Condition Based Maintenance Optimization Considering Improving Prediction Accuracy

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Abstract **-** Condition based maintenance (CBM) aims to reduce maintenance cost and improve equipment reliability by effectively utilizing condition monitoring and prediction information. It is observed that the prediction accuracy often improves with the increase of the age of the component. In this research, we develop a method to quantify the remaining life prediction uncertainty considering the prediction accuracy improvement, and an effective CBM optimization approach to optimize the maintenance schedule. Any types of prognostics methods can be used, including data-driven methods, model-based methods and integrated methods, as long as the prediction method can produce the predicted failure time distribution at any given inspection points. Furthermore, we develop a numerical method to accurately and efficiently evaluate the cost of the CBM policy. The proposed approach is demonstrated using vibration monitoring data collected from pump bearings in the field as well as simulated degradation data. The proposed policy is compared with two benchmark maintenance policies and is found to be more effective.

***Keywords* –** Maintenance, reliability, condition based maintenance, prediction, uncertainty.

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1. Introduction

Condition based maintenance (CBM) is a maintenance strategy which decides maintenance actions using information collected through condition monitoring. CBM optimization attempts to minimize maintenance cost by taking maintenance actions only when there is evidence that the failure is approaching. Effective implementation of CBM optimal policy greatly depends on the accurate prediction of the component or equipment health condition. Currently many health condition prediction methods can be used to predict the health condition of the component or equipment at certain inspection points. These methods can be roughly classified into model-based methods and data-driven methods. Model-based methods predict the health condition of equipment or component using damage propagation models based on damage mechanics (Vachtsevanos et al, 2006; Inman et al, 2005). Usually the propagation process of equipment or component is very complicated and it is difficult to accurately model the damage propagation process. Many aspects have to be considered carefully when building a physics-based model, for example, dynamics, reciprocity, etc. But it can greatly improve the prediction accuracy of health condition if an authentic physics-based model can be built successfully. Currently the reported model-based methods for prediction of health condition mainly focus on building physical models for gears and bearings. In (Kacprzynski et al, 2002), an approach for health condition prediction of gear system was proposed. This method was developed based on gear tooth crack initiation and propagation physical models. Another model-based prediction method for gears with a fatigue tooth crack was proposed by Li and Lee (2005) using a gear meshing stiffness identification model, a gear dynamic model and a fracture mechanics model. In (Marble and Morton, 2006), the method developed by Marble and Morton can predict the health condition of propulsion system bearings based on the bearing spall propagation physical model and finite element model. Different with model-based methods, data-driven methods predict the health condition for equipment or component based on the collected condition monitoring data. The condition monitoring data may be vibration analysis data, oil analysis data, acoustic emissions data, fuel consumption data, environmental conditions data, and so on. Many data-driven prediction methods are available and typical methods may be proportional hazards model (PHM), artificial neural network (ANN), proportional covariate model (PCM), etc. In (Banjevic et al, 2001), a proportional hazards model approach for CBM was developed. In this method, health condition of equipment or component is predicted using transition probability matrix. ANN has been demonstrated to be very promising in achieving accurate prediction results in equipment or component remaining useful life prediction. A ball bearing health condition prediction method was developed by Gebraeel et al. based on feedforward neural networks (Gebraeel and Lawley, 2004). This ANN model outputs a condition monitoring measurement, for example, overall vibration magnitude. Wu et al. (2007) proposed another RUL prediction method based on ANN. The output of this ANN model was the life percentage at certain inspection point of time. In (Sun et al, 2006), a PCM for CBM was developed by Sun et al. This method can reduce the number of failure test histories, and works well when historical failure data are sparse or zero.

To optimize CBM maintenance, various methods have been proposed to minimize the overall expected maintenance costs, such as PHM based methods (Elsayed and Zhang, 2007; Lugtigheid et al, 2008), multi-component system CBM methods (Castanier et al, 2005; Tian and Liao, 2011) and ANN based methods (Wu et al, 2012). For CBM optimization, we need to quantify the prediction uncertainty if health condition prediction is explicitly utilized. In (Wu et al, 2012), the ANN based replacement policy also uses prediction error to estimate the prediction uncertainty (Tian et al, 2010). It assumes that the standard deviation of prediction error is always the same during the whole history. That is, the prediction accuracy does not improve during the history of a component. This is also the situation considered in other reviewed previous work (Banjevic et al, 2001; Castanier et al, 2005; Lugtigheid et al, 2008; Tian and Liao, 2011). However, as discussed in (Gebraeel, 2006), the prediction accuracy often improves with the increase of the age of the component as it approaches the failure time. Prediction results based on our experimental data also show that prediction accuracy improves with time. In this paper, we propose a CBM optimization approach, in which the prediction uncertainty of health condition is estimated based on prediction errors. We assume that the prediction accuracy improves with time. By modeling the relationship between the mean value of prediction error and the life percentage, and the relationship between the standard deviation of prediction error and the life percentage, we can quantify the remaining life prediction uncertainty considering the prediction accuracy improvements. The cost evaluation of CBM policy is critical for CBM optimization. In this work, an accurate and efficient numerical method is also developed to evaluate the maintenance cost of the CBM policy.

The remainder of the paper is organized as follows. The proposed CBM approach considering improving prediction accuracy is discussed in Section 2. In Section 3, the effectiveness of the proposed CBM approach is demonstrated using one real-world condition monitoring data set collected from pump bearings and one simulated degradation data set. Section 4 gives the conclusion of this research.

2. The Proposed CBM Approach

The proposed CBM approach utilizes the health condition prediction information to optimize the maintenance schedules. Any type of prognostics methods can be used, including data-driven methods, model-based methods and integrated methods, as long as the prediction method can produce the predicted failure time distribution at any given inspection point. The procedure of the proposed CBM method is shown in Figure 1.

