CONDITION BASED MAINTENANCE OPTIMIZATION USING DATA DRIVEN METHODS

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ABSTRACT

Condition Based Maintenance Optimization Using Data Driven Methods

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In condition based maintenance (CBM), maintenance activities are scheduled based on the predicted equipment failure times, and the predictions are performed based on conditon monitoirng data, such as vibration and acoustic data. The reported health condition prediction methods can be roughly classified into model-based, and data-driven, and integrated methods. Our research mainly focuses on CBM optimization using data driven methods, such as proportional hazards model (PHM) and artificial neural network (ANN), which don't require equipment physical models.

In CBM optimization using PHM, the accuracy of parameter estimation for PHM greatly affects the effectiveness of the optimal maintenance policy. Directly using collected condition monitoring data may

introduce noise into the CBM optimization, and thus the optimal maintenance policy obtained based on this model may not be really optimal. Therefore, a data processing method, where the actual measurements are fitted first using the Generalized Weibull-FR function, is proposed to remove the external noise before fitting it into the PHM.

Effective 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. Therefore, we propose an ANN based CBM optimization approach and a numerical cost evaluation method to address those key challenges.

It is observed that the prediction accuracy often improves with the increase of the age of the component. Therefore, we develop a method to quantify the remaining life prediction uncertainty considering the prediction accuracy improvements by modeling the relationship between the mean value as well as standard deviation of prediction error and the life percentage. An effective CBM optimization approach is also proposed to optimize the maintenance schedule.

The proposed approaches are demonstrated using some simulated degradation data sets as well as some real-world vibration monitoring data set. They contribute to the general knowledge of CBM, and have the potential to greatly benefit various industries.

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LIST OF ACRONYMS

CBM	Condition Based Maintenance
PHM	Proportional Hazards Model
SOM	Self-Organizing Map
SSM	State Space Model
SMC	Sequential Monte Carlo
RUL	Remaining Useful Life
PLM	Product Lifecycle Management
MPD	Markov Decision Process
GA	Genetic Algorithm
PPM	Parts per Million
AHM	Additive Hazards Model
ALT	Accelerated Life Testing
EHR	Extended Hazard Regression
ELHR	Extended Linear Hazard Regression
PHL	Proportional Hazard Linear

MOS	Metal-Oxide-Semiconductor
PM	Preventive Maintenance
CO	Corrective Operation
PCA	Preliminary Correlation Analysis
OMDEC	Optimal Maintenance Decision Inc.

CHAPTER 1 INTRODUCTION

1.1. Introduction to Condition Based Maintenance

With the rapid growth of modern technology, maintenance plays a more and more important role in many industries. In some industries, such as aerospace industry and energy industry, reliability is one of the most critical issues since a tiny failure may result in inestimable loss even fatal disaster. In recent decades, people pay more attention to research in maintenance and reliability. Maintenance is defined as "all activities aimed at keeping an item in, or restoring it to, the physical state considered necessary for the fulfillment of its production function." (Jardine and Tsang, 2006). Traditional maintenance technique is basically breakdown maintenance, also called corrective maintenance, reactive maintenance and unplanned maintenance. It is limited to repair actions or item replacement caused by failures. The predominant characteristic of such maintenance is reactive since it only reacts to faults or failures.

A more recent maintenance technique is time-based preventive maintenance (PM, also called planned maintenance). It is proactive, which sets schedules to inspect or perform PM instead of just reacting to failures. One time-based PM method is constant-interval based preventive replacement method, in which failure replacements are performed immediately after failures occur and preventive replacements are performed at constant intervals, say every 6 months. The optimization problem is to find the optimal preventive replacement interval to minimize the total expected replacement cost in the long run. Another time-based PM method is the age-based replacement method, in which preventive replacements are performed when the component reaches a pre-specified age, and the optimization problem is to find the optimal preventive replacement age. The time-based maintenance technique is an improvement compared to corrective maintenance techniques, but at the same time it makes the cost of preventive maintenance higher and higher. Eventually, preventive maintenance cost has become a heavy financial burden of many industrial companies. Therefore, more effective maintenance approaches such as condition based maintenance (CBM) are being adopted to solve the problem of high preventive maintenance cost, and to prevent unexpected failures at the same time.

CBM is a maintenance process which decides maintenance actions using the information collected through condition monitoring. It is based on the understanding that a piece of equipment goes through multiple degraded states before failure. The health conditions can be monitored and predicted, and optimal maintenance actions can be scheduled to prevent equipment breakdown and minimize total operation and maintenance costs (Tian et al., 2009). CBM optimization attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence that the failure is approaching.

CBM has been widely used in many fields, such as aerospace industry (Li and Nilkitsaranont, 2009, Joshi et al., 2012, Chen et al., 2012), mining industry (Hall et al., 2000, Lin et al., 2006), automobile industry (Rabeno and Bounds, 2009, Zachos and Schohl, 2010, Grantner et al.,2010), petroleum industry (Srinivasan et al., 2005, Gao et al., 2010), and power generation industry (Gray and Watson, 2010, Byon and Yu, 2010, Tian et al., 2011, Ding et al., 2012). CBM may use condition monitoring data collected from oil analysis, vibration analysis, fuel consumption, environmental conditions, and so on, to make maintenance decisions. For example, oil analysis is the spectrometric analysis of metal particles in oil samples generally gathered from an engine's or transmission's lubricating oil, while vibration signals maybe collected at certain positions on rotating equipments, etc.

There are three key steps in CBM process: data acquisition, data processing and maintenance decision making, as shown in Figure 1-1. Data acquisition is to collect the data related to system health. Data processing is to process and analyze the acquired data. In maintenance decision making step, effective maintenance policies will be obtained based on the analyzed information (Jardine et al., 2006).

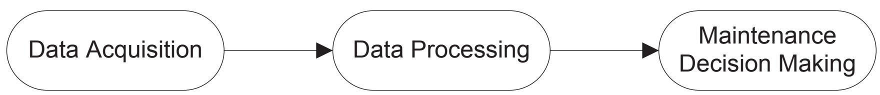

Figure 1-1 CBM process steps

The data processing step consists of two main categories of maintenance techniques: diagnostics and prognostics. Diagnostics focus on faults detection, isolation and identification when they occur, while prognostics attempts to predict faults or failures before they occur. Prognostics endeavors to prevent faults or failures, or at least has prepared spare parts and planned human resources ready for the problems, and thus avoids additional unplanned maintenance cost. Diagnostic can help improving prognostics in the way that diagnostic information can be useful for preparing more accurate event data and hence building better CBM model for prognostics. In addition, diagnostic information can be used as valuable feedback information for system redesign.

A CBM program can be used to do both diagnostics and prognostics, or either one of them.

1.2. Research Motivations

In CBM optimization using Proportional Hazards Model (PHM), fitting PHM is a very important step since the accuracy of parameter estimation for PHM has a great influence on the effectiveness of the optimal maintenance policy. Previously actual condition monitoring measurements collected from the field are directly used to fit the PHM and the optimal maintenance policy is obtained based on the fitted PHM. However directly using the actual measurements as input may introduce external noise and bring unexpected disturbs to the model. Thus the optimal maintenance policy obtained based on this model may not be really optimal. To resolve this problem, a data processing method, where the actual measurements are fitted first using the Generalized Weibull-FR function, is proposed to remove the external noise from the actual measurements before using them as input to the PHM.

Artificial Neural Network (ANN) based methods have been extensively investigated for equipment health condition prediction. However, effective 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. Therefore, we attempt to propose an ANN based CBM optimization approach and a numerical cost evaluation method to address the above-mentioned key challenges.

In many previous researches, it is assumed that the standard deviation of prediction error is always the same during the whole history. However, it is observed that the prediction accuracy often improves with the increase of the age of the component as it approaches the failure time. In Gebraeel (2006), this situation is discussed. Prediction results based on our experimental data also show that prediction accuracy improves with time. Therefore, we endeavor to develop a method to quantify the remaining life prediction uncertainty considering the prediction accuracy improvements, and an effective CBM optimization approach to optimize the maintenance schedule.

1.3. Research Contributions

In this thesis, we concentrate on the research of CBM optimization using data driven methods such as PHM and ANN. The contributions of this thesis are summarized as follows.

- We propose a data processing approach to fit the data before feeding it into the PHM model. In this approach, the external noise can be removed by fitting the actual measurements using the Generalized Weibull-FR function. Compared to the actual measurement, the fitted measurements can better represent the deterioration of the component or equipment. Two case studies using real-world vibration monitoring data are used to demonstrate the proposed approach. The data were collected from Gould pump bearings in a Canadian Kraft Mill company and from shear pump bearings in a food processing plant. The proposed approach is validated to be effective and will save the average maintenance cost by increasing the average replacement interval and making better use of remaining useful life.

- We propose a CBM optimization approach based on ANN remaining life prediction information. The CBM policy is defined by a failure probability threshold value. In this approach, the remaining life prediction uncertainty is estimated based on ANN lifetime prediction errors on the test data set during the ANN training and testing processes. A numerical method is developed to more accurately and efficiently evaluate the cost of the proposed CBM policy. Optimization can be performed to find the optimal failure probability threshold value corresponding to the lowest maintenance cost. The proposed approach can also be modified to utilize information obtained using other prognostics methods. 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. We compare the proposed approach with some benchmark maintenance policies, and the proposed approach is found to outperform the benchmark policies.
- We propose a CBM optimization approach to quantify the remaining life prediction uncertainty considering the prediction accuracy improvements, and optimize the maintenance schedule. In this approach, 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. 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 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.

1.4. Thesis Organization

The rest of this thesis is organized as follows:

- In Chapter 2, we conduct a detailed literature review on CBM and some data driven methods, such as PHM and ANN.

- In Chapter 3, we propose a data processing method for CBM using PHM. We also conduct two real-world case studies to illustrate the approach. This approach is validated to be effective and will save the average maintenance cost by increasing the average replacement interval and making better use of remaining useful life.

- In Chapter 4, we propose a CBM optimization approach based on ANN remaining life prediction information. A numerical method is also developed to more accurately and efficiently evaluate the cost of the proposed CBM policy. Two simulated degradation data sets and a real-world condition monitoring data set are used to illustrate the proposed approach.

