Condition based maintenance optimization using neural network based health condition prediction

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Abstract **–** Artificial neural network (ANN) based methods have been extensively investigated for equipment health condition prediction. However, effective condition based maintenance (CBM) optimization methods utilizing ANN prediction information are currently not available due to two key challenges: (1) ANN prediction models typically only give a single remaining life prediction value, and it is hard to quantify the uncertainty associated with the predicted value; (2) simulation methods are generally used for evaluating the cost of the CBM policies, while more accurate and efficient numerical methods are not available, which is critical for performing CBM optimization. In this paper, we propose a CBM optimization approach based on ANN remaining life prediction information, in which the above-mentioned key challenges are addressed. The CBM policy is defined by a failure probability threshold value. The remaining life prediction uncertainty is estimated based on ANN lifetime prediction errors on the test set during the ANN training and testing processes. A numerical method is developed to evaluate the cost of the proposed CBM policy more accurately and efficiently. Optimization can be performed to find the optimal failure probability threshold value corresponding to the lowest maintenance cost. The effectiveness of the proposed CBM approach is demonstrated using two simulated degradation data sets and a real-world condition monitoring data set collected from pump bearings. The proposed approach is also compared with benchmark maintenance policies, and is found to outperform the benchmark policies. The proposed CBM approach can also be adapted to utilize information obtained using other prognostics methods.

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Acronyms:

CBM Condition Based Maintenance

ANN Artificial Neural Network

1. Introduction

The development of maintenance optimization contributes greatly to equipment reliability improvement, unexpected failure reduction and maintenance cost minimization [1]-[4]. Maintenance can be generally classified into corrective maintenance, preventive maintenance and condition based maintenance (CBM) [5]-[6]. CBM is a maintenance strategy under which maintenance decisions are made based on the age data as well as condition monitoring data. CBM may use condition monitoring data collected from oil analysis, vibration analysis, acoustic emission analysis, and so on [7]-[10]. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is indication that the failure is approaching [11]-[12]. Generally a component or a piece of equipment experiences various degraded states before it eventually fails. During the degradation process, health condition can be monitored and predicted, and maintenance actions can be scheduled to prevent component or equipment breakdown and minimize the total maintenance costs.

A key to the effective implementation of CBM is the accurate prediction of the equipment health condition and thus the remaining useful life. The health condition prediction methods can generate the predicted remaining useful life value, and some methods can also give the associated prediction uncertainties. The reported health condition prediction methods can be roughly classified into model-based methods and data-driven methods. The model-based methods predict health condition using physical models of the components and damage propagation models [13, 14], such as the bearing prognostics method proposed by Marble et al

[15], and the gearbox prognostics methods developed by Kacprzynski et al [16] and Li and Lee [17]. However, for some components and systems, authentic physics-based models are very difficult to build because equipment dynamic response and damage propagation processes are very complex. Data-driven methods do not require physical models, and utilize the collected condition monitoring data for health condition prediction. Among data-driven methods, artificial neural network (ANN) based methods have been considered to be very promising for component or equipment health condition and remaining life prediction. Lee et al. [18] presented an Elman neural network method for health condition prediction. A neural network model for condition monitoring of milling cutting tools was developed by Saglam and Unuvar in [19]. The model was used to describe the relationship between cutting parameters in a milling operation and the resulting flank wear and surface roughness. Shao and Nezu [20] developed neural network models to predict the health of a roller bearing by modeling the vibration root mean square value as a time series. Using feedforward neural networks, Gebraeel et al. proposed ball bearing remaining life prediction methods in [21-22], where the output of the ANN models was a condition monitoring measurement, such as the overall vibration magnitude. Wu et al. [6] proposed another ANN-based prediction model with the life percentage as the ANN model output. Tian proposed a more generalized ANN prediction model in [23], which can deal with multiple measurements inputs and data that are not equally spaced. In [24], Tian et al. developed an ANN prediction method to utilize both failure and suspension data to improve prediction accuracy. Tian and Zuo also developed a recurrent ANN-based time series prediction method to deal with situations where sufficient failure and suspension data are not available [25].

However, effective CBM optimization methods that can take advantage of the more accurate ANN health prediction information are currently not available due to two key challenges. One challenge is that ANN prediction methods typically only give a single remaining life prediction value, and it is hard to quantify the uncertainty associated with the predicted value. The remaining life prediction uncertainty is required for optimizing CBM activities. The other key challenge is that simulation methods are generally used for the cost evaluation of CBM policies which are based on ANN-based health condition prediction methods and model-based prediction methods [15-17]. They are also used in some CBM methods based on some other data-driven prediction methods [1]. More accurate and efficient numerical methods are not available, which is critical for performing CBM optimization. In this paper, we propose a CBM optimization approach based on ANN remaining life prediction information, in which the above-mentioned key challenges are addressed. The CBM policy is defined by a failure probability threshold value. The remaining life prediction uncertainty is estimated based on ANN lifetime prediction errors on the test set during the ANN training and testing processes. A numerical method is developed to more accurately and efficiently evaluate the cost of the CBM policy. Monte Carlo simulation methods are also utilized to verify the cost calculation algorithm. Optimization can be performed to find the optimal threshold value corresponding to the lowest maintenance cost.