Figure 1 Procedure of the proposed CBM approach

2.1 Prediction Accuracy and Uncertainty Modeling

Suppose at a certain inspection point where the age of the component is t, the predicted failure time is $T_{n,t}$, and the actual failure time of the component is T_m. Here "n" is used to indicate that it is the "predicted" failure time value. The prediction error is defined in this paper as $e_{n,t} = (T_{n,t} - T_m)/T_m$. We also define the life percentage as $p_t = t/T_m$. The prediction error indicates the prediction accuracy in some way. According to our assumption regarding the prediction accuracy, the standard deviation of $e_{n,t}$ decreases with the increase of life percentage p_t, which represents how close it is to the failure time of the component. To model prediction accuracy, the prediction error values at the inspection points in the test histories are used. The general idea proposed in this paper is to model the relationship between the mean value of the prediction error $e_{n,t}$ and the life percentage p_t, and the relationship between the standard deviation of the prediction error $e_{n,t}$ and life percentage p_t. We don't use the absolute value of $e_{n,t}$ because the trend in $e_{n,t}$ can be more clearly modeled by using the original value itself.

To model the relationship between the mean value of the prediction error $e_{n,t}$ and the life percentage p_t, we can first plot the prediction error data points, and select an appropriate function type to fit the points. Generally a polynomial function will be sufficient. As an example, in the case study to be presented in this paper, it is observed that a linear function is suitable. After fitting the data points, the mean value of the prediction error can be calculated as:

$$\mu_{e_{n,t}} = a_\mu \cdot p_t + b_\mu, \tag{1}$$

This formula is used in the health condition prediction process to adjust the predicted failure time. That is, suppose at inspection point t, the predicted failure time is $T_{n,t}$, and the adjusted predicted failure time, due to the existence of the prediction error, is denoted by T_a. Based on the definition of the prediction error and Equation (1), we have:

$$\frac{T_{n,t}-T_a}{T_a} = a_\mu \cdot \left(\frac{t}{T_a}\right) + b_\mu, \tag{2}$$

and thus

$$T_a = \frac{T_{n,t}-t\cdot a_\mu}{1+b_\mu}. \tag{3}$$

To model the relationship between the standard deviation of the prediction error $e_{n,t}$ and the life percentage p_t, we need to first divide the prediction error data points into different ranges in order to estimate the standard deviation value for each range. For example, we may divide it into 10 ranges: 0-0.1, 0.1-0.2, 02.-0.3, …, 0.9-1.0. Using the standard deviation values estimated in these ranges, similarly, we can select an appropriate function type based on observation, fit these values and build the relationship between the prediction error standard deviation and the life percentage. Again in our case study, it is observed that a linear function is a suitable choice, and the function can be represented as:

$$\sigma_{n,t}^p = a_\sigma \cdot p_t + b_\sigma, \tag{4}$$

$$\sigma_{n,t} = \sigma_{n,t}^p \cdot T_a, \tag{5}$$

where $\sigma_{n,t}^p$ is the standard deviation of the life prediction percentage error, and a_σ and b_σ are function coefficients. Suppose the prediction error corresponding to inspection point t follows normal distribution with standard deviation$\sigma_{n,t}^p$, the predicted failure time corresponding to inspection point t also follows normal distribution with the same standard deviation. So $\sigma_{n,t}$ is the standard deviation of the predicted failure time corresponding to inspection point t. Since the prediction accuracy is measured by the prediction error, the standard deviation of prediction error is the key measure of the prediction accuracy. The decrease in $\sigma_{n,t}$ means the increase of prediction accuracy. Since it is assumed that the prediction accuracy improves over time, $\sigma_{n,t}$ should decrease with time. Thus, at inspection point t, the predicted failure time distribution can be represented by

$$T_{n,t} \sim N\left(T_a, \sigma_{n,t}^2\right). \tag{6}$$

For other applications, higher order polynomial functions may be needed to model the relationship between the mean value and the standard deviation of the prediction error $e_{n,t}$ and the life percentage p_t. A similar procedure can be used to build those relationships.

As can be noted, it is assumed that the predicted failure time of a specific unit based on the health condition prediction at a certain inspection time follows Normal distribution. For a specific unit being monitored, it has specific material and geometry parameters. Although these specific parameters are unknown, they can be considered using the condition monitoring and prediction information from the specific unit. The uncertainty in the predicted failure time can be summarized in the prediction error from the data-driven perspective. Thus, we assume that the predicted failure time distribution for a specific unit, based on condition monitoring data, follows Normal distribution. Such assumptions are also used in many studies in the literature, such as Ref. (Kacprzynski et al, 2002), (Marble and Morton, 2006) and (Gebraeel, 2006).

2.2 The CBM Decision Process

The CBM policy used in this paper is similar to that proposed in (Wu et al, 2012). The key differences are that the prediction accuracy improvement is considered, and the predicted failure time distribution quantification and the conditional failure probability calculation are different.

In this approach, we assume that the component is inspected at constant interval T, for example, every 20 days. At any inspection point of time, we can obtain the predicted failure time distribution using Equation (6); and the conditional failure probability during the next inspection interval, which is denoted by $\Pr_{con}$, can be calculated using Equation (14) given in Section 2.3.2.

By performing CBM optimization, the optimal threshold failure probability Pr* which corresponds to the lowest cost can be determined. Assuming that no lead time is necessary for carrying out a preventive replacement, at each inspection point of time, the proposed maintenance policy is summarized as follows:

(1) Perform preventive replacement if the conditional failure probability during next inspection interval Pr_{con} exceeds the optimal failure probability threshold Pr*. Otherwise, the component can be continued to be used.