- In Chapter 5, an improved approach, which is CBM optimization considering improving prediction accuracy, is proposed based on the previously proposed approach in Chapter 4. The proposed approach is demonstrated using vibration monitoring data collected from pump bearings in the field as well as simulated degradation data.

- Finally, in Chapter 6, we draw a conclusion from our research and present several suggestions of future work.

CHAPTER 2 LITERATURE REVIEW

Nomenclature

t	: inspection time
α	: scale parameter
β	: shape parameter
$z_i(t)$	: value of covariate i at time t
γ_i	: coefficient for covariate i
d	: risk threshold value
C	: preventive replacement cost
K	: penalty cost
$C+K$	: failure replacement cost
$\Phi(d)$	: expected average cost per unit time at the risk threshold d
T_d	: preventive time at risk threshold d
$W(d)$	: expected time until replacement at the risk threshold d .
$d*$	: optimal risk threshold value

t_{i-1} : age of the component at the previous inspection point $i-1$

t_i : age of the component at the current inspection point i

z_{i-1}^1 : measurement of covariate 1 at the previous inspection point $i-1$

z_i^1 : measurement of covariate 1 at the current inspection point i

z_{i-1}^2 : measurement of covariate 2 at the previous inspection point $i-1$

z_i^2 : measurement of covariate 2 at the current inspection point i

p_i : life percentage at current inspection point i

CBM decides maintenance actions based on condition monitoring information. It has been discovered to be very efficient in maintenance scheduling and cost reduction. Numerous research works in CBM can be found. Wang (2007) developed a probability model to predict the initiation point of the failure delay period and the remaining life based on available condition monitoring information. Goodman, et al. (2011) proposed a new concept of nonparametric signal detection and classification technique and applied the proposed technique to real-world vibration data obtained from a dedicated CBM experimental test bed. An online adaptive CBM method with pattern discovery and fault learning capabilities for mechanical systems was proposed in Wu et al. (2010). This method can reduce local clusters from the same pattern and optimize the self-organizing map (SOM) architecture to further decrease the calculation cost in matching patterns in the neuron fitting process. Neves et al. (2011) proposed CBM policies by combing an optimization model and input parameters estimation from empirical data. The proposed approach is demonstrated to be able to help managers to improve their decisions for similar cases. In Sun et al. (2012), a state space model (SSM) technique embedded with a sequential Monte Carlo (SMC) method was developed for system performance degradation prognostics. This method can provide an estimate of Remaining Useful Life (RUL) with uncertainty as well as other reliability indices of interest for operators to plan effective CBM. Prajapati and Ganesan (2013) evaluated five prediction approaches for CBM, using a case study for vehicle tire pressure monitoring as an example application. Gulledge et al. (2010) attempted to link CBM to Product Lifecycle Management (PLM) by converting prognostic and diagnostic information into actionable information which can be directed into a project-level PLM environment. Ambani et al. (2009) developed a continuous time Markov chain degradation model and a cost model to quantify the effects of maintenance and obtain optimal maintenance policies on a multiple machine system. Fouladirad and Grall (2011) proposed an adaptive maintenance model for a gradually deteriorating system. An optimal CBM policy for continuously monitored degrading systems with multiple failure modes was developed in Liu et al. (2013). This method considers multiple sudden failures that can occur during a system's degradation. Niu et al. (2010) presented a new CBM system which uses reliability-centered maintenance mechanism to optimize maintenance cost, and employs data fusion strategy for improving condition monitoring, health assessment, and prognostics. The proposed system is demonstrated that optimized maintenance performance can be obtained with good generality. In Weide et al. (2010), the authors presented a discounted cost model to evaluate the reliability and optimize the maintenance of engineering systems that are damaged by shocks or transients arriving randomly in time. This model provides a more realistic basis for optimizing the maintenance policies than those based on the asymptotic, non-discounted cost rate criterion. Based on long-term examinations, Kamei and Takai (2011) concluded that a special sensitivity and long-term stability performance of the CBM gas pressure sensor are very important for the reliable operation of power substations under the CBM strategy. Ciarapica and Giacchetta (2006) developed a CBM plan for a combined-cycle power plant to prevent sudden breakdown situations. Similarly Ghasemi et al. (2010) derived an optimal CBM replacement policy when the state of equipment is unknown but can be estimated based on observed condition. Chen and Trivedi (2005) applied Markov Decision Process (MDP) algorithm in determining the optimal maintenance policy for CBM. A joint optimization of inspection rate and its corresponding maintenance policy was also described in this paper. In Kim et al. (2010), Ghasemi et al. (2010), and Duan et al. (2012), parameter estimation problems for CBM models were solved, and numerical studies were used to illustrate the efficiency of the proposed algorithms. The approach proposed in Lu et al. (2007) can be applied on-line to provide economic and preventive maintenance solutions in order to maximize the profit of the ownership of a system. Flage et al. (2012) developed a model which can determine an optimal inspection and maintenance scheme for a deteriorating unit with a stochastic degradation process with independent and stationary increments.

CBM optimization is one of the most important techniques in CBM. It attempts to find out optimal maintenance policy which can minimize the overall maintenance cost for the equipment or component based on the condition monitoring information. In CBM optimization, the widely used way of maintenance scheduling is to set a threshold value, and once the health condition indicator exceeds the predefined threshold value, the equipment is shutdown for repair or a preventive replacement is performed (Jardine et al., 2006). In Banjevic et al. (2001), a PHM based control-limit policy was proposed, in which once the monitoring measurement exceeds the threshold risk level, a preventive replacement should be performed, and otherwise the operation can be continued. In Lu and Meeker (1993), random coefficient models were developed to estimate the remaining life distribution of degrading components. Marseguerra et al. (2002) presented an optimization model to determine the optimal threshold value using Genetic Algorithm (GA) and Monte Carlo simulation . In Jardine and Anderson (1992), CBM policies for critical components of fossilfired power plants were developed. The plant was considered to be a system that fails once the cumulative damage of its components exceeds a predetermined managerial damage level. Wang (2000) built a model to determine the optimal critical level and the monitoring intervals in CBM. In this model, components were monitored at regular intervals until the measurement being monitored exceeds a predetermined level, when a preventive replacement is performed. Maillart and Pollock (2002) proposed a predictive maintenance policy to determine the frequency of condition monitoring. Yam et al. (2001) proposed the intelligent predictive decision support system for CBM, but their focus is mainly on the application of prognosis using recurrent neural networks. In Sun et al. (2006), a Proportional Covariate Model (PCM) for CBM is developed. This method can reduce the number of failure test histories, and works well when historical failure data are sparse or zero.

A key to the effective implementation of CBM optimization is the accurate prediction of the equipment health condition. Many health condition prediction methods can predict the health condition of the component or equipment at certain inspection point 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 (Inman et al., 2005, Tian et al., 2012), such as the bearing prognostics method proposed by Marble et al. (2006), and the gearbox prognostics methods developed by Kacprzynski et al. (2002) and also by Li and Lee (2005). 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, such as PHM, ANN, etc., do not require physical models, and utilize the collected condition monitoring data for health condition prediction.

2.1. Proportional Hazards Model

2.1.1. Literature Review on PHM

PHM was introduced in 1972 by D. R. Cox. At first it is widely used in the field of biomedicine. In 1980s, people started to investigate PHM applications in mechanical engineering field. From 1990s, interest in applications of the PHM in this field has greatly increased. PHM began to be adopted in maintenance in diverse areas, such as mining industry, automobile industry, power generation industry, semiconductor industry, papermaking industry, petroleum industry, aircraft engines industry (Jardine and Anderson, 1992), construction industry (Metal, 2004), electronic components industry

(Bendell et al., 1991), locomotive diesel engines industry (Jardine et al., 1989) and many other industries. These applications can be classified into two main categories: CBM optimization and reliability analysis. Applications in maintenance optimization combine the age data with the condition monitoring data in the PHM. In these applications the effects of different covariates influencing the time to failure of the components are considered, and thus the optimal maintenance policy can be determined to minimize the maintenance cost. In the applications in reliability analysis, PHM is used in the assessment and prediction of the reliability of component or equipment by using covariates to describe different operating conditions (Tian et al., 2009).

A key reason that PHM is more effective than previous approaches is that it considers not only age data but also condition data, which influence the health of the component or equipment. In maintenance optimization, PHM can effectively estimate the risk of failure of the component under condition monitoring. For example, PHM takes into account the event data (failure data and suspension data) as well as inspection data (vibration data or oil analysis data such as the parts per million (PPM) of iron or lead found in lubrication oil sample). In reliability analysis, the reliability data is collected under different conditions. For instance, examples may be equipment being used by different operators or under different temperature and humidity. All the environment conditions may have influence on the reliability characteristics of the equipment and should be considered. These inspection data and environment conditions are called covariates and they cannot be ignored when we deal with the maintenance optimization and reliability analysis problems. PHM takes into account the age data as well as the condition monitoring data, and the effects of different covariates influencing the time to failure of a system can be estimated in this model. CBM optimization approach using PHM can represent and predict the equipment health condition more accurately and it is able to reduce unnecessary scheduled preventive maintenance actions thus to reduce the overall maintenance costs.

2.1.1.1. PHM Applications in CBM Optimization

Jardine et al. (2008) described the development of an optimal predictive maintenance program for critical pump bearings in the food processing industry. Measurements are taken in three directions for the bearings under investigation: axial, horizontal and vertical. In each of these directions, the velocity spectrum was obtained in five frequency bands. In addition, overall velocity and acceleration are also measured in the three directions. Therefore there were altogether 21 covariates in this PHM model. Significance analysis was taken to reduce the covariates and three covariates were found out to be necessary: band 1 velocity in the axial direction, band 1 velocity in the vertical direction, and band 2 velocity in the axial direction. Assuming the inspection interval is 20 days, the transition probability matrices for the three covariates were estimated. Based on all this information, the optimal CBM replacement policy was determined. The results showed that, comparing to the failure replacement only policy, the optimal policy could achieve 84.5% of cost savings.

