A Particle-Filtering Approach for Remaining Useful Life Estimation of Wind Turbine Gearbox

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Abstract—Machine failure prognostic is concerned with the generation of long term predictions and the estimation of the probability density function of the remaining useful life. For this we propose a framework for data-driven prediction of RUL. To solve the problem of lacking direct condition information in predicting equipment residual useful life (RUL), particle-filtering model is built for equipment's RUL prediction with indirect information, which is easy to get .This paper introduces a particle-filtering modeling approach for predicting the remaining lifetime of the wind turbine gearbox based on information of SCADA system monitoring. Data from the SCADA system for the wind turbine gearbox were used to validate the proposed methodology. The outcome shows that the PF method has a better effect on RUL prediction. Finally, the model verified through on-site data collection. It shows that the method is practical value in the prediction of remaining life. A new way for state recognition of complex equipment is provided.

Keywords- residual useful life prediction; particle-filtering; wind turbine gearbox; SCADA system;model

I. INTRODUCTION

Predicting the remaining lifetime of a component is an important problem, e.g. in optimizing system maintenance. The component lifetime is often modeled using only a static probability distribution that does not take into account any condition monitoring data. An important feature of new generation of condition monitoring systems is the prediction of future evolution of the fault. Even more, it can predict the remaining useful life of the component under changing operating condition, thus providing information to operators on how the different operating regimes will affect the components useful life. This is a relatively new research area and has yet to receive its prominence compared to other condition monitoring problems [1].

Development of prognostic models that can be used to predict the remaining useful life of equipment components has attracted a significant amount of research in recent years. Several good overview papers addressing the prognostic techniques exist the most recent being those of [2]. The set of proposed approaches can roughly be divided into physics based models and data-based models. The physics-based models rely on detailed physical modeling by means of finite element method, which serves to compute spatial distributions of stresses in the material [3], [4].

The idea of data-driven methods is to make use of condition monitoring data to build the model and then use the model to predict future trend. Many ideas were proposed, perhaps the most simple one is to describe the condition monitoring data as static functions of time. Model parameters are adapted on-line so that change in the trends can be promptly traced [5].

A number of authors suggested use of neural networks as an efficient time series prediction tool. For example, Wang et al. [6] apply neural network to predict crack in rolling bearing by on-line adaptation of the network parameters. Unfortunately, only one-step ahead prediction is achieved. Problems might also occur when the training data set is too short. To partly alleviate this problem Wang et al. [7] combine neuro-fuzzy predictor with expert knowledge needed to tune the predictor. Authors have also suggest the use of nonlinear state filtering and prediction based on various particle filters strategies [8]. Their idea is to calculate the probability density function of the predicted life times, based on a dynamic model with known parameter values.

The aim of this paper is to alleviate the need for extensive prior efforts related to modeling and propose a framework for data-driven prediction of the remaining useful life (RUL) with on-line estimation of the state-space model.

Wind turbine gearboxes are not always meeting 20-yeardesign life. Premature failure of gearboxes increases cost of energy. The wind turbine gearbox cost is high, and in case of failure, repair time is longer. This problem is widespread, which affects most original equipment manufacturers. As a result, the maintenance and the RUL estimation of wind turbine gearbox is of critical importance to wind farm operators[9]. Figure 1. Share of the main components of the total number of failure downtime.

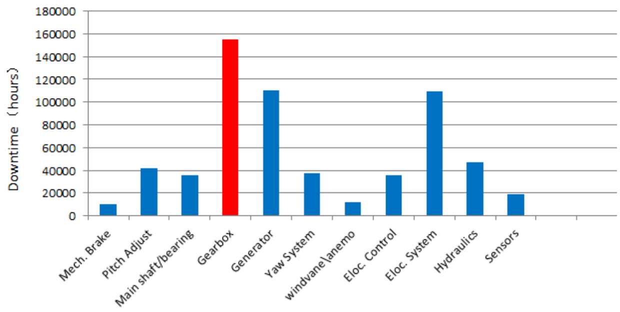

Figure 1. Share of the main components of the total number of failure downtime

II. MODEL ESTIMATION

Prognosis may be essentially understood as the generation of long-term predictions for a fault indicator, made with the purpose of estimating the RUL of a failing component. Let us assume that there exists at least one feature that provides the information about the current extent of the fault in a mechanical system and its value is available trough noisy measurements. Furthermore, different operating conditions affect the extent and the rate of change of the underlying fault as well as the current feature value. Finally, when the fault occurs, its progression can be described by a stochastic dynamical process [10], [11].

In general, we use the following equation of state and Measurement to describe the evolution of the system model and the state vector:

$$x_k = f(x_{k-1}, \mathrm{n}_{k-1}) \tag{1}$$

$$\mathrm{y}_k = \mathrm{h}(x_k, \mathrm{v}_k) \tag{2}$$

where x_k is the system state, who obeys the first-order Markov process. y_k is the vector measurement sequence. n_{k-1} and v_k are random variables describing system and measurement noise. First assume that the system initial state p(x0) is known. The state transition probability $p(x_k|x_{k-1})$ is given by the equation of state (1) and the known distribution of the type in the noise vector ω_k .