(2) Perform failure replacement at any time when a failure occurs.

2.3 Cost Evaluation and Optimization of the CBM Policy

2.3.1. The Overall Procedure

The objective of CBM optimization is to determine the optimal threshold failure probability Pr* with respect to the lowest cost. The optimization model can be briefly formulated as follows:

$$\begin{aligned} &\min\ C_E(\mathrm{Pr}) \\ &\text{s.t.} \\ &\quad \mathrm{Pr} > 0 \end{aligned} \tag{7}$$

where C_E is the expected cost corresponding to the CBM policy with threshold failure probability Pr. Pr is the only design variable in this optimization problem. The output of the optimization process is the optimal threshold failure probability Pr*.

To perform CBM optimization, we need to evaluate the cost $C_E(\mathrm{Pr})$ corresponding to a certain threshold failure probability Pr. In the proposed cost evaluation method, we first calculate the expected cost with respect to a certain actual failure time T_m, denoted by $C_T(T_m)$, and the expected replacement time with respect to a certain actual failure time T_m, denoted by $T_T(T_m)$. The actual failure time of the component population varies and follows a certain distribution, with probability density function $f(t)$. Considering all the possible component actual failure times, the expected cost with respect to failure probability threshold value Pr, denoted by C_{TA}, takes the form

$$C_{TA} = \int_0^{\infty} f(t_m) \times C_T(t_m) dt_m \ , \tag{8}$$

and the expected total replacement time with respect to failure probability threshold value Pr, denoted by T_{TA}, takes the form

$$T_{TA} = \int_0^{\infty} f(t_m) \times T_T(t_m) dt_m \ . \tag{9}$$

The actual failure time of the component population typically follows Weibull distribution. For the population of a certain type of component, different specific units have different failure times due to the variations in their material properties, geometry parameters and operating conditions. Weibull distribution has been demonstrated to be effective and flexible in modeling the failure time distribution for the component population. In this case, the two equations above can be written as:

$$C_{TA} = \int_0^{\infty} \frac{\beta}{\alpha}\left(\frac{t_m}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t_m}{\alpha}\right)^{\beta}\right] \times C_T(t_m) dt_m \ , \tag{10}$$

and

$$T_{TA} = \int_0^{\infty} \frac{\beta}{\alpha}\left(\frac{t_m}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t_m}{\alpha}\right)^{\beta}\right] \times T_T(t_m) dt_m \ . \tag{11}$$

And, the total expected cost per unit of time, $C_E(\mathrm{Pr})$, with respect to failure probability threshold value Pr can be calculated as:

$$C_E(\mathrm{Pr}) = \frac{C_{TA}}{T_{TA}} \tag{12}$$

2.3.2. Evaluation of $\boldsymbol{C_T(T_m)}$

Now we will focus on the evaluation of $C_T(T_m)$, the expected cost with respect to a certain actual failure time T_m. The general procedure is that we go from the first inspection point, corresponding to age t, to the actual failure time T_m, at which time a failure occurs. The probability that a component has not been replaced yet is denoted by P_{rem}^t, which is equal to 1 at time 0. At a certain inspection point t, P_{rem} may decrease since there is chance of preventive replacement because the preventive replacement condition, described in Section 2.2, is satisfied. At time T_m, the probability of failure replacement is thus $P_{rem}^{T_m}$.

At a certain inspection point t, when we perform failure time prediction, the predicted failure time follows the normal distribution with mean T_m and standard deviation $\sigma_{m,t}$:

$$\sigma_{m,t} = (a_\sigma \cdot t/T_m + b_\sigma) \cdot T_m, \tag{13}$$

according to the method described in Section 2.1 if the standard deviation can be described using a linear function. Otherwise, a higher order polynomial function can be used. Suppose the adjusted predicted failure time is T_a, the associated standard deviation $\sigma_{n,t}$ can be obtained using Equation (5). Thus, the predicted failure time distribution can be represented as $T_{n,t} \sim N\left(T_a, \sigma_{n,t}^2\right)$. The conditional failure probability can be calculated for interval [t, t+T] as follows:

$$\Pr_{con} = \frac{\int_t^{t+T} \frac{1}{\sigma_{n,t}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-T_a}{\sigma_{n,t}}\right)^2} dx}{\int_t^{\infty} \frac{1}{\sigma_{n,t}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-T_a}{\sigma_{n,t}}\right)^2} dx} \tag{14}$$

If $\Pr_{con} > \Pr$, the preventive replacement should be performed. Thus, at inspection point t, the probability that a preventive replacement will be performed is:

$$P(T_m, t) = \int \frac{1}{\sigma_{m,t}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{T_a-T_m}{\sigma_{m,t}}\right)^2} \cdot I\left(\Pr_{con}(T_a) \geq \Pr\right) dT_a \tag{15}$$

where $I\left(\Pr_{con}(T_a) \geq \Pr\right) = 1$ if $\Pr_{con}(T_a) \geq \Pr$. $P_{rem}^{T_m}$ should be updated by reducing $P(T_m, t)$:

$$\Delta P_{rem}^{T_m} = P_{rem}^{T_m}[1 - P(T_m, t)] \tag{16}$$

Such actions will lead to cost and time changes. The total time and total cost increments are:

$$\Delta T_{TT}(T_m) = P_{rem}^{T_m} \cdot P(T_m, t) \cdot t \tag{17}$$

$$\Delta C_{TT}(T_m) = P_{rem}^{T_m} \cdot P(T_m, t) \cdot C_p \tag{18}$$

Finally, at the actual failure time T_m, the probability $P_{rem}^{T_m}$ corresponds to the failure probability, and the total time and total cost increments are:

$$\Delta T_{TT}(T_m) = P_{rem}^{T_m} \cdot T_m \tag{19}$$

$$\Delta C_{TT}(T_m) = P_{rem}^{T_m} \cdot C_f \tag{20}$$

At the end of this procedure, $C_T(T_m)$, the expected cost with respect to a certain actual failure time T_m, can be calculated as:

$$C_T(T_m) = C_{TT}(T_m)/T_{TT}(T_m). \tag{21}$$

Now, combining what have been described in this section and Section 2.3.1, we can evaluate the total expected cost per unit of time, $C_E(\mathrm{Pr})$.