EXAKT (Makis and Jardine, 1992) is a commercial software widely used in industry for CBM decision making. It was developed by Optimal Maintenance Decision Inc. (OMDEC). Jardine et al. (2003) used the EXAKT software to build a CBM optimization model for the interpretation of inspection data from a nuclear reactor station. The data set included the information of 11-year period from 1990 onwards. In the nuclear reactors, hydro-dyne seals perform a vital function, and they can prevent the leakage of heavy water from the reactor. So site engineers would like to optimize the preventive seal replacement intervals in order to minimize the overall failure and maintenance costs. Therefore PHM based statistical decision methodology was applied to determine the optimal moment at which to perform proactive maintenance. In this case, two types of data were used to determine the optimal CBM policy: inspection data and events data. Inspection data is referred to as the condition monitoring data (called covariates), which affect the health of each hydro-dyne seal along with the date of inspection and the corresponding working age of the seal. The event data comprises the dates and working ages at particular events, including beginning event (the installation of a new seal), failure event (the failure of a seal), and suspension event (the replacement of a seal that has not yet failed). A PHM was fitted to the data by maximum likelihood method and the Leak Rate was found out to be the only significant covariate. Finally the optimal replacing policy was determined and around 52.5% saving may be realized over the current replace-on-failure policy.

Lin et al. (2006) proposed the application of a principal components proportional hazards regression model in CBM optimization. They gave two examples to illustrate this application. The oil analysis data set of the first example was collected from transmissions on haul trucks in a mining company. After a series of analysis, the original 11 covariates: sodium, potassium, iron, aluminum, titanium, phosphorus, zinc, calcium, magnesium, molybdenum and vanadium were reduced to six significant covariates: iron, aluminum, titanium, magnesium, molybdenum and vanadium. Three models (SW, PC_23 and PC_236) were built and compared. The final results suggested that the PHM PC_23 and the corresponding optimal replacement policy performed better than the other two models for the transmissions in this example. The other example was vibration analysis data set taken from a pulp and paper company. This data set contains event records and vibration measurements collected from water pumps every month. The pumps basically work 24 hour per day, 7 days per week. Vibration signals were taken at seven different locations. For each vibration signal, the overall amplitude and the amplitude for six different frequency bands were recorded. So, altogether there are 49 covariates recorded. Preliminary correlation analysis (PCA) was applied to eliminate the covariates and the 49 original covariates were transformed into 49 principal components. The final model included only one covariate, the fifth principal component (model PC_5). At the same time, a 'simple' Weibull model (model SW) without considering covariates was also built for comparative study purpose. The result of comparison of these two models indicated that the model PC_5 is more effective.

PHM was also utilized by Vlok et al. (2002) to determine the optimal replacement policy for a vital item which is subject to vibration monitoring. In their study they chose circulating pumps in a coal wash plant as the research case. The lifetime data was collected during a period of two years. Their study shows that, even with some problems in the collected data, vibration measurements can be used in proportional hazards modeling and that a useful decision policy can be obtained.

In the research by Rao and Prasad (2001), the PHM was used to analyze failure data and plan maintenance intervals for material handling equipments in mining industry, such as loaders, trucks, dozers, dumpers and etc. In this paper, PHM was applied to model the repairable equipment whose performance is affected by concomitant variables. Graphical methods were used to calculate maintenance intervals.

Kobbacy et al. (1997) proposed a heuristic approach for implementing the PHM to schedule future preventive maintenance actions on the basis of the equipment's full condition history. An example based on data for four similar pumps used in four different plants was taken to illustrate their approach. This approach can be applied to repairable systems and does not require any restrictive assumption such as renewal regarding the quality of corrective work or planned maintenance. The main assumption in this approach is that lives of components following preventive maintenance (PM) or corrective operation (CO) depend on covariates values measured at points in time just before the maintenance work, and that lengths of these lives are conditionally independent. There were altogether 8 covariates: (a) age (age), (b) average PM interval, (c) total number of failures, (d) total number of PMs, (e) total down time of all PMs, (f) total man hours of all PMs, (g) time since last corrective work, (h) time since last PM. After detailed analysis, three covariates, (c), (g), and (h), were selected to build a model for preventive maintenance; two covariates, (f) and (g), were selected to build a model for corrective operation. Their study results indicated a higher availability for the recommended schedule than the availability resulting from applying the optimal preventive maintenance intervals as suggested by using the conventional stationary models.

2.1.1.2. PHM Applications in Reliability Analysis

Elsayed and Chan (1990) used PHM to estimate thin oxide dielectric reliability and time-dependent dielectric breakdown hazard rates. These models are distribution free since no assumptions need to be made about the failure time distribution. However, there is a necessary assumption that the hazard rate functions for various devices when tested at various stress levels are proportional to one another. The need for proportionality can be relaxed by using time-dependent explanatory variables or stratified baseline hazard rates. In this approach, two groups of models are considered: group one ignores interactions between temperature and electric field while group two considers several forms of interaction.

Elsayed et al. (2006) applied extended linear hazard regression (ELHR) model to study the time-dependent dielectric breakdown of thermal oxides on n-type 6H-SiC using laboratory data. The ELHR model was extended from the extended hazard regression (EHR) model by generalizing the EHR model and proportional hazard linear (PHL) model; here the PHL model expands the PHM in a way that it considers covariate interactions. Their results suggest that the reliability of oxides on 6H-SiC will be satisfactory for long-term operation only if the oxide field is kept below 5 MV/cm at temperatures up to 150^0C. So their research effectively concluded SiC MOS (metal-oxide-semiconductor) devices from many high-temperature applications although SiC has a high inherent temperature capability.

Kumar et al. (1992) used PHM to examine the effects of two different designs and maintenance on the reliability of a power transmission cable of an electric mine loader. In this paper, 6 covariates were excluded out of 8 covariates and only the cable type and the first repair were found to have a significant effect on the hazard rate of the cable. The plotting of the estimated log-cumulative hazard rates showed that the hazard rate for the cable type B is less than the cable type A. Based on these results they suggested that cable type B be used so that unplanned interruption of production can be reduced.

The study of Prasad and Rao (2002) involved failure data of an electro-mechanical equipment in an underground coal mine. The failures due to electrical problems, compressed air and cable fault were found to be significant. Maximum likelihood method was used to estimate the parameters and a PHM was built with the data set. The results indicated that the failure rate due to electrical problems was 19% more than compressed air problems and 42% more than cable fault problems. Thus additional attention should be paid to reduce the failures due to electrical problems. In this paper, they gave another example of thermal power unit to study the reliability of repairable systems considering the effect of operating conditions. In this case, the failure time data was collected through a long period of four years, and the failures due to boiler, electrical and turbine were selected as significant covariates. A PHM model was built with the data set to optimize preventive maintenance interval in the thermal power unit.

Campean et al. (2001) presented a general PHM based methodology for automotive systems life prediction modeling. This approach aimed to establish a correlation among the degradation mechanism, the real-world customer usage profile and the rig life testing. An example of development of a life model for the camshaft-timing belt was given to illustrate this approach. In this example, tooth shear fatigue mechanism led to the common cause failure mode and the covariates were found to be the tooth deflection and belt operating temperature. The contribution of building this timing-belt model is that it can directly establish a correlation between damage accumulation in real-world conditions and belt life testing under laboratory conditions. Practically it can be used either as a life prediction tool for different usage profiles, or as a risk assessment tool in establishing the service interval.

In the paper by Eliashberg et al. (1997), PHM was utilized to calculate the reserve for a time and usage indexed automobile warranty. Purchased time and used mileage are selected as concomitant variables.

The PHM is also used in multi-sample reliability modeling. In the paper by Mudholkar and Sarkar (1999), the analysis of multi-sample data was illustrated using the bus motor failure. Multi-sample reliability data are often found in the monitoring of repair-reuse systems. The PHM based multi-sample reliability model follows distributions with unimodal and bathtub hazard functions, yields a broader class of monotone hazard rates, and can be analyzed and computed in a simple way. Generally, it can be used for proportional hazards modeling in comparative studies of lifetime data from several populations.

Gasmi et al. (2003) developed a PHM based statistical model of complex repairable systems. These systems are observed to operate in either loaded or unloaded mode. In most cases, a system is in loaded operation. But sometimes the system is placed in an unloaded status even though it is mechanically still running. It is assumed that the failure intensity of an unloaded operation is lower than loaded operation because the operating intensity is reduced in the unloaded mode. In their research, a PHM was used to capture this potential reduction in failure intensity due to switching of operating models. A case in the B. C. Hydro Power was used to illustrate this model. The data was collected from a specific turbine in this power station in a period of one year. Altogether 466 sojourns (the time between two actions) were recorded, of which 142 ended with failure (140 in loaded mode and 2 in unloaded mode). There were also 60 major repairs, 88 minor repairs and the remaining data were minimal repairs (the unit was stopped due to being taken off line and was restarted when needed). The purpose of building this model is to quantify the impacts of performing these repair actions on the failure intensities.

JoWiak (1992) developed an approach to utilize PHM in reliability analysis of microcomputer systems. In this approach, he examined the influence of two concomitant variables, temperature and mean daily user's exploitation time of the system, on system reliability and found that the PHM with Weibull baseline failure rate had considerable potential for estimating equipment failure rate in the presence of time-dependent and time-independent concomitant variables. He recommended that PHM should be used more frequently in this field of engineering reliability. The fully parametric PHM allows engineers to examine the relative influences of equipment age and covariates on equipment failure, including only those covariates which have a statistically significant effect on time to failure.

Ansell and Phillips (1997) used PHM to represent the repairable data from the hydrocarbon industry. The data set consisted of two parts: (1) failure data in a pipeline arising from a set of different causes; (2) information supplied on a daily basis on average temperature and the stress the system was under. Using the two covariates, stress and temperature, several models were built to fit the data set. Residuals based diagnostic techniques using PHM and graphical methods were used in this paper to interpret these repairable data.

