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Adaptive Prognostics for Rotary Machineries

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Abstract

The success of condition-based-maintenance (CBM) of mechanical components, in terms of cost and reliability, hinges closely on the ability to accurately estimate the remaining life of the components at point. In the case of rotary machineries, special attention for remaining life estimation is warranted in view of the dynamic behaviors associated with repetitive contact motions. This paper discusses the rotary machinery prognostics using rolling element bearing – one of the foremost causes of breakdown in rotary machinery – as an example to illustrate the treatments of self-leaning prediction of remaining life. To date bearing remaining life prediction issue has not been fully addressed, as a result of the highly random nature of the bearing defect growth behavior in fatigue cycles. This paper addresses the lack of current bearing condition monitoring techniques by proposing a remaining life adaptation methodology based on the approaches of mechanistic modeling of vibration and self-training of parameter adaptation, thus the instantaneous rate of defect propagation can be apprehended, even when the initial health condition is unknown and the defect growth behavior is time-varying, to deliver a reliable prediction of the remaining life.

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Keywords: Adaptive, Prognostics, Fault, Diagnostic, Rotary

1. Introduction

The fatigue failure of rotary machinery is often stochastic in nature, that is, the life of a rotating mechanical component under a specific environment can differ significantly from another apparently identical unit under similar environment. Therefore, scheduled maintenance based on statistical reasoning has many limitations. The alternative maintenance method that employs techniques such as vibration analysis and acoustic emission analysis has made available the concept of condition-based-maintenance (CBM) in an attempt to minimize risk and maximize machinery utilization.

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In the example of bearing CBM, time domain methods such as shock pulse counting [1], root mean square (RMS), peak value, crest factor and kurtosis [2~4] have been examined. Frequency domain methods including bicoherence analysis [5], cepstrum analysis [6], and high frequency resonance technique (HFRT) [7] have been presented. An adaptive noise cancellation method has also been developed to enhance the envelope spectrum obtained by HFRT [8].

The main road block for effective implementation of bearing prognostics is the highly stochastic nature of defect growth. For instance, the variation to reach the final failure size from the point where a defect can be detected may be greater than its L_{10} life [9]. Deterministic models based on fracture or damage mechanics [10, 11] do not accurately describe the variable process of bearing defect propagation. Given that it is possible to predict breakdown time of machinery at the running stage based on vibration monitoring, it has not shown to be able to deal with time-varying nature of defect propagation. As a result, reliable prognostic techniques have not been well developed to date.

This paper presents the formulation of in-process adaptation of defect propagation rate with vibration signal analysis, using bearing prognostics as a case study. It utilizes a deterministic defect propagation model and an adaptive algorithm to fine tune the predicted rate of defect propagation real-time. The variable nature of defect propagation is addressed by a mechanistic model with time-varying parameters. The adaptive alteration of the model parameters offers the best prediction, in the least square error sense, of the bearing future state for any given diagnostic system.

2. Methodology Development

2.1. Deterministic Defect Growth Model

With respect to bearing defect analysis in industry, the defect severity of a bearing is often represented by the surface area size, rather than the length, of the defect [12]. A deterministic bearing defect growth model can be given in a manner similar to Paris's formula [13] as follows:

1.

$$\dot{D} = \frac{dD}{dt} = C_0\left(D\right)^n \tag{1}$$

which states that the rate of defect growth is related to the instantaneous defect area D under a constant operating condition. The parameters C_0 and n are material constants that need to be determined experimentally, and they often vary with factors other than the instantaneous defect size.

2.2. Adaptation of Remaining Life Prediction

Figure 1 illustrates an adaptive prognostic system developed to estimate the size of defect and the rate of defect growth. The system includes the deterministic defect propagation model, as specified by eq. (1), that calculates the future bearing defect size at a future time, $t + \Delta$, based on given bearing running condition and the defect size at the current time, t. Since the defect area size at the current time is often unavailable from direct measurements without interrupting the machinery operation; therefore, indirect and non-intrusive measurements – of vibration, temperature, acoustic emission, etc – are commonly pursued.

The future defect size as estimated by the prognostic model is compared to the measurement-inferred condition at time instant of $t + \Delta$. The comparison shows a certain amount of prediction error that can be employed by an adaptive algorithm to fine-tune the model parameters. In this manner the propagation model continuously improve its accuracy in following the time-varying defect growth behavior.