2.3.3. A Procedure to Improve the Cost Evaluation Efficiency

A procedure to improve the efficiency in evaluating $C_T(T_m)$ is presented in this section. The procedure described in Equation (15) is very time-consuming, since the evaluation of $\mathrm{Pr}_{con}(T_a)$ demands heavy computation, and it needs to be performed a large number of times for the integral calculation. From sample calculations, we observe that at any inspection point, $I(\mathrm{Pr}_{con}(T_a) \geq \mathrm{Pr}) = 1$ when T_a is smaller than or equal to a certain value T_{a0}, and $I(\mathrm{Pr}_{con}(T_a) \geq \mathrm{Pr}) = 0$ when $T_a > T_{a0}$. This is reasonable since when the predicted failure time becomes larger, and thus moves away to the right from the current inspection age, the conditional failure probability becomes smaller, and it is less likely that a preventive replacement will be performed. In another word, the value $\mathrm{Pr}_{con}(T_a) - \mathrm{Pr}$ is a decreasing function and is equal to 0 at point T_{a0}. The objective of Equation (15) is to find the probability that a preventive replacement will be performed at inspection point *t*, denoted by $P(T_m, t)$. Thus, we can first find point T_{a0} by solving equation $\mathrm{Pr}_{con}(T_{a0}) - \mathrm{Pr} = 0$, and then evaluate the preventive replacement probability as follows:

$$P(T_m, t) = \int_{-\infty}^{T_{a0}} \frac{1}{\sigma_{m,t}\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{T_a - T_m}{\sigma_{m,t}}\right)^2} dT_a \tag{22}$$

To solve equation $\Pr_{con}(T_{a0}) - \Pr = 0$, a bisection method is utilized. We first define the function $f(x) = \Pr_{con}(x) - \Pr$, which is a decreasing function, and try to find the value to make the function equal to 0. The procedure is described as follows. (1) Let $a = T_m - 6\sigma_{m,t}$, $b = T_m + 6\sigma_{m,t}$, and calculate $f(a)$, $f(b)$. (2) At a certain iteration i, let $x_i = (a+b)/2$, and calculate $f(x_i)$. If $f(x_i) \geq 0$, $a = x_i$. Otherwise, $b = x_i$. (3) If $b - a < 1$, stop the algorithm, and $x^* = x_i$. Otherwise, go to step (1).

The $C_T(T_m)$ evaluation results obtained using this method agree with those obtained using Equation (15). But by using this method, the evaluation process is thousands of times faster, which is very important for the overall cost evaluation and the CBM optimization.

3. Examples

In this section, we will demonstrate the proposed CBM approach using one real-world condition monitoring data set collected from bearings in a group of Gould pumps (Stevens, 2006), and one simulated degradation data set.

3.1 Case Study

3.1.1. Case Study Introduction

In this section, the proposed CBM optimization approach is demonstrated using a real-world case. This condition monitoring data with 10 failure histories and 14 suspension histories was collected from bearings on a group of Gould pumps at a Canadian kraft pulp mill company (Stevens, 2006). For each pump, seven types of measurements were recorded at eight sensor locations: five different vibration frequency bands (8×5), and the overall vibration reading (8×1) plus the bearing's acceleration data (8×1). So the original inspection data includes 56 ($=8\times5+8\times1+8\times1$) vibration measurements. Significance analysis was performed for the 56 vibration measurements by the software EXAKT (Stevens, 2006). Two measurements were identified to be significantly correlated to the health of bearings: P1H_Par5 (band 5 vibration frequency in Pump location P1H), and P1V_Par5 (band 5 vibration frequency in Pump location P1V).

3.1.2. Prediction Accuracy and Uncertainty Modeling

As discussed previously, any type of prognostics methods which can produce the predicted failure time distribution at any given inspection point can be used to obtain prediction results for the proposed approach. Because of its great promise in achieving accurate remaining useful life, ANN is selected as prediction method in this case study.

In this case, 5 failure histories and 10 suspension histories are used to train the ANN model. And then another 5 test histories are used to test the prediction performance of the trained ANN model and the test process is repeated for three times. Altogether there are 468 inspection points at which the prediction performance is tested. Based on the probability plot result, prediction error $e_{n,t}$ follows normal distribution. Next we will model the relationship between the mean value of prediction error $e_{n,t}$ and the life percentage p_t, and the relationship between the standard deviation of prediction error $e_{n,t}$ and life percentage p_t.