2.1.2. PHM Basic Model

In CBM optimization process using PHM, the Weibull distribution function PHM is used to model the data. PHM is a valuable statistical procedure to estimate the risk of failure of a component or equipment when it is under condition monitoring. The most important advantage of PHM is that it considers the age data as well as the condition monitoring data thus optimal maintenance actions can be effectively scheduled. The PHM function combines the baseline hazard function and the covariates which affects the failure time. The age of the equipment is the main variable while the condition monitoring measurements can be considered as a series of covariates. The basic model of PHM is described as follows (Jardine et al., 2006):

$$h(t, z(t)) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{\sum_{i=1}^{m}\gamma_i z_i(t)} \tag{2-1}$$

Where t is the inspection time; α and β denote scale parameter and shape parameter respectively. $z_i(t)$ is value of covariate i at time t and γ_i is the coefficient for covariate i. In this model, $h(t, z(t))$ is the conditional probability of failure at t, given the values of $z_i(t)$. The first part of this model is a baseline hazard function $\beta/\alpha(t/\alpha)^{\beta-1}$, which takes into account the age of the equipment at time of inspection, given the values of parameters. The second part $\exp\sum_{i=1}^{m}\gamma_i z_i(t)$ takes into account the covariates which may be considered as the key factors influencing the health of equipment and their associated weights.

2.1.3. Optimal Maintenance Policy for PHM

CBM optimization method using PHM has been developed and the main objective is to determine an optimal replacement policy to minimize long-run replacement cost (Banjevic et al., 2001, Markis and Jardine, 1992). In this method, the maintenance cost is calculated based on PHM and a risk threshold control limit policy. CBM optimization using PHM can significantly decrease maintenance cost by reducing the number of unnecessary scheduled preventive maintenance operations (Jardine et al., 2006). A summary of this method is described as follows.

Let $h(t, z(t))$ be the hazard rate at time t and K be the penalty cost. The basic theory of this approach can be described in the following way: if the observed risk $K \times h(t, z(t))$ at the given inspection point of time is greater than a certain risk threshold level d, preventive replacement action should be taken; otherwise operation can continue. Nevertheless, there is also possible that failure occurs between two inspection points of time. In that case, failure replacement will be performed. Thus, the objective of the CBM optimization using PHM is to find the optimal threshold value of the hazard rate to minimize maintenance cost. In this model, the expected long run average cost per unit time is a function of d, which is shown as follows:

$$\Phi(d) = \frac{C(1-Q(d)) + (C+K)Q(d)}{W(d)} = \frac{C + KQ(d)}{W(d)} \qquad (2\text{-}2)$$

Here $\Phi(d)$ is the expected average cost per unit of time and it is a function of risk threshold value d, C is the preventive replacement cost and $C+K$ is the failure replacement cost. $Q(d)$ is the probability that failure replacement will occur, and

$$Q(d) = P(T_d \geq T) \tag{2-3}$$

$$T_d = \inf\{t \geq 0 : Kh(t, z(t) \geq d)\} \tag{2-4}$$

where T_d is the preventive time at the risk threshold d. $W(d)$ denotes the expected time until replacement at the risk threshold d, regardless of whether it is a preventive action or a failure replacement, that is, $W(d) = E(\min\{T_d, T\})$. If the hazard rate is non-decreasing, for example, if $\beta \geq 1$ and all covariates are non-decreasing and covariate parameters are positive, the optimal risk threshold value d^*, can be determined with the fixed-point iteration method to get $\Phi(d^*) = \min_{d>0} \Phi(d) = d^*$. If the hazard rate is not monotonic, the fixed-point iteration does not work, and $\min_{d>0}, \Phi(d)$ could be found by direct search. Numerically more convenient is a forward version of that procedure, which can be suitably adjusted for non-monotonic hazard rates. Once the optimal risk threshold value d^* is determined, the item is replaced at the first moment when

$$\frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{\sum_{i=1}^{m}\gamma_i z_i(t)} \geq \frac{d^*}{K}. \tag{2-5}$$

This optimal maintenance policy for PHM has been developed into the CBM optimization software EXAKT (Banjevic et al., 2001). EXAKT has been successfully implemented in many industries, including mining industry, food processing industry, utility industry, manufacturing industry, and so on.

2.2. Artificial Neural Network

2.2.1. Literature Review on ANN

Among data-driven methods, ANN based methods have been considered to be very promising tools for component or equipment health condition and remaining life prediction. Research studies which focus on ANN applications in CBM optimization are summarized as follows:

Lee et al. (2006) presented a neural network method for continuous assessment and prediction of a particular product's performance. The proposed method is able to prevent machine from breakdowns by proactive maintenance. Several case studies were introduced to validate these developed technologies and tools.

A neural network model for condition monitoring of milling cutting tools was developed by Saglam and Unuvar (2003). This model was used to describe the relationship between cutting parameters in a milling operation and the resulting flank wear and surface roughness. In selection of the network training patterns, the authors took tool life as a reference for a feature selection criterion and they also performed variance analysis for factor selection. The selected model had five input features and 10 nodes in one hidden layer. It was trained using 16 training patterns which were obtained under a variety of machining parameters. In this paper, ANN presents an alternative solution for a human operator who behaves subjectively and is not reliable in making a decision on the state of the tool. The results of neural network show close matching between the model output and directly measured flank wear and surface roughness.

Shao and Nezu (2000) developed a compound neural network model to predict the health of a roller bearing by modeling the root mean square vibration value as a time series. The proposed model utilizes linear and non-linear signal processing techniques and neural networks to determine the current state of the bearing and a future state forecasting technique to predict the time to failure. Therefore it is able to forecast a bearing defect development process and the exact remaining bearing life. It can also automatically adapt to changes in environmental factors. In addition, multi-step prediction is possible. The proposed approach improves the traditional prediction methods of remaining bearing life.

Gebraeel et al. (2004) proposed neural-network-based models for predicting bearing failures. In this paper, two classes of models, single-bearing and clustered-bearing neural network models were developed. Degradation signals are required as inputs of these models to predict the failure time of a partially degraded bearing at any time during its service life. Therefore, the authors set up an experiment to perform accelerated bearing tests where vibration information was collected from a number of bearings that were run until failure. They used this information to train neural network models on predicting bearing operating times. Vibration data from a set of validation bearings were then applied to these network models and prediction results were used to estimate the bearing failure time. After that, they compared the predicted bearing failure times with the actual lives of the validation bearings and evaluated the effectiveness of each model. The compared results showed that models which used a weighted average of the exponential parameters coupled with the parameter updating algorithm to compute a bearing failure time prediction provided the best results. The results showed that 92% of the failure time predictions computed using validation bearings were within 20% of the actual bearing life. In conclusion, the best estimate of bearing failure times are computed using a weighted average of the exponential parameters.

In Gebraeel et al. (2005), the authors proposed ball bearing remaining life prediction methods where the output of the ANN models was a condition monitoring measurement. The presented methods combined two sources of information, which were the reliability characteristics of a device's population and real-time sensor information from the functioning device, to periodically update the distribution of the device's residual life. A Bayesian approach for updating the estimates of the stochastic parameters in exponential random-coefficient models was developed. These models with their updated parameters were then used to develop residual-life distributions for a partially degraded device. The proposed models were demonstrated using bearing degradation signals that were collected through accelerated testing.

Gebraeel et al. (2008) proposed a neural-network-based degradation model which utilizes real-time sensory signals to estimate the failure time of partially degraded components. The proposed method is able to update a component's remaining life distribution using real-time condition-based sensory signals. The sensory signals capture the latest degradation state of the component and the resulting updated distributions are directly linked to the physical degradation state of the component. The proposed model was tested and validated using thrust ball bearings as the test bed component. The authors used the vibration signals resulting from bearing degradation to estimate prior bearing failure time distributions with a neural network model. And then they updated the prior distribution with subsequent signals using a Bayesian approach and compute posterior residual life distributions. The testing results were compared with results from two benchmark policies and the proposed model was validated to be more effective.

Wu et al. (2007) proposed an integrated neural-network based decision support system for predictive maintenance of rotational equipment. In this paper, this artificial neural network model was used to estimate the life percentile and failure times of roller bearings. The proposed system was illustrated using vibration-based degradation database which consisted of a series of bearing vibration spectra associated with bearings that had been tested from the point of installation until bearing failure. It can be applied in various industries and different kinds of equipment that possess well-defined degradation characteristics.

Tian proposed a more generalized ANN prediction model in (Tian, 2012), which can deal with multiple measurements inputs and data that are not equally spaced. The proposed model can achieve more accurate remaining useful life prediction of equipment subject to condition monitoring. The ANN model takes the age and multiple condition monitoring measurement values at the present and previous inspection points as the inputs, and the life percentage as the output. It is not necessary to define a failure threshold for this model, which is hard to clearly define in many practical applications. A condition monitoring data set collected in the field from bearings on a group of Gould pumps was used to demonstrate the proposed ANN prediction model. This model was also compared with the Modified Wu's method (Wu et al., 2007), and it showed that the proposed approach can achieve more accurate predictions.

Tian et al. (2010) developed an ANN prediction method to utilize both failure and suspension data to improve prediction accuracy. Since the underlying relationship between the inputs and output of ANN is the same for all failure and suspension histories, the optimal life for a suspension history is the one resulting in the lowest ANN validation error. Based on this idea, Tian determined the optimal predicted life for suspension history by minimizing the validation mean square error in the training process using the suspension history and the failure histories. The proposed approach was validated to be able to produce more accurate remaining life prediction results using real-world vibration monitoring data collected from pump bearings in the field.

Tian and Zuo (2010) also developed an extended recurrent ANN-based time series prediction method to deal with situations in which sufficient failure and suspension data are not available. The proposed approach was illustrated using vibration data collected from a gearbox experimental system. A comparative study based on the gearbox experiment data was performed between the proposed extended recurrent neural network model and the fully connected recurrent neural network model. The comparative results demonstrated the capability of the proposed approach for producing satisfactory health condition prediction results.

2.2.2. ANN Prediction Model

The ANN model used in our research is proposed by Tian et al. (2010). It is a feed forward 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 Figure 2-1. 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, 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, they 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. Figure 2-1 gives an example of ANN structure with two condition monitoring covariates. Specifically, 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 i, 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, and 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. 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.