The remainder of the paper is organized as follows. The ANN prediction model used in this work is described in Section 2. Section 3 presents the proposed CBM approach utilizing ANN prediction information. In Section 4, the effectiveness of the proposed CBM approach is demonstrated using two simulated degradation data sets and a real-world condition monitoring data set collected from pump bearings. Concluding remarks are given in Section 5.

2. The Artificial Neural Network Prediction Model

The ANN model proposed by Tian et al. [24] is used in this work. It is a feedforward neural network model and it consists of one input layer, two hidden layers and one output layer. The structure of the ANN model is shown in Fig. 1. The inputs of the ANN include the age values and the condition monitoring measurements at the current inspection point and those at the previous inspection point. Assume that there are totally I significant condition monitoring measurements to be considered in the ANN model, and the total number of input nodes will be $(2+2I)$. Based on experiments by comparing the option of using two time points and that using three time points, Tian et al. found that ANN using two time points is able to produce slightly more accurate prediction results. In addition, it is more computationally efficient to use data at two time points. Fig. 1 gives an example of ANN structure with two condition monitoring covariates. t_i is the age of the component at the current inspection point i, and t_{i-1} is the age at the previous inspection point $i-1$. z_i^1 and z_{i-1}^1 are the measurements of covariate 1 at the current and previous inspection points, respectively. z_i^2 and z_{i-1}^2 are the measurements of covariate 2 at the current and previous inspection points, respectively. The ANN model outputs the life percentage at current inspection time, which is denoted by P_i. As an example, suppose the failure time of a component is 850 days and, at an inspection point i, the age of the component is 500 days, then the life percentage at inspection point i would be $P_i = 500/850 \times 100\% = 58.82\%$.

The ANN model utilizes suspension histories as well as failure histories. A failure history of a unit refers to the period from the beginning of its life to the end of its life, a failure, and the inspection data collected during this period. In a suspension history, though, the unit is preventively replaced before the failure occurs. Usually we have a small number of failure histories and much more suspension histories. Proper utilization of the suspension histories provides more information to model the relationship between the input data and the output life percentage value, and as a result more accurate remaining life prediction can be achieved. For suspension histories, with the actual failure time unknown, we cannot determine the life percentage values to train the ANN model. Tian et al. addressed this problem by first determining the optimal failure time for each suspension history. The ANN can be trained based on the suspension histories with optimal failure times and the failure histories. The detailed procedure of the ANN-based prediction approach can be found in [24]. After being trained, the ANN prediction model can be used to predict the remaining useful life based on the age value of the component and the collected condition monitoring measurements. As mentioned above, the output of the ANN model is life percentage. Suppose, at a certain inspection point, the age of the component is 400 days and the life percentage predicted using ANN is 80%, then the predicted failure time will be 500 days.

Fig. 1. Structure of the ANN model for remaining useful life prediction [24]

3. The Proposed CBM Approach

The procedure of the proposed CBM approach is described in Fig. 2, and is divided into three phases. A method for estimating the ANN remaining life prediction uncertainty is proposed to address the above-mentioned key challenge in using the existing ANN prediction methods, and the method is implemented in Phase 1 of the proposed CBM approach. The optimal CBM policy corresponding to the lowest long-run maintenance cost per unit of time is obtained in Phase 2. And in Phase 3, the optimal CBM policy is applied to components currently being monitored. In this section, the proposed CBM policy is described in Section 3.2. A numerical method for the cost evaluation of the CBM policy and the CBM optimization model are presented in Section 3.3.

Fig. 2. Procedure of the proposed CBM approach

3.1 Estimation of the ANN remaining life prediction uncertainty

The ANN prediction method in [24] can only give the predicted failure time or remaining useful life. However, the uncertainty associated with the predicted failure time, in another word, the predicted failure time distribution, is required to implement a CBM policy and perform the CBM optimization. In this section, we propose a method for estimating the predicted failure time distribution based on the ANN lifetime prediction errors obtained during the ANN training and testing processes.

In the ANN training process, the ANN model is trained based on the available failure histories and suspension histories. The ANN model inputs include the age data and the condition monitoring measurements at the current and previous inspection points. The output of the ANN model is the life percentage of the inspected component at the current inspection point, denoted by P_i. In the training process, the weights and the bias values of the ANN model are adjusted to minimize the error between the ANN output and the actual life percentage, as presented in Ref. [24]. After ANN training is completed, the prediction performance of the trained ANN model is tested using testing histories which are not used in the training process. Here, the ANN prediction error is defined as the difference between the ANN predicted failure time obtained at an inspection point and the actual failure time in the test histories. That is, the ANN prediction error at inspection point k in a test history is equal to (k/P_k -T_f), where P_k denotes the predicted life percentage using ANN. Since a test history contains many inspection points, with several test histories, we can obtain a set of ANN lifetime prediction error values. In this paper, it is assumed that the prediction accuracy does not improve over time.