To model the relationship between the mean value of prediction error $e_{n,t}$ and the life percentage p_t, firstly we plot the obtained 468 points, and it is observed that a linear function is good enough to describe the relationship between the mean value of prediction error $e_{n,t}$ and the life percentage p_t, After fitting the data points using function (1), the relationship between mean value of prediction error and the life percentage can be modeled as:

$$\mu_{e_{n,t}} = 0.7371 p_t - 0.6765 \quad (23)$$

As discuss beforehand, to model the relationship between the standard deviation of prediction error $e_{n,t}$ and the life percentage p_t, we need to first divide the prediction error data points into different ranges in order to estimate the standard deviation value for each range. In this case, we can divide the 468 points into 10 ranges: 0-0.1, 0.1-0.2, 02.-0.3,…, 0.9-1.0. Again by plotting these standard deviation values, it is observed that a linear function is sufficient to model the relationship between the standard deviation of the prediction error and the life percentage as follows:

$$\sigma_{n,t}^{p} = -0.1076 p_t + 0.1440 \quad (24)$$

3.1.3. Cost Evaluation and Optimization of the CBM Policy

In this section, we will evaluate the total expected maintenance cost for each possible failure probability threshold and find the optimal threshold Pr* using the proposed algorithms in Section 2.3.1. Based on Equations (10) and (11), we need to model the lifetime distribution of the components as a population based on the available failure data and suspension data. Generally the lifetime distribution of bearings follows Weibull distribution and in this case the parameters of Weibull distribution are estimated as: $\alpha = 1386.3, \beta = 1.8$. Based on expertise and experience the total cost of a preventive replacement C_p is estimated to be $3000 and the total cost of a failure replacement C_f is $16000. Using the algorithm presented in Section 2.3.1, the optimal threshold failure probability Pr* is found to be 0.1096, and the corresponding total expected replacement cost is 2.65 $/day, as shown in Figure 2.

Figure 2 Expected replacement cost corresponding to different threshold failure probability values

3.1.4. Maintenance Decision Making

After obtaining the optimal threshold failure probability Pr*, we can determine the optimal CBM policy. To perform the optimal CBM policy, firstly we inspect a new component at constant interval. At each inspection point, the conditional failure probability $\Pr_{con}$ during next interval is calculated and compared with the optimal threshold failure probability Pr*. Perform preventive replacement when $\Pr_{con}$ exceeds Pr* and continue to use the component if it doesn't exceed the threshold. Whenever a failure occurs, we have to perform a failure replacement. In this case, 5 test histories are used to demonstrate the proposed CBM optimization approach. These data were collected at unequally spaced inspection points but the ANN model in the policy can handle this situation.

Next an example is given to illustrate the implementation of the optimal CBM policy. The selected inspection point is the 567th day in a failure history. In this case the inspection interval is assumed to be 20 days. Using the age data and condition monitoring measurements at the previous inspection point 545th day and the current inspection point 567th day as input into the trained ANN model, the lifetime of this bearing is predicted as 616.10 days. Considering the prediction error, the predicted failure time is adjusted as 612.57 days using Equation (2) and (3). And using Equation (4) and (5), the standard deviation of the lifetime prediction error is calculated as 26.03 days. Thus, at inspection point 567th day, the predicted failure time follows the following normal distribution:

$$T_p \sim N\left(612.57, 26.03^2\right) \tag{25}$$

So the failure probability during the next inspection interval can be obtained as 0.1329, as shown in Figure 3. Since this failure probability exceeds the optimal failure probability threshold 0.1096, we need to perform a preventive replacement to avoid a very highly possible failure during next inspection interval.

Figure 3 Failure probability value at age 567 days

Using the same procedure we can calculate the failure probability at each inspection point for all the test histories. And the replacement decisions can be made for each history, as shown in Table 1. In this table, the replacement time according to the proposed CBM approach and the actual failure time are given for each history. From this table we can see all the 5 histories are preventive replacements.

Table 1: Test results using the proposed CBM approach

3.1.5. Comparison between Proposed Approach and Benchmark Replacement Policies

For individual component, age-based replacement policy usually performs better than constant interval replacement policy. So in this paper, we will compare the performance of the proposed approach with the age-based replacement policy, and the ANN based replacement policy which is developed by Wu et al (2012) where prediction accuracy improvement is not considered. The comparison is performed both in optimization results and in practical implementation results. The lifetime distribution parameters and the cost information have already been obtained in the previous section, which are $\alpha = 1386.3, \beta = 1.8$, $C_p = \$3000$, $C_f = \$16000$. By performing optimization, the optimal replacement interval is found to be 715.40 days for the age-based replacement policy, and the corresponding expected cost is 9.94 $/day. For the ANN based replacement policy, the expected replacement cost is 3.88 $/day. In Section 3.1.3, we can find the optimal expected total maintenance cost for the proposed CBM approach is 2.65$/day. Thus by implement the proposed CBM approach we can achieve a cost saving of 74.67% comparing to the age-based replacement policy, and 31.80% comparing to the ANN based replacement policy reported in (Wu et al, 2012). The comparison results can be found in Table 2.

Table 2: Comparison between the proposed approach and two benchmark policies

Next we will apply the three maintenance policies to 5 testing histories respectively, and investigate how they perform when applying to real inspection histories. Using the same procedure illustrated in Section 3.1.4., the implementation results for the 5 histories are shown in Table 3. In this table, for each history and for all the three maintenance policies, the replacement times, replacement types and replacement costs are listed. The average replacement cost using the proposed CBM approach considering prediction accuracy improvement is again the lowest, which is 2.89 $/day. It is around 31.13% lower than age-based replacement policy and 26.30% lower than the ANN based replacement policy in (Wu et al, 2012). The results further demonstrate the advantage of the proposed CBM approach over the two benchmark maintenance policies.