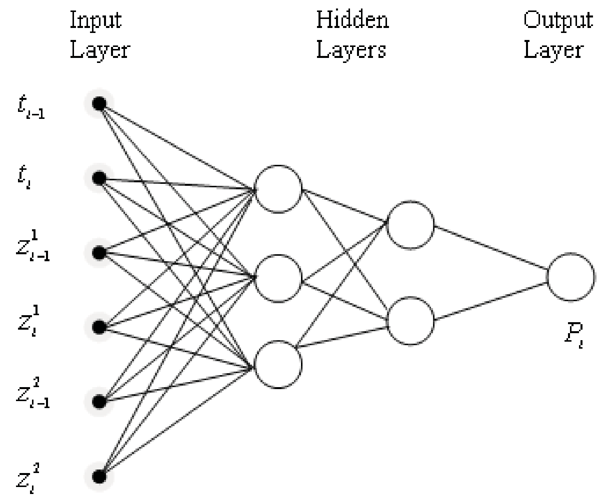

Figure 2-1 Structure of the ANN model for remaining useful life prediction

CHAPTER 3 A DATA PROCESSING METHOD FOR CBM USING PHM

Nomenclature

$\hat{Z}(t)$: fitted measurement value

k : parameter introduced to scale the fitted measurement values to any ranges

Y : covariate value when the age is 0

$C*$: optimal maintenance cost

3.1. Motivation

In CBM using PHM, fitting the PHM is an important step and the effectiveness of the optimal maintenance policy greatly depends on the accuracy of parameter estimation. Usually actual condition monitoring measurement values are used as the inputs to the PHM model. However the actual measurements are often affected by external noise when they are collected as inspection points in the field. The example in Figure 3-1 shows an actual measurement series of a bearing failure history, which was collected from a pump in Canadian Kraft Mill. A history refers to the series of inspection data collected from the beginning to the end of its life. A history can be a failure or a suspension history. This example is a failure history. It contains 23 inspection points and the bearing failed at the age of 591 days. In this figure, we can see that the actual measurement values do not show a monotonic increasing trend. There are still a lot of fluctuations at various inspection points although its general trend is increasing. But as we all know, the deterioration of the health condition of a component or equipment, such as the propagation of a rolling element in a bearing or the propagation of a root crack in a gear tooth, is generally a monotonic process. Therefore, directly using the actual measurement values without any processing as input into the PHM model may introduce external noise into the model; thus the model built based on the actual measurement values may not represent the health condition of the component or equipment very accurately and the optimal maintenance policy obtained based on the PHM model may not be really optimal (Tian, 2012). To resolve this problem, we propose an approach to remove the external noise and fit the data before feeding it into the PHM model. Compared to the actual measurement, the fitted measurements can better represent the deterioration of the component or equipment.

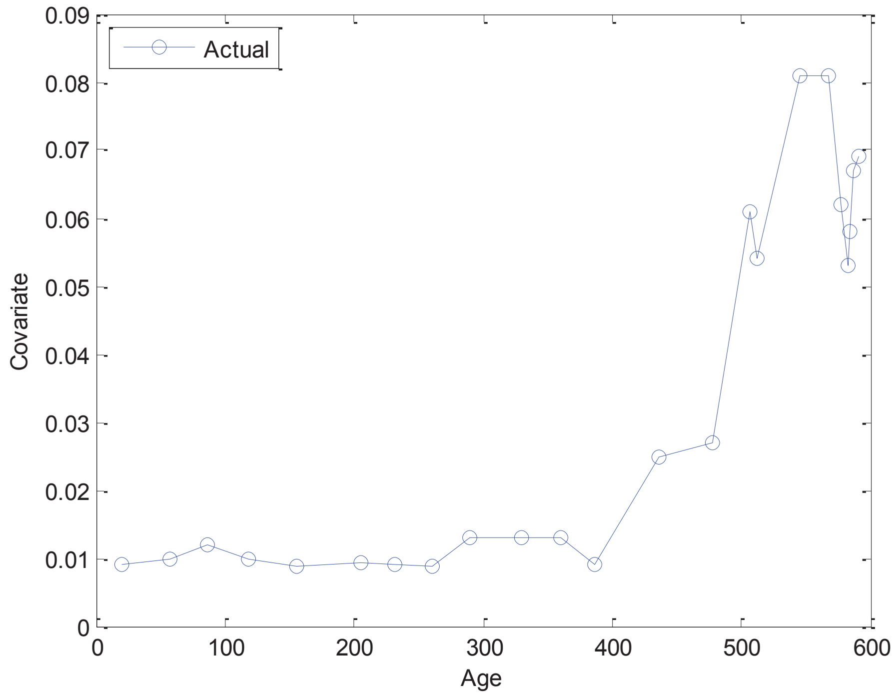

Figure 3-1 An actual inspection measurements for a sample failure history

3.2. Function for Fitting the Actual Inspection Measurement

To better represent the deterioration process of the equipment or component, an appropriate function is proposed to fit the actual measurements before they are used as input of the PHM. The fitting function is extracted from the Weibull distribution failure rate function. In reliability analysis, the health condition of equipment or component at a specified time is usually indicated by its failure rate at the given time. Weibull distribution is widely used in representing various practical lifetime distributions, and it is very flexible to represent distributions with different scales and shapes (Kuo and Zuo, 2003). Therefore, the following function generalized from the Weibull distribution failure rate function is used to fit the inspection measurements (Tian, 2012):

$$\hat{Z}(t) = Y + k\frac{\beta}{\alpha^{\beta}}t^{\beta-1} \tag{3-1}$$

where $\hat{Z}(t)$ denotes the fitted measurement value and Y is the covariate value when the age of the component is 0. k is a parameter introduced to scale the fitted measurement values to any ranges. $\left(\beta/\alpha^{\beta}\right)t^{\beta-1}$ is the failure rate function for the 2-parameter Weibull distribution.

The function in Equation (3-1) is named as the "Generalized Weibull-FR function" (Tian., 2012). There are four parameters in the Generalized Weibull-FR function to be determined: α, β, k and Y. Usually the parameters can be estimated using least-square method or maximum likelihood method based on the inspection measurements. In our research, GA is used to find the optimal values for the four parameters because of the good global optimization performance of GA (Levitin, 2005, Levitin et al., 1998). After being tested using many actual inspection histories collected from the field, the Generalized Weibull-FR function is proved to have the capability of fitting all the tested measurement series very well. An example is given as follows to show how the Generalized Weibull-FR function works.

Figure 3-1 is the plot of an actual inspection history which is collected from a pump bearing in the field. This history contains 23 inspection points and the bearing failed at the age of 591 days.

Using GA, the four parameters in the Generalized Weibull-FR function can be estimated. With the global optimization ability of GA, the obtained function can best fit the inspection measurements, which is shown as follows:

$$\hat{Z}(t) = 0.008 + 9.65 \frac{4.43}{610.2^{4.43}} t^{4.43-1} \tag{3-2}$$

The fitted results for the actual inspection measurements (vibration magnitude in the horizontal direction in frequency band 5) in Figure 3-1 are plotted in Figure 3-2, represented by "*". By removing the external noise from the actual inspection measurements, we can observe that the fitted measurements give a better indication of the degradation of the component.

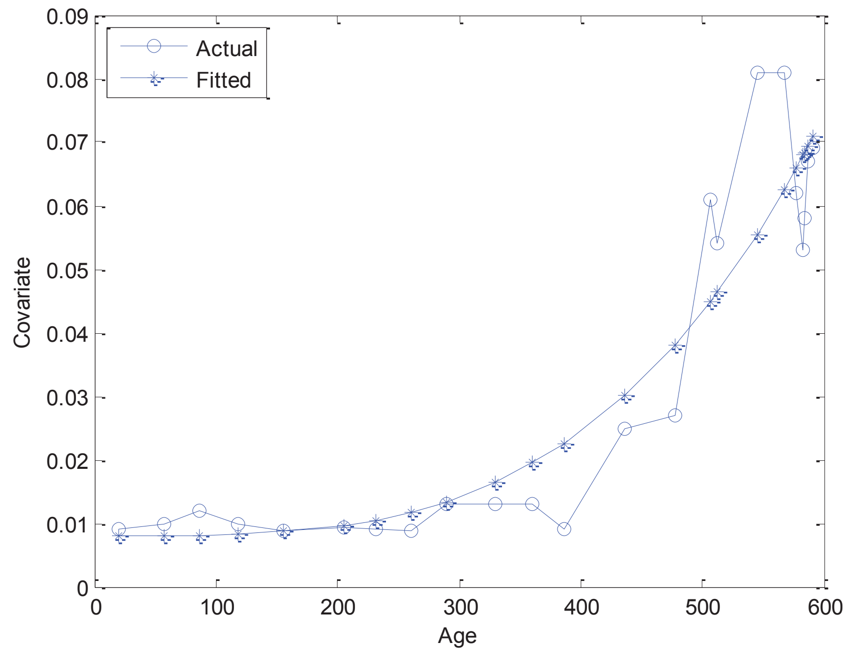

Figure 3-2 An actual inspection measurements and the fitted measurement series

3.3. Case Studies

To validate the proposed approaches, two case studies are conducted using real-world vibration monitoring data, which was collected from bearings on a group of Gould pumps at a Canadian Kraft Mill company and from shear pump bearings in a food processing plant, respectively. The Gould pump bearings case can be found in Stevens (2006) and the shear pump bearings case was reported in Banjevic et al. (2001). The objectives of both cases are to find an optimal condition based replacement policy to minimize the long-run expected replacement cost per unit of time, and to improve reliability, given the condition monitoring data (vibration data) and replacement histories.

3.3.1. Gould Pump Bearings Case

In this case study, we use data collected from Gould pump bearings at a Canadian Kraft Mill company (Stevens, 2006). This case is presented to demonstrate the proposed approach. Pulp produced in this company is used to make facial tissues, paper towels and similar products. Facing tough competition in the pulp and paper market, the company has to focus on the key objectives of bringing costs down and production up. The company was confronted with a critical problem of high incidence of unpredicted failures among a small group of its fleet of Gould pumps. Hence eliminating or substantially reducing the frequency of pump failure was evidently the key objective. The units being examined were Gould 3175L pumps which were used 24/7, as shown in Figure 3-3. Bearings were critical components of these pumps, so failure of bearing definitely caused the pump failure. Figure 3-4 is an example of bearing failure.