In this study, it is assumed that the ANN lifetime prediction error is normally distributed, since the prediction uncertainty is mainly due to the capability of the ANN prediction model. With the obtained set of ANN prediction error values, we can estimate the mean μ and standard deviation σ of the ANN lifetime prediction error. Suppose at a certain inspection point t, the ANN life percentage output is P_t, the predicted failure time considering the prediction error will be $t/P_t - \mu$, and the standard deviation of the predicted failure time will be σ. That is, the predicted failure time T_p follows the following normal distribution:

$$T_p \sim N\left(t/P_t - \mu, \sigma^2\right). \tag{1}$$

3.2 The proposed CBM policy

The component under consideration is being monitored and condition monitoring measurements can be collected at different inspection points. It is assumed that the component is inspected at constant interval T, for example, every 20 days. At a certain inspection point, the predicted failure time distribution can be obtained as described in Section 3.1. The failure probability, denoted by $\Pr_{con}$, during the next inspection interval can be calculated. By performing CBM optimization, an optimal threshold failure probability value can be obtained, which is denoted by Pr*. Thus, at each inspection point, a decision needs to be made on whether a replacement should be performed or the operation should continue without replacements.

It is assumed in this paper that a preventive replacement can be carried out immediately upon requirement, i.e., no lead time is necessary for carrying out a preventive replacement. At a certain inspection point, the proposed maintenance policy using ANN is summarized as follows:

(1) Perform failure replacement if a failure occurs during the previous inspection interval.

(2) Perform preventive replacement if the predicted failure probability $\Pr_{con}$ during the next inspection interval exceeds the failure probability threshold Pr*. Otherwise, the operation can be continued.

Thus, the CBM policy is defined by the failure probability threshold value, denoted by Pr. In this paper, the inspection cost is not considered in the maintenance optimization, and it may be considered in a joint inspection/maintenance optimization problem in future investigation.

3.3 Determination of the optimal CBM policy

This section corresponds to Phase 2 in the proposed CBM approach shown in Fig. 2. A numerical method is developed for accurate and efficient cost evaluation of the CBM policy given a specified failure probability threshold Pr. This phase can also be divided into three steps.

In Step 1, the lifetime distribution of the components as a population is estimated based on the available failure data and suspension data. Age data including failure times and suspension times are used to model the lifetime distribution for the components. By performing distribution plot we can find out the type of lifetime distribution the components follow. Generally, Weibull distribution is adequate for modelling the component lifetime distribution, and it is assumed this way in this paper [26]. The maximum likelihood method can be used to estimate the lifetime distribution parameters α, β , which are the Weibull scale parameter and shape parameter, respectively. The likelihood function is expressed as follows [26]:

$$L = \prod_{i=1}^{n_E} f(t_i;\theta) \cdot \prod_{j=1}^{n_R} R(t_j^+;\theta) \tag{2}$$

where t_i denotes the failure time of unit *i* and t_j^+ is the right censoring/suspension time of unit *j*. n_E denotes the number of exact failure data, and n_R denotes the number of right censoring/suspension data. The first part of the likelihood function is the probability density function of the distribution and it is used to describe the failure data. The second part is the reliability function of the distribution and it is used for the suspension data. To simplify the calculation process, we can take logarithm of the likelihood function. After that optimization can be performed to find the optimal parameters set which can maximize the objective function LnL.

In Step 2, the expected replacement cost per unit of time, denoted by $C_{\exp ected}$, is calculated given a specific failure probability threshold Pr. This is the key step in CBM optimization. In the reported studies, simulation methods were typically used for cost evaluation, because the collected condition monitoring data is used as input to predict the failure time and it is impossible to exhaust all the input combinations [27-28]. In this paper, we develop an innovative numerical method for the cost evaluation of CBM policy given a specific failure probability threshold Pr. The condition monitoring data is used by ANN to compute the life percentage output and thus the predicted failure time. And the effect of the condition monitoring data, from the perspective of CBM decision making, is on the relationship between the actual failure time and the ANN predicted failure time. This relationship, though, can be modeled using the ANN lifetime prediction error distribution obtained in the ANN testing process, as discussed in Section 3.1. The proposed algorithm is based on the observation above.