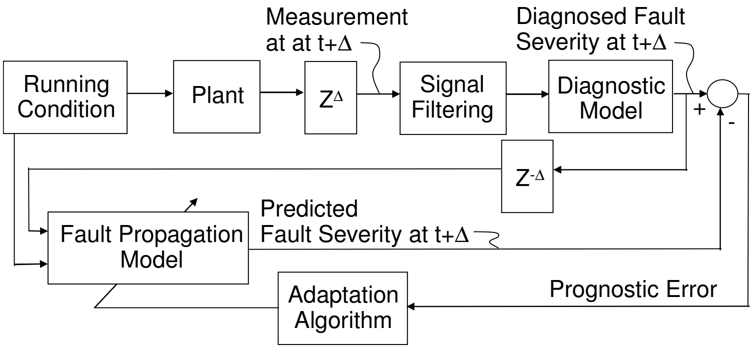

Figure1. Adaptive prognostic methodology

2.3. Nonlinear Recursive Least Square (RLS) Scheme

Equation (1) can be integrated in the time domain to yield

$$\ln(D) = \alpha + \beta \ln(t + t_0) \tag{2}$$

where $t_0 = (C_0/(1-n))D_0^{n+1}$ is the time the smallest defect D_0 occurs, D_0 is the smallest defect that can be detected by a given diagnostic system, $\alpha = (1/(n-1))\ln(C_0/(1-n))$, $\beta = (1/(1-n))$, and t is the component running time relative to t_0.

The model parameters $\alpha, \beta,$ and t_0 need to be estimated. As they are time-varying in a defect propagation process, a recursive least square (RLS) algorithm with a forgetting factor is used to adaptively update the values of $\alpha, \beta,$ and t_0 [14] as:

2.

$$\mathbf{e}(t) = \mathbf{Y}(t) - \hat{\mathbf{Y}}(t, \hat{\theta}(t-1)), \quad \psi(t) = \left.\frac{d\hat{\mathbf{Y}}(t,\theta)}{d\theta}\right|_{\theta=\hat{\theta}(t-1)},$$

$$\mathbf{P}(t) = \lambda^{-1}\left(\mathbf{P}(t-1) - \frac{\mathbf{P}(t-1)\psi(t)\psi^T(t)\mathbf{P}(t-1)}{\lambda + \psi^T(t)\mathbf{P}(t-1)\psi(t)}\right), \text{ and } \hat{\theta}(t) = \hat{\theta}(t-1) + \mathbf{P}(t)\psi(t)\mathbf{e}(t) \tag{3}$$

where the unknown parameters are contained in $\theta(t) = [\alpha \quad \beta \quad t_0]^T$, $\mathbf{e}(t)$ is the prediction error, $\mathbf{Y}(t) = \ln(D)$, $\hat{\mathbf{Y}}(t)$ the estimated value of $\mathbf{Y}(t)$, and $\mathbf{P}(t)$ is covariance matrix with initial values chosen as a unit matrix scaled by a positive scalar that is typically in between 1 and 1000 to reflect uncertainty in a system. Without less knowledge of a system, larger scalar should be selected. The forgetting factor λ falls within 0 and 1.

3. Experimental Evaluation

An experimental test rig was established to perform bearing life test in assessing the effectiveness of the adaptive prognostic methodology. The set-up consists of a test housing, a hydraulic load applicator, a shaft drive, accelerometers and a data acquisition system as shown in Figure 2. The test housing seen has a 5 inch bore and a built-in radial load cylinder. The house accommodates 4 bearings with the leftmost one being the test bearing. Timken LM50130 cup and LM501349 cone bearing were used in the study.

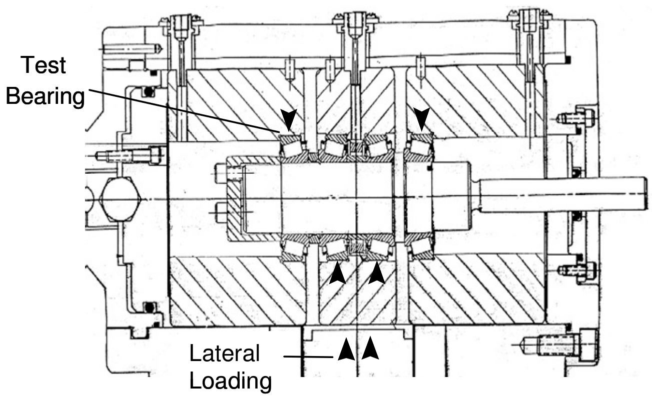

Figure 2. Life test housing schematic.

The radial load is provided by a hydraulic pump that to offer pressure to the load cylinder on the housing. The shaft is driven by a DC servomotor with a speed controller. A tri-axial accelerometer was attached to the housing to acquire vibration signals. Measured signals are low-pass filtered at 10 kHz for anti-aliasing before sampling at 30,000 points per second.

To accelerate a defect propagation process, an initial defect is artificially generated on the cup raceway by an electrical discharge machine to form a crack oriented along the bearing axial direction with width of 300 □m. In order to approach the realistic situation of natural defect propagation, the prognostic scheme is not implemented until the bearing had run for 20 million cycles when the maximum width of defect increased to 1,000 microns and a natural spall defect shape was generated. Experiments were performed at a shaft speed of 1,600 rpm, a preload of 1,300 lb., and a radial load of 5,522 lb. which is about 167% of the rated radial load. The defect is positioned in the loading zone. The system is lubricated by thin spindle oil with viscosity of 54-60 SSU at 100°F.

All physical damage in the tests takes the form of scratches made to the outer raceway center by diamond scribing. All scratches are approximately 2.54 mm (0.1 in.) in length. The width of the damage ranges from 15.4 µm to 408.48 µm and is controlled by the number of passes that a scribe makes over the raceway.

