A hybrid feature selection and health indicator construction scheme for delay-time-based degradation modelling of rolling element bearings

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Abstract. Rolling element bearings are mechanical components used frequently in most rotating machinery and they are also vulnerable links representing the main source of failures in such systems. Thus, health condition monitoring and fault diagnosis of rolling element bearings have long been studied to improve operational reliability and maintenance efficiency of rotatory machines. Over the past decade, prognosis that enables forewarning of failure and estimation of residual life attracted increasing attention. To accurately and efficiently predict failure of the rolling element bearing, the degradation requires to be well represented and modelled. For this purpose, degradation of the rolling element bearing is analysed with the delay-time-based model in this paper. Also, a hybrid feature selection and health indicator construction scheme is proposed for extraction of the bearing health relevant information from condition monitoring sensor data. Effectiveness of the presented approach is validated through case studies on rolling element bearing run-to-failure experiments.

1. Introduction

Rolling element bearings are widely used mechanical components in machinery and their malfunctions is one of the major causes for breakdowns in rotating machines. According to [1], abnormalities of the rolling element bearing account for almost 45–55% of these equipment failures. In practice, bearings usually undergo degraded processes from their normal states till final failures, and condition monitoring of the bearings were extensively studied in the past few decades [2, 3]. To implement more proactive and predictive maintenance paradigm, the last decade witnessed the developing of prognosis which enables early failure warning and prediction of residual life. Even one aircraft saved from turbine engine bearing failures with prognosis would pay its development cost [4]. Currently, diagnostic technologies for rolling element bearings are relatively well developed, but accurate and efficient prognosis of bearing failure is considerably more difficult.

Generally, prognostics approaches are grouped as: 1) physics-based, 2) data-driven, and 3) hybrid. Physics-based techniques are important if accuracy is a critical factor and testing is restricted, since prognosis is predicted with mathematical models of physics failure mechanism [5]. However, only a few physics models are now available for bearing prognosis, especially for those used in sophisticated systems. Data-driven methods rely on models learned directly from historical data to predict future health. Statistical and artificial intelligence approaches are the mainly data-driven prognostics and their applications in bearing failure prognosis are gaining popularity [6]. To take advantage of both the physics-based and data-driven prognosis, hybrid approaches require the physics failure knowledge as...
well as the learned degradation models [7]. In many practical cases when it is easier to gather data than to build physics-of-failure models, data-driven prognosis is often the more applicable solution. Extraction of health relevant information from the background knowledge of historical sensor data is the first important step for a data-driven prognosis. For health monitoring of motors, gears and bearings, sensor data often comes in the waveform of vibration or acoustic signals, etc. Thus, signal processing is applied to extract features. Traditionally, the features for bearing fault diagnosis (such as kurtosis, RMS and peak-to-peak value) are also used for its prognosis. However, due to reasons of not sensitive to incipient deterioration or lacking of consistent trend, these features are only effective for certain defect during certain service stage. To address this issue, construction of health indicators that relate to the bearing degradation is considered. In [8], empirical mode decomposition and self-organizing map (SOM) are used to calculate a confidence value on the bearing health state. With feature selection and weighting before fusing by SOM, Lei et al [9] constructed a health indicator of weighted minimum quantization error. Also, a recurrent neural network based health indicator was proposed in [10]. Before construction of a health index, features for the synthetization should be selected. Nevertheless, compared to the feature selection for diagnosis, much needs to be done on sensor selection for prognosis [4,11,12]. In this paper, a hybrid scheme for feature selection and health indicator construction is proposed to extract bearing health relevant information from sensory signals.

Degradation modelling for characterizing evolution of the degradation is another crucial task for a data-driven prognosis. If a proper model is established for the health indicator, then the model can be used for online prognosis or directly for maintenance decision-making. Stochastic process models and general path models are the two large classes used to model degradation [13]. After the introduction to degradation literature by Lu et al [14], general path models have found widely applications [15]. On the other hand, Wiener process, Gamma process and inverse Gaussian (IG) process are the frequently used stochastic process models for degradation modelling [16]. Recently, in view that the failure of a bearing is generally a slow degradation process instead of a sudden breakdown, some researchers proposed to model the bearing degradation with two stages. Deterioration modelling is not focused on the whole life of the bearing, but on the second stage once an incipient fault is detected [17,18]. Actually, these degradation models fall in the delay-time concept which has been studied in industrial asset inspection and maintenance [19], and can be generalized to cases of more than two stages. For the modelling of the bearing degradation, delay-time-based framework is considered in this paper.

The remaining parts of the paper are organized as follows. Section 2 formulates bearing degradation in the delay-time concept. Section 3 presents a detailed description of the proposed hybrid scheme. Section 4 demonstrates the developed method with experimental case studies on rolling element bearing degradation. And Section 5 summaries the presented research and future work.