The way to calculate the failure probability at a certain inspection point is given as follows. As shown in Fig. 3, suppose the actual failure time of a component is $t_m = 800$ days. Suppose the mean and the standard deviation of the ANN lifetime prediction error are μ and σ, respectively. Then the predicted failure time using ANN follows the normal distribution $T_{pA} \sim N(t_m, \sigma^2)$, that is, $T_{pA} \sim N(800, \sigma^2)$. For a certain possible predicted failure time using ANN, t_n, which is equal to 600 days in Fig. 3, the predicted failure time considering prediction uncertainty follows the normal distribution $T_p \sim N(t_n, \sigma^2)$, that is, $T_p \sim N(600, \sigma^2)$. Note that t_n is calculated based on μ, the current inspection time t, and the ANN life percentage output P_t, i.e., $t/P_t - \mu$, as stated in Section 3.1. The failure probability during the next inspection interval is defined as the conditional failure probability as follows:

$$\Pr_{con} = \frac{F_n(t+T) - F_n(t)}{1 - F_n(t)} \tag{3}$$

where t is the age of the component at the current inspection point, T is the length of the inspection interval, and F_n is the cumulative normal distribution function of predicted failure time using ANN, with mean t_n and standard deviation σ. In Fig. 3, $t = 500$ days, the failure probability during the next inspection interval is equal to the area of the shaded region, which is on the numerator, divided by the area of the region on the right side of $t = 500$ days, which is on the denominator of Equation (3). It represents the conditional failure probability during the next inspection interval.

Fig. 3. Predicted failure time distribution and the failure probability during the next inspection interval

Thus, for a certain predicted failure time using ANN, t_n, we can obtain a preventive replacement time $t_{PR}(t_n)$, which is the inspection time when the failure probability $\Pr_{con}$ exceeds the pre-specified failure probability threshold, denoted by Pr, for the first time. We first look at the expected total replacement cost for a random actual failure time t_m. The expected total replacement cost, $C_T(t_m)$, can be calculated as follows:

$$C_T(t_m) = C_{TP}(t_m) + C_{TF}(t_m) \tag{4}$$

$$C_{TP}(t_m) = \int_0^{\infty} f_m(t_n) \cdot C_p \cdot I\big(t_{PR}(t_n) < t_m\big) dt_n \tag{5}$$

$$C_{TF}(t_m) = \int_0^{\infty} f_m(t_n) \cdot C_f \cdot I\big(t_{PR}(t_n) \geq t_m\big) dt_n \tag{6}$$

where $f_m(t_n) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t_n - t_m}{\sigma}\right)^2}$. $C_{TP}(t_m)$ is the expected preventive replacement cost and $C_{TF}(t_m)$ is the expected failure replacement cost with respect to actual failure time t_m. C_p is the total cost of a preventive replacement, and C_f is the total cost of a failure replacement. σ is the standard deviation of the predicted failure times using ANN. $I(t_{PR}(t_n) < t_m) = 1$ if $t_{PR}(t_n) < t_m$, and $I(t_{PR}(t_n) < t_m) = 0$ otherwise. Similarly, $I(t_{PR}(t_n) \geq t_m) = 1$ if $t_{PR}(t_n) \geq t_m$, and $I(t_{PR}(t_n) \geq t_m) = 0$ otherwise. Equation (5) gives the expected preventive replacement cost while Equation (6) gives the expected failure replacement cost. The expected total replacement time, $T_T(t_m)$, can be calculated as follows:

$$T_T(t_m) = T_{TP}(t_m) + T_{TF}(t_m) \tag{7}$$

$$T_{TP}(t_m) = \int_0^\infty f_m(t_n) \cdot t_{PR}(t_n) \cdot I(t_{PR}(t_n) < t_m) dt_n \tag{8}$$

$$T_{TF}(t_m) = \int_0^\infty f_m(t_n) \cdot t_m \cdot I(t_{PR}(t_n) \geq t_m) dt_n \tag{9}$$

where $T_{TP}(t_m)$ is the expected preventive replacement time and $T_{TF}(t_m)$ is the expected failure replacement time with respect to actual failure time t_m.

Suppose the component population follows Weibull distribution with parameter α and β. Considering all the possible component actual failure times, the expected total replacement cost with respect to failure probability threshold value Pr, denoted by C_{TA}, takes the form

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

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

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

Finally, the expected total replacement cost per unit of time of the CBM policy with respect to failure probability threshold value Pr can be calculated as:

$$C_{\text{expected}}(\text{Pr}) = \frac{C_{TA}}{T_{TA}} \tag{12}$$

In Step 3, optimization is performed to determine the optimal threshold failure probability Pr* with respect to the lowest cost. The optimization model can be briefly formulated as follows:

$$\begin{aligned} &\min\ C_{\mathrm{expected}}(\mathrm{Pr}) \\ &\text{s.t.} \\ &\qquad \mathrm{Pr} > 0 \end{aligned} \tag{13}$$

Pr is the only design variable in this optimization problem. The optimization functions built in Matlab can be used to solve this optimization problem, and find the optimal threshold failure probability Pr*.