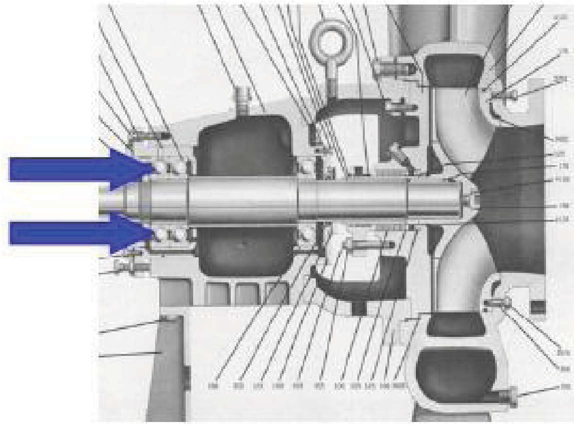

Figure 3-3 Gould 3175L pump

Figure 3-4 Bearing failure

Important data including event data, operating starts, out-of-service intervals and failure dates were extracted from the work history database. After sorting up these data, two categories of data were obtained, that is, event data and inspection data. There were three types of event data: beginning event, failure event and suspension event. For inspection data, 56(=8*5+8*1+8*1) vibration measurements were recorded. For each pump, seven measurements were analyzed at 5 different vibration frequency bands (8*5), and the overall vibration reading (8*1) plus the bearing's acceleration data (8*1). In this case, 33 histories, including failure replacements (ended with failure) and preventive replacements (ended with suspension), were collected from the 8 pump locations. The actual inspection measurements and the fitted measurements obtaind by the proposed approach will be used as input to the PHM respectively and their average toal maintenance cost will be compared.

There are five steps to perform CBM optimization using PHM: significance analysis, parameter estimation, transition probability matrix development, cost data estimation and CBM optimization.

Step1 – significant analysis

Using the software EXAKT, we can perform the significance analysis for the 56 vibration measurements. Two covariates 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).

Step 2- parameter estimation

In this case, there are four parameters to be estimated: α (scale parameter), β (shape parameter), γ_1 (covariate weight for P1H_Par5), γ_2 (covariate weight for P1V_Par5). Using the actual inspection measurements as input to the PHM, the four parameters are estimated as follows:

$$\begin{aligned} h(t, Z(t)) &= \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{(\gamma_1 z_{P1H}(t)+\gamma_2 z_{P1V}(t))} \\ &= \frac{3.394}{2757}\left(\frac{t}{2757}\right)^{3.394-1} e^{(21.05 z_{P1H}(t)+57.16 z_{P1V}(t))} \end{aligned} \tag{3-3}$$

Next, the actual inspection measurements are fitted using the proposed fitting function. The parameters estimated based on the fitted measurement value are given as follows:

$$
\begin{aligned}
h(t, Z(t)) &= \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} e^{(\gamma_1 z_{P1H}(t)+\gamma_2 z_{P1V}(t))} \\
&= \frac{3.936}{2786}\left(\frac{t}{2786}\right)^{3.936-1} e^{(17.41 z_{P1H}(t)+72.01 z_{P1V}(t))}
\end{aligned} \tag{3-4}
$$

Step 3 – transition probability matrix development

To calculate the maintenance cost we need to specify the transition probability matrix. The transition probability matrix indicates the probabilities of a covariate in different ranges at the next inspection time given its current range. EXAKT can be used to estimate the transition probability matrices for the two covariates. Assuming the inspection interval is 28 days, the transition probability matrices obtained based on the actual inspection measurements and fitted measurements are given respectively, in Table 3-1, 3-2, 3-3 and 3-4:

Table 3-1 Transition probability for covariate P1H_Par5 based on actual measurements

P1H_Par5	**0 to 0.00792**	**0.00792 to 0.014256**	**0.014256 to 0.05016**	**0.05016 to 0.136752**	**Above 0.136752**
0 to 0.00792	0.784755	0.199967	0.0150435	0.000228608	5.48137E-06
0.00792 to 0.014256	0.0460993	0.8281	0.122933	0.00277821	8.95293E-05
0.014256 to 0.05016	0.00344127	0.121984	0.835499	0.0372439	0.00183203
0.05016 to 0.136752	0.000157207	0.00828724	0.111961	0.797492	0.0821025
Above 0.136752	0	0	0	0	1

Table 3-2 Transition probability for covariate P1V_Par5 based on actual measurements

P1V_Par5	0 to 0.00741	0.00741 to 0.01404	0.01404 to 0.048165	0.048165 to 0.13299	Above 0.13299
0 to 0.00741	0.778123	0.209235	0.0124585	0.000180682	2.19389E-06
0.00741 to 0.01404	0.0453969	0.852736	0.0996783	0.00215347	3.49498E-05
0.01404 to 0.048165	0.00272389	0.100446	0.858878	0.037041	0.000911191
0.048165 to 0.13299	8.61624E-05	0.00473316	0.0807912	0.870673	0.0437164
Above 0.13299	0	0	0	0	1

Table 3-3 Transition probability for covariate P1H_Par5 based on fitted measurements

P1H_Par5	0 to 0.0084952	0.0084952 to 0.0153832	0.0153832 to 0.047068	0.047068 to 0.135234	Above 0.135234
0 to 0.0084952	0.865102	0.132331	0.0025341	3.19206E-05	6.44605E-07
0.0084952 to 0.0153832	0	0.963069	0.0362363	0.000676333	1.81731E-05
0.0153832 to 0.047068	0	0	0.962856	0.0356956	0.00144835
0.047068 to 0.135234	0	0	0	0.923511	0.0764892
Above 0.135234	0	0	0	0	1

Table 3-4 Transition probability for covariate P1V_Par5 based on fitted measurements

P1V_Par5	0 to 0.0081648	0.0081648 to 0.0151632	0.0151632 to 0.0452952	0.0452952 to 0.132386	Above 0.132386
0 to 0.0081648	0.879413	0.118227	0.0023298	3.00238E-05	3.37876E-07
0.0081648 to 0.0151632	0	0.961917	0.037356	0.000716413	1.07245E-05
0.0151632 to 0.0452952	0	0	0.962299	0.0368705	0.000830971
0.0452952 to 0.132386	0	0	0	0.956519	0.0434811
Above 0.132386	0	0	0	0	1

Step 4 – maintenance cost determination

After the transition probability matrices are obtained, we need to estimate the preventive replacement cost and failure replacement cost. Based on the expertise and previous experiences, the preventive replacement cost *C* is estimated to be \$4,000, and the failure replacement cost *C*+*K* is \$12,000 for this case. Thus the penalty cost *K* equals \$8,000.

Step 5 –maintenance policy optimization

Now, the CBM optimization policy can be determined using the estimated parameters, transition probability matrices and cost data information. Using the parameters estimated based on the actual inspection measurements, which are:

$$\alpha = 2757, \beta = 3.394, \gamma_1 = 21.05, \gamma_2 = 57.16 \tag{3-5}$$

the optimal maintenance policy is obtained as:

$$d^* = 7.23\$ / day, C^* = 5.74\$ / day \tag{3-6}$$

In this policy, the optimal risk threshold level $d*$ is obtained as 7.23$/day, which means it is time to perform preventive replacement when the observed risk $K \times h(t, z(t))$ is greater than 7.23$/day. With this optimal policy, the optimal maintenance cost $C*$ is around 5.74$/day and the average preventive replacement interval is 867.2 days.

Now we calculate the optimal policy based on the parameters obtained using fitted measurements as input, which are:

$$\alpha = 2786, \beta = 3.936, \gamma_1 = 17.41, \gamma_2 = 72.01 \tag{3-7}$$

The optimal maintenance policy is determined as:

$$d* = 5.06\$ / day, C* = 5.06\$ / day \tag{3-8}$$

The risk threshold level $d*$ is calculated as 5.06$/day and the optimal maintenance cost $C*$ is shown as around 5.06$/day. Based on the optimal policy, the average preventive replacement interval will be 949.6 days.

By comparing the optimized maintenance results before and after fitting the inspection measurements using the Generalized Weibull-FR function, we can see the average maintenance cost based on the actual inspection measurements will be 5.74$/day while the average cost based on the fitted measurements will be 5.06$/day, as shown in Table 3-5. So using the proposed approach to fit the inspection measurements before applying to PHM will save the average maintenance cost around 11.81%. The average replacement interval is increased from 867.2 days to 949.6 days, which is around 9.5%. So we can conclude that fitting the actual measurements before using them as input to the PHM will save the average maintenance cost.

Table 3-5 CBM optimization results comparison before and after fitting the data

Results / Method	**Average Maintenance Cost ($/day)**	**Average Replacement Interval (days)**
Before	5.74	867.2
After	5.06	949.6
Changes	11.81%	9.5%

3.3.2. Shear Pump Bearings Case

The second case is shear pump bearings in a food processing company. Figure 3-5 is a shear pump used in the case and Figure 3-6 is one of the bearings in the shear pump. Totally 21 (3+3*5+3) vibration measurements were collected using accelerometers, including vibration data in axial, horizontal and vertical directions for the overall velocity (3), velocities in 5 bands (3*5=15) and acceleration in three directions (3). There are 25 histories in the recorded data, including 13 failure replacements and 12 preventive replacements.

Figure 3-5 Shear pump

Figure 3-6 Bearing

Again, there are five steps to perform CBM optimization using PHM.

Step1 – significant analysis

Using the software EXAKT, the significance analysis was performed, and three significant covariates were identified: VEL#1A (band 1 velocity in the axial direction), VEL#1V (band 1 velocity in the vertical direction), and VEL#2A (band 2 velocity in the axial direction).

Step 2- parameter estimation:

Since the proposed approach works well for those covariates which show increasing trend but not so well for decreasing covariates. By plotting the three covariates we found out only two covariates (VEL#1A and VEL#2A) showing increasing pattern. An example of failure history is given in Figure 3-7:

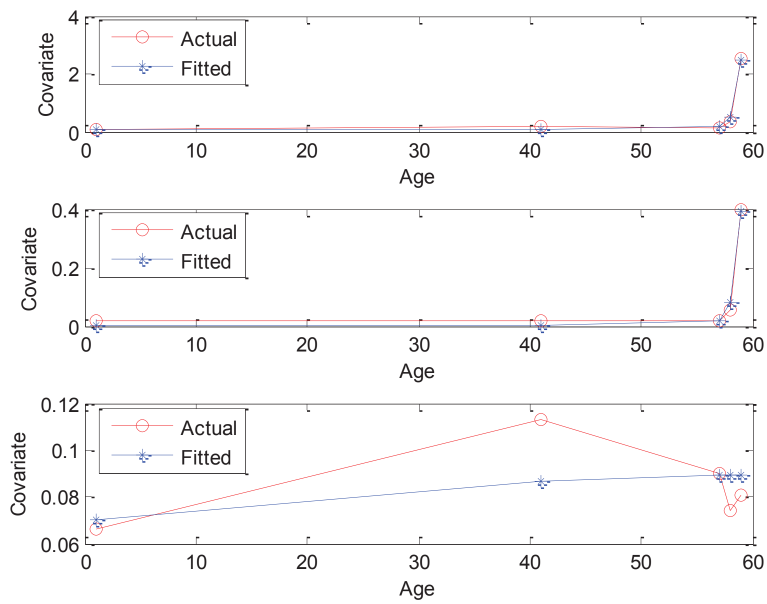

Figure 3-7 Plots of VEL#1A, VEL#2A and VEL#1V

Therefore we will use covariate VEL#1A and VEL#2A in this case to further demonstrate the proposed approach. So there are four parameters to be estimated: α (scale parameter), β (shape parameter), γ_1 (covariate weight for VEL#1A), γ_2 (covariate weight for VEL#2A).