Table 3: Comparison between the proposed approach and two benchmark policies applying to the 5 failure histories

3.2 Simulated Degradation Data Set

In this example, the degradation signals are simulated using the degradation model presented in (Wu et al, 2012) and (Gebraeel et al, 2005):

$$S(t) = \phi + \theta \exp(\beta t + \varepsilon(t) - \frac{\sigma^2 t}{2}) \tag{26}$$

where $S(t)$ denotes a continuous degradation signal, ϕ is a constant and θ is a lognormal random variable, and $\ln\theta$ has mean μ_0 and variance σ_0^2. β is a normal random variable with mean μ_1 and variance σ_1^2. $\varepsilon(t) = \sigma W(t)$ is a centered Brownian motion with mean 0 and variance $\sigma^2 t$. θ, β and $\varepsilon(t)$ are assumed to be mutually independent. The logarithm of the degradation signal, $L(t)$, is:

$$L(t) = \ln\theta + \left(\beta - \frac{\sigma^2}{2}\right)t + \varepsilon(t) \tag{27}$$

Let $\beta' = \beta - \frac{\sigma^2}{2}$ be a normal random variable with mean $\mu_1^{'}$ and variance σ'^2_1. And the parameters in the equations for generating the simulated degradation signals are: $\mu_0 = 5,\ \sigma_0 = 1,$ $\mu_1^{'} = 5,\ \sigma_1^{'} = 1.5,\ \sigma = 2$. And the failure threshold D is set as 400. That is, when the degradation signal goes beyond the failure threshold, the unit is considered to be failed.

Same as the case study, ANN is selected as prediction method in this example. Totally 50 degradation paths are generated, as shown in Figure 4. 20 failure histories and 10 failure histories are selected randomly as training histories and testing histories respectively. Altogether there are 154 lifetime prediction error data points for the 10 testing histories. Using probability plot the prediction error $e_{n,t}$ is found to follow normal distribution. Same as the case study, next we can model the relationship between the mean value of prediction error $e_{n,t}$ and the life percentage p_t, and the relationship between the standard deviation of prediction error $e_{n,t}$ and the life percentage p_t.

Figure 4: 50 simulated degradation paths

After plotting the obtained data points, it is found that 4th order polynomial function is suitable to model the relationship between the mean value of prediction error $e_{n,t}$ and the life percentage p_t as follows:

$$\mu_{e_{n,t}} = a_1 p_t^4 + a_2 p_t^3 + a_3 p_t^2 + a_4 p_t + a_5 \quad (28)$$

By fitting the 154 data points, the relationship between mean value of prediction error and the life percentage can be modeled as:

$$\mu_{e_{n,t}} = 5.4775 p_t^4 - 11.5624 p_t^3 + 8.0164 p_t^2 - 1.9814 p_t + 0.1042 \quad (29)$$

For the relationship between the standard deviation of prediction error $e_{n,t}$ and the life percentage p_t, the 154 points in this case can be divided into 9 ranges: 0.1-0.2, 0.2-0.3, … , 0.9-1.0 to estimate the standard deviation. By plotting these standard deviation values, it is observed that a linear function is good enough to model the relationship between the standard deviation of the prediction error and the life percentage as follows:

$$\sigma_{n,t}^p = -0.0382 p_t + 0.0748 \quad (30)$$

The total cost of a preventive replacement C_p is assumed to be \$3000 and the total cost of a failure replacement C_f is \$16000. And the lifetime of the components is determined to follow Weibull distribution with $\alpha = 106.9373, \beta = 4.7895$. The inspection interval is set to be 5 days, that is $T = 5$. After performing optimization, the optimal threshold probability Pr* is found to be 0.1995 and the corresponding expected total replacement cost per day is 32.97 \$/day, as shown in Figure 5.

By applying the two benchmark policies to the degradation signal data respectively, we can obtain the comparison results as shown in Table 4. Again we can see the expected total replacement cost for the proposed CBM approach is still the lowest, which is 32.97 \$/day. It saves 48.37% comparing to the age-based replacement policy, and 13.60% comparing to the

ANN based replacement policy reported in (Wu et al, 2012) considering constant prediction accuracy.

Figure 5: Expected replacement cost corresponding to different failure probability values

Table 4: Comparison between the proposed approach and two benchmark policies

Next we will apply the three maintenance policies to 10 testing histories respectively to investigate the practical implementation results. In this example, the inspection interval is set to be 5 days. But since the lifetime is relatively short, we reduce the inspection interval from 5 days to 1 day when approaching the end of the history. Table 5 is the practical implementation results for each maintenance policy.

Table 5: Comparison between the proposed approach and two benchmark policies when applying to the 10 failure histories

From the comparison results we can see that the average replacement cost using the proposed CBM approach considering prediction accuracy improvement is the lowest, which is $33.41/day. It results in 33.18% cost savings comparing to the age-based replacement policy, and 8.46% cost savings comparing to the ANN based replacement policy considering constant prediction accuracy (Wu et al, 2012). The results further demonstrate the advantage of the proposed CBM approach over the two benchmark maintenance policies.

4. Concluding Remarks

In this paper, we propose a CBM optimization approach considering improved prediction accuracy. In this approach, we quantify the remaining life prediction uncertainty by modelling the relationship between the mean value of prediction error and the life percentage, and the relationship between the standard deviation of prediction error and the life percentage. An effective method is also developed to accurately evaluate the cost of the CBM policy. We demonstrate the effectiveness of the proposed approach using vibration monitoring data collected from pump bearings in the field and another data set from simulated degradation. For mechanical components such as bearings and gears, it is true that the prediction accuracy improves over time. However, for other components, the prediction accuracy improvement may not be obvious. Thus, we need to study the historical data first to determine if the prediction accuracy does improve significantly with age by applying the prediction models, and decide if it is necessary to explicitly consider this effect. The proposed approach is compared with two benchmark maintenance policies: age-based maintenance policy and an ANN based maintenance policy considering constant prediction accuracy, and it has been found to be more effective.