3.4 Implementation of the optimal CBM policy

This section corresponds to Phase 3 in the proposed CBM approach shown in Fig. 2. Once the optimal threshold failure probability Pr* is determined, the optimal CBM policy is determined. The procedure for implementing the optimal CBM policy is given as follows.

Step 1: Inspect a component and obtain the condition monitoring data at constant interval T, say 20 days. Step 2: Predict the lifetime percentage at the current inspection time *t*, represented by P_t, using the trained ANN prediction model based on the age data and condition monitoring data at current and previous inspection points. Step 3: Build the predicted failure time distribution $T_p \sim N(t/P_t - \mu, \sigma)$, where μ and σ are the mean and standard deviation of the ANN lifetime prediction error, respectively. Step 4: Calculate the failure probability during next inspection interval, Pr_{con}, using Equation (3). Step 5: Make replacement decisions. If a failure occurs during the previous inspection interval, perform failure replacement. If the failure probability Pr_{con} during the next inspection interval exceeds the optimal threshold failure probability Pr*, perform preventive replacement. Otherwise, the operation can be continued. Repeat Step 1 to Step 5 at the next inspection point.

4. Examples

In this section, we first demonstrate the proposed CBM approach using two sets of simulated degradation signals. Then the proposed approach is demonstrated in details using a real-world condition monitoring data set collected from bearings in a group of Gould pumps [29].

4.1 Numerical examples

In this numerical example, simulated degradation signals are generated using the degradation model presented in [30, 31]. The degradation model can be expressed as follows [31]:

$$S(t) = \phi + \theta \exp(\beta t + \varepsilon(t) - \frac{\sigma^2 t}{2}) \quad (14)$$

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

$$L(t) = \ln\theta + \left(\beta - \frac{\sigma^2}{2}\right)t + \varepsilon(t) \quad (15)$$

Let $\theta' = \ln\theta$ be a normal random variable with mean μ_0 and variance σ_0^2, and $\beta' = \beta - \frac{\sigma^2}{2}$ also be a normal random variable with mean $\mu_1^{'}$ and variance σ'^2_1. So, Equation (15) can be simplified as

$$L(t) = \theta' + \beta' t + \varepsilon(t) . \quad (16)$$

4.1.1 Simulated degradation set 1

We set the parameters in Equation (16) as: $\mu_0 = 5,\ \sigma_0 = 1,\ \mu_1^{'} = 5,\ \sigma_1^{'} = 1.5,\ \sigma = 0.5$. And the failure threshold D is set as 500. It is assumed that failure occurs when the degradation signal reaches D. Using the degradation model and the parameters, we generate 50 degradation paths as shown in Fig. 4.

Fig. 4. Plot of 50 generated degradation paths in the simulated degradation set 1

From the 50 paths, we randomly choose 20 failure histories to train the ANN and another 10 failure histories as test histories. The inspection interval is set to be 5 days, that is $T = 5$. Since the components are not likely to fail in the very early age, we start the inspection from the 6th inspection point for each test history. After training the ANN with 20 failure histories, we apply the 10 test histories to the trained ANN and obtain 153 ANN lifetime prediction error data points. The lifetime percentage prediction error follows normal distribution, according to the probability plot result. The mean and standard deviation of the ANN lifetime prediction errors are found to be: $\mu = -0.1859$ days, $\sigma = 3.5911$ days. To calculate the expected total replacement cost per unit of time, we need to model the lifetime distribution for all the components first. By performing distribution plot and using Maximum Likelihood Method [26], the lifetime of the components was identified to follow Weibull distribution with parameters $\alpha = 106.0666, \beta = 4.9624$.

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. Using the algorithm developed in Section 3.3, the optimal threshold probability Pr* is found to be 0.009 and the corresponding expected total replacement cost per unit of time is \$35.0928/day. Once the optimal threshold failure probability Pr* has been found, the optimal maintenance policy is also determined: inspect a new component at constant interval $T = 5$ days. If the conditional failure probability $\Pr_{con}$ during next interval exceeds the optimal threshold failure probability 0.009, perform preventive replacement. Otherwise, the operation can be continued. Perform failure replacement whenever a failure occurs.

We apply the obtained optimal CBM policy, with optimal threshold probability 0.009, to the available failure histories, so that the actual replacement times and the actual average replacement cost can be obtained. It is found that the actual average replacement cost when applying the optimal CBM policy is 35.2170$/day, which is very close to the optimal replacement cost value 35.0928 $/day. This further verifies the correctness of the proposed numerical algorithm for the CBM replacement cost evaluation.

Next we compare the performance of our proposed CBM approach with two benchmark maintenance policies: constant interval replacement policy and age-based replacement policy [33]. In the constant interval replacement policy, preventive replacements are performed at fixed constant intervals, and failure replacement is performed when a failure occurs. The objective of this policy is to determine the optimal interval length t_p between the preventive replacements to minimize the total expected replacement cost per unit of time. In the age-based replacement policy, a preventive replacement is performed when the component reaches a specified age t_p, and a failure replacement is performed when a failure occurs. After any replacement, the age of the component is reset to 0. The objective of age-based replacement optimization is to find the optimal replacement age to minimize the long-run replacement cost.

