in our next-step research.

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