Acknowledgments

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List of Figure Captions

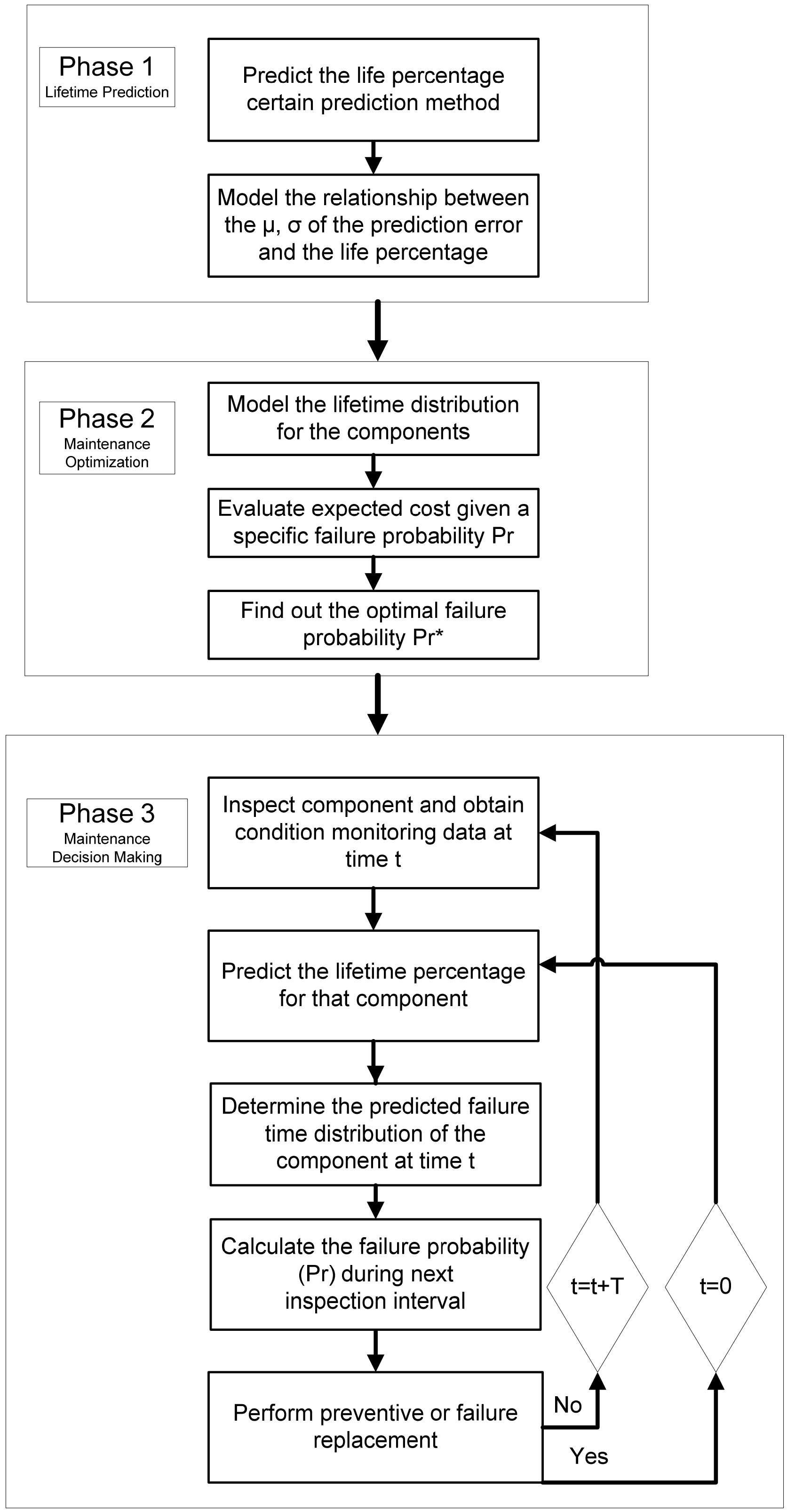

Figure 1: Procedure of the proposed CBM approach

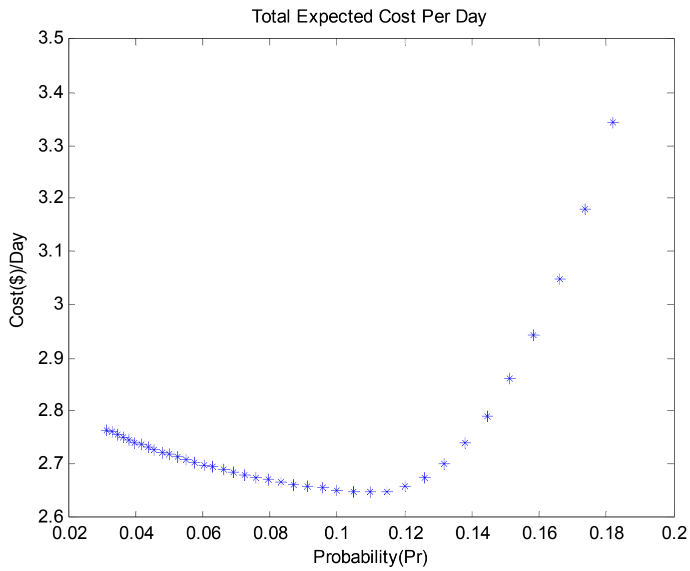

Figure 2: Expected replacement cost corresponding to different threshold failure probability values