For the two benchmark maintenance policies, the lifetime distribution of the components has been identified to follow Weibull distribution with $\alpha = 106.0666, \beta = 4.9624$. Performing replacement optimization using the methods presented in [26], for the constant interval replacement policy, the optimal replacement interval is found to be 58 days and the expected total replacement cost is 65.1848 $/day. For the age-based replacement policy, the optimal replacement age is determined to be 59.8655 days and the average total maintenance cost is 63.0654 $/day. The results are listed in Table I, together with the optimal results using the proposed CBM approach. We can see that the proposed CBM approach results in the lowest cost, which is 35.0928 $/day. It costs 46.16% less than constant interval replacement policy and

44.35% less than aged-based replacement policy, as shown in Table I. Note that we did not consider the inspection cost in the proposed CBM method. However, in many applications, condition monitoring systems are already in place and condition monitoring data are being collected by the enterprise asset management systems, the inspection costs will be relatively low and will not affect the advantage of the proposed CBM method.

4.1.2 Simulated degradation set 2

Now we investigate a set of simulated degradation signals with increased fluctuations in each degradation path. We did it by increasing the variance of the centered Brownian motion $\varepsilon(t)$ from 0.5 to 2 and decrease the failure threshold D from 500 to 400. 50 degradation paths are generated, as shown in Fig. 5. The lifetime percentage prediction error follows normal distribution, according to the probability plot result. The mean and standard deviation of the ANN lifetime prediction errors are found to be: $\mu = -1.1505$ days, $\sigma = 6.7469$ days. And the lifetime of the components are determined to follow Weibull distribution with $\alpha = 106.9373, \beta = 4.7895$. The optimal threshold probability Pr* is found to be 0.009 and the corresponding expected total replacement cost per day is 38.1653 $/day.

Fig. 5. Plot of 50 generated degradation paths in the simulated degradation set 2

By applying the two benchmark policies to the degradation signal data, we can obtain the comparison results as shown in Table II. We can see the expected total replacement cost for the proposed CBM approach is still the lowest, which is 38.1653 $/day. It saves 43.03% comparing to the constant interval replacement policy, and 40.24% comparing to the aged-based replacement policy.

4.2 Case Study

4.2.1. Case study introduction

In this section we demonstrate the proposed CBM approach using the real-world condition monitoring data collected from bearings on a group of Gould pumps at a Canadian kraft pulp mill company [29]. Totally there are 10 bearing failure histories and 14 suspension histories available. For each pump, seven types of measurements were recorded at 8 sensor locations: 5 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*5+8*1+8*1) vibration measurements. Significance analysis was performed for the 56 vibration measurements by the software EXAKT [29]. Two measurements were identified to have significant influence on 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).

Based on the ANN approach developed in [24], we trained the ANN model using 5 failure histories and 10 suspension histories. Then we test the prediction performance of the trained ANN model using the other 5 test histories, and altogether there 156 inspection points at which the prediction performance is tested. The lifetime percentage prediction error follows normal distribution, according to the probability plot result. With this ANN lifetime prediction error dataset, it is found that the mean of prediction error is -246.8450 days and the standard deviation is 204.4521 days.

4.2.2. Maintenance cost calculation using the proposed algorithm

First of all, it is necessary to model the lifetime distribution of the components as a population based on the available failure data and suspension data. The fitness test is done using Weibull distribution to model the reliability data. The estimated parameters of Weibull distribution are: $\alpha = 1386.3, \beta = 1.8$. 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, based on input from industry. Using the algorithm presented in Section 3.3, the total expected replacement cost per unit of time ($/day) can be calculated given a certain threshold failure probability. By performing optimization, the optimal threshold failure probability Pr* is found to be 0.005, and the corresponding total expected replacement cost is 3.8833 $/day, as shown in Fig. 6.

Fig.6. The expected replacement cost corresponding to different threshold failure probability values