The results we want to get the posterior probability distribution $p(x_k|z0_{,k})$. In the Bayesian framework, probability distribution $p(x_{k-1}|z_{0,k-1})$ is known at k-1 moment, according to state equations (1) to predict the state of the prior probability distribution system. Obtained by the Chapman-Kolmogorov equation:

$$\begin{aligned}
&\mathrm{p}(x_k \mid z_{0,k-1}) \\
&= \int \mathrm{p}(x_k \mid x_{k-1}, z_{0:k-1}) \mathrm{p}(x_{k-1} \mid z_{0:k-1}) dx_{k-1} \\
&= \int \mathrm{p}(x_k \mid x_{k-1}) \mathrm{p}(x_{k-1} \mid z_{0:k-1}) dx_{k-1}
\end{aligned} \tag{3}$$

At k moment we collect new observations zk, the posterior distribution of the system state updates based on Bayes rule, to obtain the current status xk of the distribution system:

$$\mathrm{p}(x_k \mid z_{0,k-1}) = \frac{\mathrm{p}(x_k \mid z_{0:k-1}) \mathrm{p}(\mathrm{z}_k \mid \mathrm{x}_k)}{\mathrm{p}(z_k \mid z_{0:k-1})} \tag{4}$$

Recursion formula (3) and (4) form the basis of Bayesian recursive solving. Analytically it is difficult to solve the above distribution, because the calculation requires a lot of computing and high-dimensional integration operations. This requires an effective method for solving.

Using $\{\mathrm{x}_{0:k}^i, \mathrm{w}_k^i\}_{i=1}^{Ns}$ to describe the posterior probability distribution p(x0:k,z1:k) of the target state xk at k moment. $\{\mathrm{x}_{0:k}^{\mathrm{i}}, i = 0,1,\cdots,Ns\}$ is the set of particles, whose value is $\{\mathrm{w}_k^{\mathrm{i}}, i = 0,1,\cdots,Ns\}$. The weights are normalized $\sum_i \mathrm{w}_k^i = 1$, so the posterior probability distribution of the target state at k moment to be discrete:

$$\mathrm{p}(x_{0:k} \mid z_{1:k}) \approx \sum_{i=1}^{Ns} \omega_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{5}$$

The weight is chosen by the importance sampling method. $\{\mathrm{x}_{0:k}^{\mathrm{i}}, i = 0,1,\cdots,Ns\}$ set of particles obtained by the importance density function $q(x_{0:k},z_{1:k})$.

$$\omega_{\mathrm{k}}^i \propto \frac{\mathrm{p}(x_{0:k}^i \mid z_{1:k})}{\mathrm{q}(x_{0:k}^i \mid z_{1:k})} \tag{6}$$

The posterior probability density p can be expressed as:

$$\mathrm{p}(x_k \mid z_{1:k}) \approx \sum_{i=1}^{Ns} \omega_k^i \delta(x_k - x_k^i) \tag{7}$$

This model can be used to estimate the current state, predict the future evolution of the fault and assess the RUL.

III. CASE STUDY

A model of a wind farm with 1.5MW wind turbine gearbox is verified. Gearbox is the main power source to work the entire wind turbine operation, the impeller plays a role in providing a wind, wind power delivered by gearbox increases the speed, the rotational speed of the output shaft of the generator required to reach the rated speed, leading to normal power generators. The basic structure of a wind farm wind turbine drive train can be seen in Figure 2. Figure 2 shows that the wind turbine gearbox transmission system uses three gear.

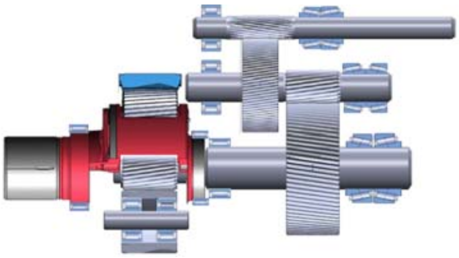

Figure 2. The basic structure diagram of the wind turbine

Get thirty days before gearbox failure SCADA system records the data to verify the validity of this model. Next, we need to calculate the specific band signal energy. Suppose E is the energy of the specific band signal.

$$E = \sum_{k=1}^{M} \left| p(k) \right|^2 \tag{8}$$

where k is the length of the band sample signal. By calculation, the value of the vibration energy of each vibration signal detection time, as shown in Figure 3. As we can see from the figure rising trend of energy, it can be a good characterization of the fault condition.

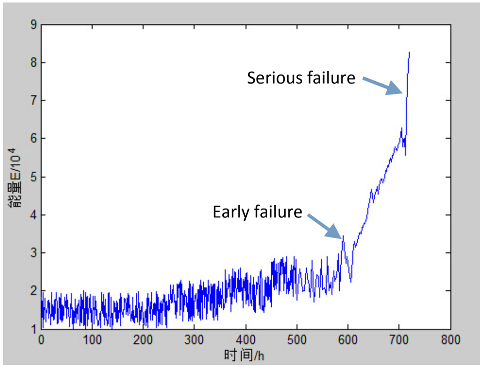

Figure 3. Gearbox vibration energy.

According particle filter model simulation using MATLAB can get the remaining life of the gearbox probability density function, shown in Figure 4. Set the start time forecast t=0.

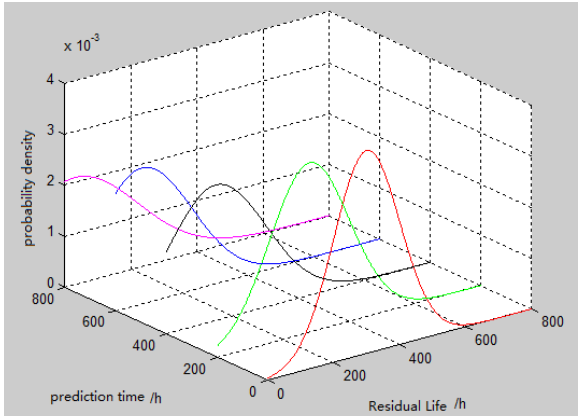

Figure 4.The remaining life of probability density

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