2. Delay-time-based modelling of bearing degradation

2.1 The delay-time concept

The delay-time concept itself is simple to divide the failure process of an asset into two stages. The first stage is the normal operating stage from new to the point that an identifiable defect has been detected. The second stage defined as the failure delay time is from the point of defect identification to failure. It is the existence of such a failure delay time that provides the opportunity for carrying out maintenance to predictively and proactively remove or rectify the identified defects before final failure happens. With the durations of these two stages appropriately modelled, optimal inspection intervals can be identified to optimise an objective function of interest.

Originally developed by operational research researchers, delay-time-based models have attracted significant attention from mathematical modellers and found widely applications in the maintenance field [20, 21]. Relaxing the binary state description of one industrial item (i.e. normal and failure) to step closer to reality, assumption of two-stage failure has been generalized to three-stage process by Wang [22]. For its impacts on industrial plant maintenance from both theoretical and practical point of views, the delay-time concept is tailored to model degradation of the bearing in this paper.

2.2 Modelling of bearing degradation
The failure of deployed bearings is not a sudden case, but generally a gradual process, taking place in one stage when the bearing is in normal working status without any identifiable fault and the irreversible degradation stage. To practice better operational management in the industrial field, the second stage may further be divided into two or more substages to account for slight, middle and severe bearing degradation, etc. This coincides well with the delay-time concept. Thus, degradation process $Y(t)$ of the bearing can be modelled as

$$Y(t) = g(t, \Theta) + \epsilon, \ t \geq t_0$$

where $g(\cdot)$ is the degradation path with parameter set $\Theta$, $t_0$ is a random variable relevant to the fault detected point, and $\epsilon$ is the error term normally distributed with zero mean and constant variance.

In the delay-time-based model for bearings degradation, modelling is only focused on the later stage triggered by the incipient fault identification. In contrast to the few two-stage degradation modelling for bearings, the degradation path in the proposed model is not assumed to follow one functional forms till failure but can be consisted of two or more segments demonstrating quite different patterns. Stochastic process and general path models can then be used to model the segments of the degradation stage upon change-point detection. For detection of the bearing incipient fault and the change point in the degradation stage, approaches as statistical process control can be applied. Also, the rich source of methodologies by the delay-time framework will facilitate the bearing degradation modelling.

3. The proposed hybrid scheme

3.1 Flowchart of the hybrid scheme

![Flowchart of the proposed hybrid scheme](image)

The proposed scheme is given in figure 1. Bearing condition monitoring sensor data is pre-processed using signal processing techniques and a number of candidate features are thus generated. Then these generated features are evaluated by goodness metrics and informative features are selected. Fusing the selected features into one-dimensional health indicator that represents health condition of the bearing, SOM is used here. Finally, the bearing degradation is modelled with the delay-time concept into stages.

3.2 Feature evaluation and selection

To mine features for bearing fault diagnosis and prognosis, signal processing has progressed from time or frequency techniques to advanced time-frequency or time-scale approaches. Unfortunately, appropriateness of the features often varies with nature of the failure, severity of the degradation and signal to noise ratio, etc. It is better to process the vibration signals with different methods simultaneously, and then evaluate the possible features based on metrics and select the optimal ones.

Focusing on bearing deterioration and failure prediction, statistical features of dimensional and non-dimensional ones as RMS and crest factor (CF), and wavelet packet node energy (WPNE) have been considered in this paper. Specifically, 29 features can be obtained upon processing each vibration waveform signal. To evaluate the effectiveness of an individual feature, the three goodness metrics proposed in our previous work [11] are revisited as Equation (2).

Among the three metrics, Corr measures the linearity between the feature and the usage time, Mon assess consistently increasing or decreasing trend of the feature, and Rob reflects the tolerance of the
feature to outliers. Features with high scores of the three metrics should be selected and retained as optimal features, since these features have better correlations with the bearing lifetime and depict consistent trends with less vulnerability to interferences.

\[
f(t_j) = f_r(t_j) + f_s(t_j), \quad \text{Corr}(F) = \frac{|K \sum f_r(t_j) t_j - \sum f_r(t_j) \sum t_j|}{\left( K \sum f_r(t_j)^2 \right)^{\frac{1}{2}} \left( K \sum t_j^2 - \left( \sum t_j \right)^2 \right)^{\frac{1}{2}}}
\]

\[
\text{Mon}(F) = \frac{\sum \delta(f_r(t_j) - f_r(t_{j-1})) - \sum \delta(f_r(t_{j-1}) - f_r(t_j))}{K-1}, \quad \text{Rob}(F) = \frac{1}{K} \sum \exp \left[ -\frac{|f_s(t_j)|}{f_r(t_j)} \right]
\]

where \(f(t_j)\) is value of the feature \(F\) at the time \(t_j\) \((j = 1, 2, \ldots, K)\) with the trend of \(f_r(t_j)\) and residual \(f_s(t_j)\), and \(\delta(\cdot)\) is simply the unit step function.