4.2.3. Maintenance cost calculation verification using the simulation method

Simulation is an important way to verify the performance of maintenance policies [32]. In this section, Monte Carlo simulation is utilized to verify the proposed algorithms for cost calculation. In the simulation, we first randomly generate 10,000 actual failure time data points which follow Weibull distribution with the parameters $\alpha = 1386.3, \beta = 1.8$. For each generated actual failure time t_m, the predicted failure time t_n follows normal distribution with the parameters $\mu = t_m$ and $\sigma = 204.4521$ So, we also randomly generate 10,000 predicted failure time which follow normal distribution with the parameters $\mu = t_m, \sigma = 204.4521$ for each actual failure time t_m. For each history, we will inspect the component at a constant interval of 20 days. At each inspection point, the conditional failure probability $\Pr_{con}$ during next inspection interval is calculated and a maintenance decision will be made: if $\Pr_{con}$ exceeds the failure probability threshold Pr, a preventive replacement is performed; otherwise the operation can be continued. If a preventive replacement occurs at the inspection time t, the preventive replacement time for that specific history is t and it is suspension history. If there is no preventive replacement until actual failure time t_m, that specific history is a failure history and the failure time is t_m. After simulating the inspection processes for all the 10,000 histories, the expected total replacement cost per day can be achieved. In Section 4.2.2, the optimal failure probability threshold Pr* is determined to be 0.005, and the expected replacement cost is 3.8833 $/day. Using the simulation method, the average replacement cost is 3.8806 $/day given that the failure probability threshold Pr equals

0.005, which is very close to the result achieved using the proposed numerical algorithm, and this demonstrates the correctness of the proposed numerical algorithm.

4.2.4. Maintenance decision making

Once the optimal threshold failure probability Pr* is determined, the optimal CBM policy is also determined: inspect a new component at constant interval, for example 20 days. If the conditional failure probability $\Pr_{con}$ during next interval exceeds the optimal threshold failure probability 0.005, perform preventive replacement. Otherwise, the operation can be continued. Perform failure replacement whenever there a failure occurs. In this section we will use 10 failure histories to illustrate the implementation of the optimal maintenance policy. Although these data were collected at unequally spaced inspection points, the ANN model in the policy can handle this situation.

Consider one failure history as an example of the implementation of the optimal CBM policy. The first inspection point of the history to test is the 147th day. The inspection interval is assumed to be 20 days. Based on the trained ANN model, using the age data and condition monitoring measurements at 119th day and 147th day, which are the previous and the current inspection points, the predicted lifetime using ANN is obtained as 418.8034 days. Based on Equation (1), the predicted lifetime is adjusted to be 665.6484 days. The standard deviation of the lifetime prediction error has been found to be 204.4521 days. Thus, the parameters of predicted failure time distribution for this inspected component are $t_n = 665.6484$ days, and $\sigma = 204.4521$ days. Using Equation (3), the failure probability during the next inspection interval is 0.0018, which is less than the threshold failure probability (Pr*) 0.005, as shown in Fig. 7. So, the operation of the component can be continued at the age of 147 days and no replacements should be performed.

Fig. 7. Failure probability value at age 147 days

Similarly we can obtain the failure probability at each inspection point for all the 10 test histories. And the replacement decisions can be made for each history, as displayed in Table III, where the replacement times according to the proposed CBM approach and the actual failure time are given each history. It can be seen that no failure replacement is performed for the components.

4.2.5. Comparison between the proposed approach and benchmark replacement policies

In this section, using the data in this case study, we first compare the performance of the proposed CBM approach with two benchmark maintenance policies: constant interval replacement policy and age-based replacement policy. Again the Weibull distribution parameters are $\alpha = 1386.3, \beta = 1.8$, and the cost data is kept as the same: $C_p = \$3000$, $C_f = \$16000$. For the constant interval replacement policy, the optimal replacement interval is found to be 776.9999 days, and the corresponding expected cost is 10.4570 \$/day. For the age-based replacement policy, the optimal replacement age is found to be 715.3979 days, and the corresponding expected replacement cost is 9.9432 \$/day. As discussed in Section 4.2.2, the optimal expected cost using the proposed CBM approach is 3.8833 \$/day. Thus, comparing to the two benchmark maintenance policies, the proposed CBM approach can achieve a cost saving of 62.86% comparing to the constant interval replacement policy, and 60.95% comparing to the aged-based replacement policy. The comparison results are shown in Table IV.

The comparison performed above is based on the maintenance optimization results. Next we apply the three optimal maintenance policies to the 10 failure histories respectively, and investigate how they perform when applying to real condition monitoring and replacement histories. The results are shown in Table V, where for each history, the calculated replacement times, replacement types and replacement costs are listed for all the three maintenance policies. The average replacement cost using the proposed CBM approach is again the lowest, which is 5.28 \$/day. It is around 58.39% lower than constant interval replacement policy and 65.89% lower than aged-based replacement policy. The results further demonstrate the advantage of the proposed CBM approach over the two benchmark maintenance policies.

We also compare the proposed CBM approach with the widely used PHM method using the data in this case study. The same cost data are used, and the same 5 failure histories and 10 suspension histories are used to optimize the PHM policy. For this set of data, the PHM parameters estimated using EXAKT are found to be the following: the scale and shape parameters are 7,934 and 1, and the covariate coefficients are 36.73 and 0, respectively. The obtained optimal risk threshold is 12.76 $/day, and the corresponding optimal cost is 6.45 $/day. Then, similarly, we apply the optimal policy to the 10 failure histories, and the actual average replacement cost is found to be 8.35 $/day. It can be observed that the proposed CBM approach also outperforms the PHM method in this case study.