The parameter estimation result for actual inspection measurements is shown as follows:

$$
\begin{aligned}
h(t,Z(t)) &= \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1} e^{(\gamma_1 z_{1A}(t)+\gamma_2 z_{2A}(t))} \\
&= \frac{4.695}{739.9}\left(\frac{t}{739.9}\right)^{4.695-1} e^{(6.358 z_{1A}(t)+24.27 z_{2A}(t))}
\end{aligned}
\tag{3-9}
$$

After fitting the actual measurements, the parameters estimated are given as follows:

$$
\begin{aligned}
h(t,Z(t)) &= \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1} e^{(\gamma_1 z_{1A}(t)+\gamma_2 z_{2A}(t))} \\
&= \frac{5.226}{765.7}\left(\frac{t}{765.7}\right)^{5.226-1} e^{(6.688 z_{1A}(t)+28.19 z_{2A})}
\end{aligned}
\tag{3-10}
$$

Step 3- transition probability matrices:

Transition probability matrices obtained based on actual inspection measurements are shown in Table 3-6 and 3-7:

Table 3-6 Transition probability for covariate VEL_1A based on actual measurements

VEL_1A	**0 to 0.035266**	**0.035266 to 0.2519**	**0.2519 to 1.08821**	**1.08821 to 2.51648**	**Above 2.51648**
0 to 0.035266	0.765522	0.214501	0.0187137	0.00123314	3.01141E-05
0.035266 to 0.2519	0.0419512	0.809202	0.134907	0.0134952	0.000445182
0.2519 to 1.08821	0.00436408	0.160862	0.683157	0.144277	0.00734044
1.08821 to 2.51648	0.000138356	0.00774194	0.0694142	0.838071	0.0846349
Above 2.51648	0	0	0	0	1

Table 3-7 Transition probability for covariate VEL_2A based on actual measurements

VEL_2A	0 to 0.018036	0.018036 to 0.047428	0.047428 to 0.11356	0.11356 to 0.394788	Above 0.394788
0 to 0.018036	0.579321	0.371903	0.0459901	0.00269327	9.27563E-05
0.018036 to 0.047428	0.0852781	0.731248	0.168793	0.0140551	0.000625567
0.047428 to 0.11356	0.0114118	0.182657	0.691931	0.10703	0.00696988
0.11356 to 0.394788	0.0023802	0.0541698	0.381196	0.499451	0.0628029
Above 0.394788	0.000559654	0.0164605	0.169477	0.428769	0.384734

Following are the transition probability matrices obtained based on fitted measurements, as shown in Table 3-8 and 3-9:

Table 3-8 Transition probability for covariate VEL_1A based on fitted measurements

VEL_1A	0 to 0.064792	0.064792 to 0.269136	0.269136 to 1.089	1.089 to 2.48951	Above 2.48951
0 to 0.064792	0.833298	0.156365	0.0095781	0.00074095	1.83627E-05
0.064792 to 0.269136	0	0.882027	0.105274	0.0122909	0.000408521
0.269136 to 1.089	0	0	0.796653	0.193536	0.00981047
1.089 to 2.48951	0	0	0	0.90844	0.0915605
Above 2.48951	0	0	0	0	1

Table 3-9 Transition probability for covariate VEL_2A based on fitted measurements

VEL_2A	0 to 0.0262707	0.0262707 to 0.0501888	0.0501888 to 1.089	0.100378 to 0.391708	Above 0.391708
0 to 0.0262707	0.822468	0.164492	0.0124907	0.00053343	1.53564E-05
0.0262707 to 0.0501888	0	0.861082	0.130274	0.00832373	0.000320528
0.0501888 to 0.100378	0	0	0.881023	0.112434	0.00654325
0.100378 to 0.391708	0	0	0	0.894211	0.105789
Above 0.391708	0	0	0	0	1

Step 4 – specify the maintenance cost:

Now the preventive replacement cost and failure replacement cost are estimated based on the expertise and previous experiences. The preventive replacement cost C is estimated to be \$1,800, and the failure replacement cost ($C+K$) is \$16,200, so K is calculated to be \$14,400.

Step 5 – optimize maintenance policy

In this case, the parameters estimated based on the actual inspection measurements are:

$$\alpha = 739.9, \beta = 4.695, \gamma_1 = 6.358, \gamma_2 = 24.27 \tag{3-11}$$

Using the estimated parameters, transition probability matrices and cost data information the optimal maintenance policy is obtained as follows:

$$d^* = 16.96\$ / day, C^* = 12.34\$ / day \tag{3-12}$$

So in this policy the optimal risk threshold level d^* is 16.96\$/day. In this case, we will perform preventive replacement once the observed risk $K \times h(t, z(t))$ exceeds 16.96\$/day. By performing this optimal policy, the average preventive replacement interval is found to be 168.3 days, and the optimal maintenance cost C^* is controlled to be around 12.34\$/day.

Next we will calculate the optimal policy based on the parameters obtained using fitted measurements as input, which are: $\alpha = 765.7, \beta = 5.226, \gamma_1 = 6.688, \gamma_2 = 28.19$. This time we have the optimal maintenance policy as:

$$d^* = 10.36\$ / day, C^* = 10.36\$ / day \tag{3-13}$$

From function (3-13), we can see using fitted measurements, the risk threshold level d^* is determined to be 10.36\$/day and the optimal maintenance cost C^* obtained is 10.36\$/day. With this optimal policy, the average preventive replacement interval will be 196.4 days.

The comparison result given in Table 3-10 shows that the average maintenance cost based on the fitted measurements is around 10.36\$/day while the average cost based on the actual inspection measurements is around 12.34\$/day. So it will bring a saving of 16.36% in average maintenance cost by using the proposed approach to fit the inspection measurements before applying to PHM. At the same time, the average replacement interval is increased from 168.3 days to 196.4 days, which is around 16.72%. So we can draw a conclusion that by fitting the actual measurements using the Generalized Weibull-

FR function will save the average maintenance cost and prolong the average replacement interval to make better use of remaining useful life.

Table 3-10 CBM optimization results comparison before and after fitting the data

Results / Method	**Average Maintenance Cost ($/day)**	**Average Replacement Interval (days)**
Before	10.36	168.3
After	12.34	196.4
Changes	16.36%	16.72%

3.4. Concluding Remarks

In CBM using PHM, the accuracy of parameter estimation for PHM has a great influence on the effectiveness of the optimal maintenance policy. Generally actual condition monitoring measurement values are directly used to estimate the parameters for the PHM model. Nevertheless, the existing of external noise will change the monotonic increasing trend of inspection measurements and brings fluctuations in the deterioration process. Therefore the model built based on the actual measurement values may not accurately represent the health condition of the equipment or component and the optimal maintenance policy obtained based on the PHM model may not be really optimal. In this research, an approach where the actual measurements are fitted first using the Generalized Weibull-FR function, is proposed to remove the external noise and fit the inspection measurements before feeding them into the PHM model.

Two case studies using real-world vibration monitoring data, collected from Gould pump bearing in a Canadian Kraft Mill company and from shear pump bearings in a food processing plant, respectively, are used to demonstrate the proposed approach. Our studies show that the proposed approach will save the average maintenance cost and increase the average replacement interval to make better use of remaining useful life.

This research has been organized into a journal paper and has been published (Wu and Tian, 2012).

CHAPTER 4 CBM OPTIMIZATION USING ANN-BASED HEALTH CONDITION PREDICTION

Nomenclature

p_t : ANN life percentage output at inspection point t

T_p : predicted failure time considering prediction uncertainty

μ : mean of the prediction error.

σ : standard deviation of the prediction error; standard deviation of the predicted failure times

T : constant inspection interval

Pr : failure probability threshold

Pr* : optimal failure probability threshold

$\Pr_{con}$: conditional failure probability during next inspection interval

t_i : failure time of unit i

t_j^+ : right censoring/suspension time of unit j

n_E : number of exact failure data

n_R : number of right censoring/suspension data

C_{expected} : expected replacement cost per unit of time

t_m : actual failure time of a component

t_n : predicted failure time of a component

T_{pA} : predicted failure time with respect to t_m

$t_{PR}(t_n)$: preventive replacement time for t_n

$C_T(t_m)$: expected total replacement cost with respect to actual failure time t_m

$C_{TP}(t_m)$: expected preventive replacement cost with respect to actual failure time t_m

$C_{TF}(t_m)$: expected failure replacement cost with respect to actual failure time t_m

C_p : total cost of a preventive replacement

C_f : total cost of a failure replacement

$T_T(t_m)$: expected total replacement time with respect to actual failure time t_m

$T_{TP}(t_m)$: expected preventive replacement time with respect to actual failure time t_m

$T_{TF}(t_m)$: expected failure replacement time with respect to actual failure time t_m

C_{TA} : expected total replacement cost with respect to failure probability threshold value Pr

T_{TA} : expected total replacement time with respect to failure probability threshold value Pr

$S(t)$: a continuous degradation signal with respect to time t

ϕ : a constant

θ : a lognormal random variable

μ_0 : mean of $\ln\theta$

σ_0^2 : variance of $\ln\theta$

β' : a normal random variable with mean μ_1 and variance σ_1^2

$\varepsilon(t) = \sigma' W(t)$: a centered Brownian motion such that the mean of $\varepsilon(t)$ is zero and the variance of $\varepsilon(t)$ is $\sigma'^2 t$

$\theta' = \ln\theta$: a normal random variable with mean μ_0 and variance σ_0^2

$\beta'' = \beta' - \dfrac{\sigma'^2}{2}$: a normal random variable with mean $\mu_1^{'}$ and variance σ'^2_1

D : failure threshold

4.1. Motivation

ANN based methods have demonstrated to be very effective in equipment remaining useful life prediction. 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 (Marble and Morton, 2006, Kacprzynski et al., 2002, Li and Lee, 2005). They are also used in some CBM methods based on some other data-driven prediction methods (Kaiser and Gebraeel, 2009). More accurate and efficient numerical methods are not available, which is critical for performing CBM optimization. In our research, 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.