3.3 Health indicator construction

SOM is an unsupervised neural network that provides a way of representing multi-dimensional features into a one or two-dimensional space [23]. Each neuron in the SOM network is represented by a weight vector and only data under normal operation of the bearings is needed in the training of the SOM. With the trained SOM, for each input feature vector \(F\) composed of the optimally selected features, there is a best matching unit (BMU) whose weight vector \(m\) is the closest to the input vector. And the distance (usually in the form of Euclidean distance) between the input feature vector and the weight vector of the BMU, which actually quantizes how far the current condition is from the normal operation state, is defined as minimum quantization error (MQE). Then based on the MQE, a health indicator (HI) \(y\) that represents the health state of the bearing is constructed as

\[
y = \exp \left( -\frac{\text{MQE}}{c_0} \right), \quad \text{with MQE} = \|F - m_{\text{BMU}}\|
\]

where \(m_{\text{BMU}}\) is the weight vector of the BMU of the input \(F\), and \(c_0\) is a scale constant determined by the MQE under normal conditions.

This HI synthesized with SOM integrates the optimally selected multi-dimensional features. In fact, the proposed HI describes the degradation of one bearing well in the range of [0, 1], in that HI lessens with worsens of the bearing condition. With the proposed hybrid scheme for selection of degrading features and construction of health indicator, background health knowledge of the bearings can be constructed in the offline modelling to lay basis for the online prediction in a data-driven prognosis.

4. Experiment and analysis

4.1 Description of the experiment

The bearing run-to-failure data sets used to validate the presented method are taken from the bearing accelerated life tests by the PRONOSTIA platform [24]. In the experiment, both horizontal and vertical vibration accelerations of the bearing housing were recorded with a sampling frequency of 25.6 kHz and the data length of 2.56 k, while the recording interval was 10 s. Failure of the bearing was claimed when the amplitude of the vibration signal overpassed 20 g. All the tested bearings were run till failure, thus each bearing could fail due to any of the possible failure modes like failure of balls, rings, cage or their combinations. Such data is very common in the real industrial applications and has been utilized for validation of bearing prognostics approaches [8,9,12]. More details about the experiments can be found in [24]. In this paper, the seven bearings tested under the operational condition (i.e.1800 rpm and 4000 N) are analysed.
The horizontal vibration signals for the whole lifetime of two tested bearings are illustrated in figure 2. Although they were from the same category and experimented under the same condition, the two bearings depict very different patterns with the usage time. Life durations of the seven bearings range from shorter than 3 h to longer than 7 h and demonstrate a high variability. This and the undocumented failure modes pose additional challenges in degradation modelling and prognosis.

4.2 Results and analysis

Based on the signal processing techniques in the proposed hybrid scheme, a total of 58 features are extracted for each bearing using both the horizontal and vertical vibration signals. Then the three goodness metrics of Corr, Mon and Rob are calculated for each kind of feature of the seven bearings. In the analysis, the feature is trended with the moving average method. And evaluation results of the tested bearings are further statistically analysed to sift the consistent features to secure appropriateness for all the seven bearings. After these steps, four features are optimally selected and two of them are shown in figure 3. The two features F1 and F2 respectively have an increasing and decreasing trend with consumption of the bearing lifetimes, and share consistency among the seven bearings.

With the feature vector of four optimally selected features as input, the HI of each bearing is constructed following the hybrid scheme presented in Section 3. Two stages of normal working before any identifiable fault and the degrading stage for all the seven bearings can be obviously observed from figure 4(a). However, mainly due to different failure modes, as also discussed in [12], the deteriorative paths diverge in the second stage and this stage can further be divided into two substages or segments that demonstrate quite different varying patterns. In the following, the proposed delay-time-based model is further analysed on the degradation of three bearings.
To analysis the failure process of the bearings, the second stage of deterioration can be modelled into two segments of degradation substage I and II with the delay-time-based model in this paper. For bearing 1 and 7, degradation substage I consumes most of their lifetimes. While for bearing 2, it operates in the normal condition with a long duration and then runs into breakdown quickly. Based on the constructed HI and delay-time modelling, sharp degradation can be detected long before the bearing fails. Actually, degradation substage II accounts no less than 1% of the bearing life for all the seven tested bearings. With the detectable defect identified and change points for substage partition detected by statistical methods, each substage of bearing degradation can be fitted with parametric or nonparametric approaches, and then bearing failure can be further prognosed.

**Figure 4.** HI of the tested bearings: (a) HI of all seven bearings; (b) HI of bearing 1; (c) HI of bearing 2; (d) HI of bearing 7.

5. Conclusion
For accurate and efficient prognosis, degradation of rolling element bearings is modelled with delay-time-based model in this paper. Feature selection based on goodness metrics and health indicator construction with SOM are presented in a hybrid scheme. With the incipient fault identified, bearing degradation can be modelled by two or more substages using the delay-time framework. Case studies on bearing run-to-failure experiments validate effectiveness of the presented approach. To easy and enrich applicability of the proposed method, identification of the incipient fault as well as detection of the change points will be explored in the future.

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