5. Concluding Remarks

ANN-based methods have demonstrated to be very effective in equipment remaining useful life prediction. In this paper, we develop a CBM optimization approach based on ANN remaining life prediction information, and two key challenges are addressed. Firstly, the remaining life prediction uncertainty is estimated based on ANN lifetime prediction errors on the test set during the ANN training and testing processes. This method requires that multiple degradation histories are available for obtaining the prediction error dataset. Secondly, a numerical method is developed to evaluate the cost of the CBM policy more accurately and efficiently, which provides clear advantage over the simulation methods which are currently generally used. The effectiveness of the proposed CBM approach is demonstrated using two simulated degradation data sets, and a real-world condition monitoring data set collected from pump bearings. The proposed CBM approach can also be adapted to utilize information obtained using other prognostics methods such as model-based methods and integrated prediction methods, as long as the predicted component failure time and the associated uncertainty can be determined.

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TABLE I

COMPARISON BETWEEN THE PROPOSED CBM APPROACH AND TWO BENCHMARK POLICIES USING THE SIMULATED DEGRADATION SET 1

Maintenance policy	Expected total replacement cost per unit of time ($/day)	Optimal Replacement Time (days)
Constant interval replacement policy	65.1848	58.0000
Age-based replacement policy	63.0654	59.8655
The proposed CBM approach	35.0928	

TABLE II

COMPARISON BETWEEN THE PROPOSED CBM APPROACH AND TWO BENCHMARK POLICIES USING THE SIMULATED DEGRADATION SET 2

Maintenance policy	Expected total replacement cost per unit of time ($/day)	Optimal Replacement Time (days)
Constant interval replacement policy	66.9951	63.0000
Age-based replacement policy	63.8654	59.6813
The proposed CBM approach	38.1653	

TABLE III

TEST RESULTS USING THE PROPOSED CBM APPROACH

History	Replacement age (days)	Pr_{con}	Actual failure time (days)
1	286	0.0061	473
2	233	0.0051	283
3	477	0.0085	601
4	370	0.0060	511
5	521	0.0074	692
6	944	0.0118	986
7	516	0.0059	1402
8	785	0.0052	1246
9	803	0.0058	1468
10	778	0.0086	964

TABLE IV

COMPARISON BETWEEN THE PROPOSED APPROACH AND TWO BENCHMARK POLICIES USING THE BEARING CONDITION MONITORING DATA

Maintenance policy	Expected total replacement cost per unit of time ($/day)	Optimal Replacement Time (days)
Constant interval replacement policy	10.4570	776.9999
Age-based replacement policy	9.9432	715.3979
The proposed CBM approach	3.8833	

TABLE V

(a) COMPARISON BETWEEN THE PROPOSED CBM APPROACH AND TWO BENCHMARK POLICIES WHEN APPLYING TO THE 10 FAILURE HISTORIES

History	Actual Failure Time (days)	Constant interval replacement policy			Age-based replacement policy			The proposed CBM approach		
		Time (days)	Type	Cost ($)	Time (days)	Type	Cost ($)	Time (days)	Type	Cost ($)
1	473	473	F	16000	473	F	16000	286	P	3000
2	283	283	F	16000	283	F	16000	233	P	3000
3	601	21	P	3000	601	F	16000	477	P	3000
4	511	511	F	16000	511	F	16000	341	P	3000
5	692	266	P	3000	692	F	16000	521	P	3000
6	986	777	P	3000	715	P	3000	944	P	3000
7	1402	777	P	3000	715	P	3000	516	P	3000
8	1246	777	P	3000	715	P	3000	785	P	3000
9	1468	777	P	3000	715	P	3000	803	P	3000
10	964	777	P	3000	715	P	3000	778	P	3000
Total		5439		69000	6135		95000	5684		30000
Average Replacement Time (days)		543.9			613.5			568.4		
Average Cost ($/day)		12.69			15.48			5.28		

F: Failure replacement; P: Preventive replacement.

(b) COMPARISON WITH PHM

History	Actual Failure Time (days)	PHM approach			The proposed CBM approach		
		Time (days)	Type	Cost ($)	Time (days)	Type	Cost ($)
1	473	358	P	3000	286	P	3000
2	283	248	P	3000	233	P	3000
3	601	506	P	3000	477	P	3000
4	511	425	P	3000	341	P	3000
5	692	692	F	16000	521	P	3000
6	986	982	P	3000	944	P	3000
7	1402	1378	P	3000	516	P	3000
8	1246	1246	F	16000	785	P	3000
9	1468	1468	F	16000	803	P	3000
10	964	958	P	3000	778	P	3000
Total		8261		69000	5684		30000
Average Replacement Time (days)		826.1			568.4		
Average Cost ($/day)		8.35			5.28		

List of Figure Captions

Biographies

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