As the diagnostic model, as shown in Fig. 2, is an essential part of the adaptive prognostics, the relationship between fault size and the measurement signal has to be reliably established prior to the execution of prognostics. The testing involved seven bearings of damage levels ranging from 0.00 µm to 34.93 µm in width. The most significant result obtained from outer race damage experiments is the determination of a relationship between accelerometer signal peak value and defect width, as shown in Figure 3. At least four data sets for each condition were taken and averaged to obtain each data point. The method was able to determine the presence of defects in all six cases. It was found from the Figure that the peak ratios for defective bearings are substantially higher than that of the good bearing. The vertical variation for a given defect size represents a margin for error in measurements. Moreover, the y-intercept represents the noise level of the system. This directly affects the system sensitivity which lies between a defect of width 0.00 µm and 15.40 µm.

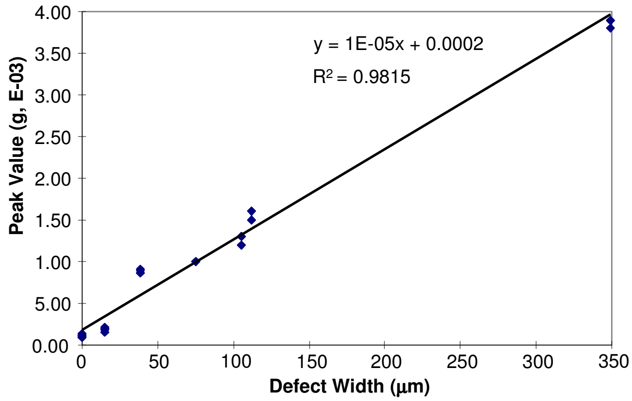

Figure 3. Peak value relationship with defect size.

In the prognostics study the procedure began by recording the accelerometer measurements during the running of a defected bearing while no artificial crack started was used. The running was interrupted about every 10 hours, the defective bearing removed from the test set-up, and the defect size physically measured with a profilometer. Then the bearing was re-assembled into the set-up to repeat the experimental procedure. The growth of bearing defect as measured by the profilometer is shown by the cross-marks in Figure 4.

Figure 4 also shows the defect areas as forecasted by the adaptive prognostic model with various initial values of the model parameters. Note that the prognostic model utilized only the diagnostic model for adaptation purpose while remaining ignorant of the profilometer measurements. This situation emulates practical applications in which bearing operations cannot be interrupted for physical defect inspection. The results in Figure 4 point out that the adaptive prognostic system can effectively predict the defect propagation. It is noted that the prediction accuracy is not strongly affected by the choice of initial parameter values, and this suggests that the prognostic system can perform well without a priori knowledge of the model parameters. This aspect is particularly important for real life applications since a priori and precise knowledge of the fracture mechanics model is usually unavailable.

The sources of prediction error are likely attributed to the uncertainty in the defect propagation process as well as in the diagnostic model based on accelerometer signals. Since the prognostic system cannot rely upon accurate measurement of the defect size in practical application cases, the reliability of the diagnostic model can be a critical factor to the overall performance of the prognostic system.

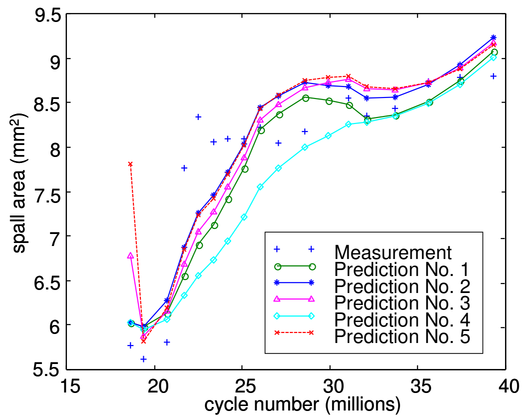

Figure 4. Predicted defect areas by the adaptive algorithm and measured defect areas by the profilometer with respect to running cycle numbers

4. Summary and Conclusions

A self-learning and self-tuning adaptive prognostic methodology is presented for the prediction of remaining life of rotary machinery, with the example of bearing defect growth. The machinery health estimation, based upon a diagnostic model, is compared to the defect size as predicted by a fatigue crack propagation analysis to allow adjustment of the model parameters step-by-step. This methodology automatically factors in the time-variant nature of defect growth while providing the best prediction possible, in the least square error sense, for any given diagnostic system.

Experimental study with vibration measurement in life testing of rotating bearings was performed to evaluate the capability of the proposed methodology. It was seen that the adaptive prognostics effectively predicted the bearing defect propagation process without the need of a priori knowledge of the prognostic model parameters. In addition, the fidelity of the diagnostic model is found to be a key element to the overall effectiveness of the adaptive prognostic system, as this model is not self-tuned throughout the machinery runtime. Future studies could include the adaptation of the diagnostic model based upon independent source of information in connection to the accuracy of the diagnostic and prognostic results.

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