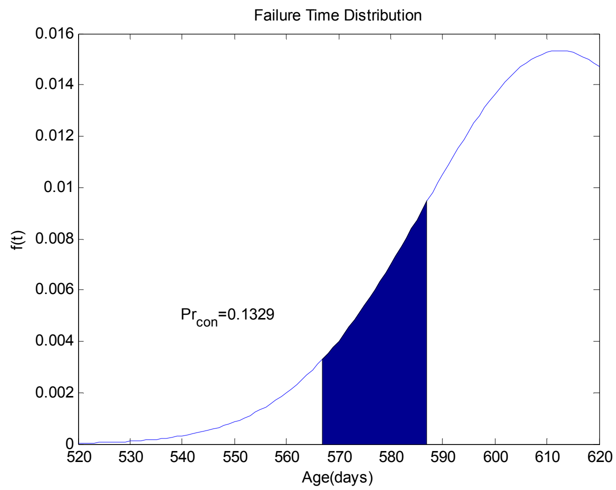

Figure 3: Failure probability value at age 567 days

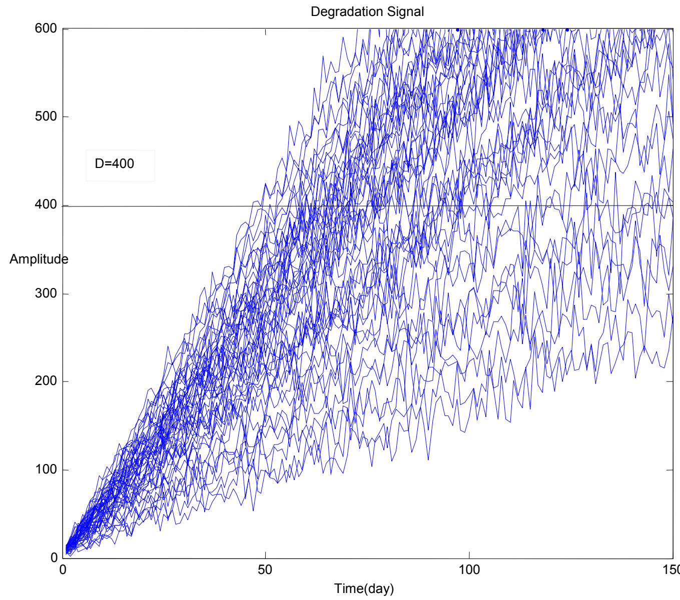

Figure 4: 50 simulated degradation paths

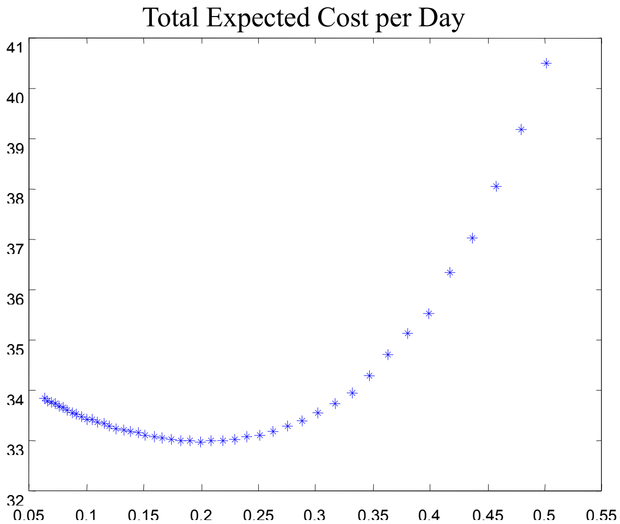

Figure 5: Expected replacement cost corresponding to different failure probability values

Table 1: Test results using the proposed CBM approach

History	**Replacement age (days)**	**Pr_{con}**	**Actual failure time (days)**
1	945	0.1869	986
2	1062	0.2463	1402
3	1049	0.1792	1246
4	1177	0.1531	1468
5	958	0.6507	964

Table 2: Comparison between the proposed approach and two benchmark policies

Maintenance policy	Expected total replacement cost per unit of time ($/day)	Optimal replacement time (days)
Age-based replacement policy	9.94	715.40
ANN based replacement policy (Wu et al, 2012)	3.88	
The proposed CBM approach	2.65	

Table 3: Comparison between the proposed approach and two benchmark policies applying to the 5 failure histories

History	**Actual failure time**	**Age-based replacement policy**			**ANN based replacement policy (Wu et al, 2012)**			**The proposed CBM policy**		
		Time	**Type**	**Cost**	**Time**	**Type**	**Cost**	**Time**	**Type**	**Cost**
1	986	715	P	3000	944	P	3000	945	P	3000
2	1402	715	P	3000	516	P	3000	1062	P	3000
3	1246	715	P	3000	785	P	3000	1049	P	3000
4	1468	715	P	3000	803	P	3000	1177	P	3000
5	964	715	P	3000	778	P	3000	958	P	3000
Total		3575		15000	3826		15000	5191		15000
Average replacement time		715			765.2			1038.2		
Average cost per day		$4.20			$3.92			$2.89		

Table 4: Comparison between the proposed approach and two benchmark policies

Maintenance policy	**Expected total replacement cost per unit of time ($/day)**	**Optimal replacement time (days)**
Age-based replacement policy	63.87	59.68
ANN based replacement policy (Wu et al, 2012)	38.17	
The proposed CBM approach	32.97	

Table 5: Comparison between the proposed approach and two benchmark policies when applying to the 10 failure histories

History	**Actual failure time**	**Age-based replacement policy**			**ANN based replacement policy (Wu et al, 2012)**			**The proposed CBM policy**		
		Time	**Type**	**Cost**	**Time**	**Type**	**Cost**	**Time**	**Type**	**Cost**
1	86	60	P	3000	76	P	3000	81	P	3000
2	111	60	P	3000	101	P	3000	107	P	3000
3	126	60	P	3000	106	P	3000	117	P	3000
4	91	60	P	3000	81	P	3000	87	P	3000
5	101	60	P	3000	81	P	3000	87	P	3000
6	101	60	P	3000	86	P	3000	92	P	3000
7	66	60	P	3000	56	P	3000	62	P	3000
8	86	60	P	3000	67	P	3000	76	P	3000
9	66	60	P	3000	52	P	3000	57	P	3000
10	146	60	P	3000	116	P	3000	132	P	3000
Total		600		30000	822		30000	898		30000
Average replacement time		60			82.2			89.8		
Average cost per day		$50.00			$36.50			$33.41		