4.2. The Proposed CBM Optimization Approach Using ANN-Based Prediction

In condition based maintenance, the objective of inspection is to determine the health condition of equipment or component. Indicators of inspection may be bearing wear, gauge readings, root crack of gear tooth, etc. Inspection interval is determined based on inspection costs and inspection benefits. Inspection costs include inspection tools and other inspection materials, wages of inspection person, and loss of production due to scheduled downtime and so on. An example of inspection benefit may be detection and correction of minor defects before major breakdown occurs (Jardine and Tsang, 2006). In our research, the inspection cost is not considered in the maintenance optimization. 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. It may be considered in a joint inspection/maintenance optimization problem in future investigation.

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The procedure of the proposed CBM approach is described in Figure 4-1, 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.

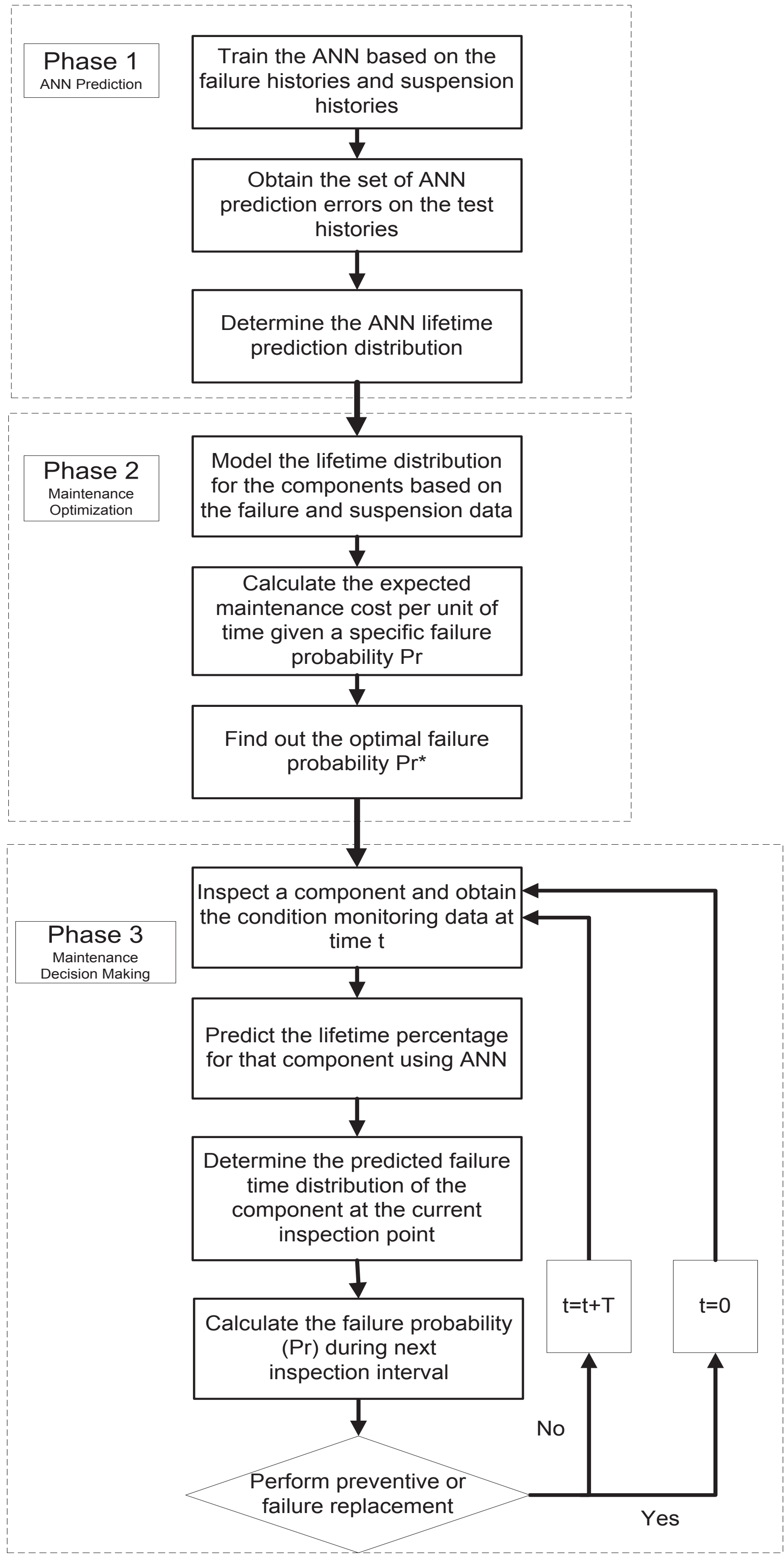

Figure 4-1 Procedure of the proposed CBM approach

4.2.1. Estimation of the ANN Remaining Life Prediction Uncertainty

The ANN prediction method in Tian et al. (2010) 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. 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 Tian et al. (2010). 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 t in a test history is equal to ($t/p_t - t_m$), where p_t denotes the ANN life percentage output at inspection point t and t_m is the actual failure time of the component. 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 research, 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. Thus the predicted failure time considering the prediction error at inspection point t, can be calculated as $t/p_t - \mu$, and the standard deviation of the predicted failure time will also be σ. That is, the predicted failure time considering the prediction error, denoted by T_p, follows the following normal distribution:

$$T_p \sim N\left(t/p_t - \mu, \sigma^2\right). \tag{4-1}$$

4.2.2. 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 a constant inspection interval, denoted by T, for example, every 20 days. At a certain inspection point, the predicted failure time distribution can be obtained. The conditional failure probability during next inspection interval, denoted by $\Pr_{con}$, 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 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 next inspection interval exceeds the optimal 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.

4.2.3. Determination of the Optimal CBM Policy

This section corresponds to Phase 2 in the proposed CBM approach shown in Figure 3-3. 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 our research (Jardine and Tsang, 2006). The maximum likelihood method can be used to estimate the lifetime distribution parameters α, β. The likelihood function is expressed as follows (Jardine and Tsang, 2006):

$$L = \prod_{i=1}^{n_E} f(t_i;\theta) \cdot \prod_{j=1}^{n_R} R(t_j^+;\theta) \tag{4-2}$$

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_{expected}, is calculated given a specific failure probability threshold Pr. This is the key step in the 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 (Rausch and Liao, 2010, Tran et al., 2008). In our research, 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. 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 Figure 4-2, suppose the actual failure time of a component is $t_m = 800$ days and the mean and standard deviation of the ANN lifetime prediction error is μ and σ, respectively. Then, the predicted failure time with respect to t_m, denoted by T_{pA}, 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 Figure 4-2, the predicted failure time considering prediction uncertainty, denoted by T_p, 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., $t/p_t - \mu$. The failure probability during the next inspection interval is defined as the conditional failure probability as follows:

$$\Pr_{con} = \frac{\int_t^{t+T} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-t_n}{\sigma}\right)^2} dx}{\int_t^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-t_n}{\sigma}\right)^2} dx} \tag{4-3}$$

In Figure 4-2, $t = 500$ 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 (4-3). It represents the conditional failure probability during the next inspection interval.

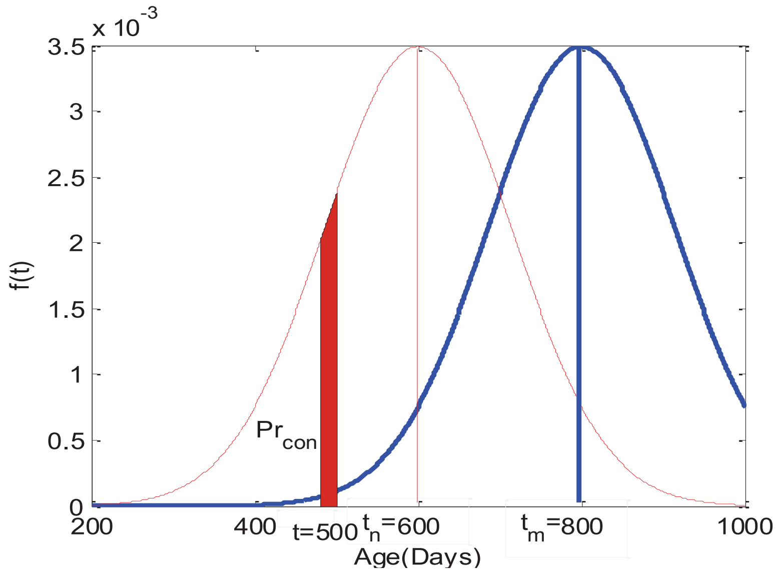

Figure 4-2 Predicted failure time distribution and failure probability during next interval

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 with respect to actual failure time t_m, $C_T(t_m)$, can be calculated as follows:

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

$$C_{TP}(t_m) = \int_0^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{t_n - t_m}{\sigma}\right)^2} \cdot C_p \cdot I\left(t_{PR}(t_n) < t_m\right) dt_n \tag{4-5}$$

$$C_{TF}(t_m)=\int_0^{\infty}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{t_n-t_m}{\sigma}\right)^2}\cdot C_f\cdot I\left(t_{PR}(t_n)\geq t_m\right)dt_n \tag{4-6}$$

where $C_{TP}(t_m)$ is the expected preventive replacement cost with respect to actual failure time t_m 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. $I\left(t_{PR}(t_n)<t_m\right)=1$ if $t_{PR}(t_n)<t_m$, and $I\left(t_{PR}(t_n)<t_m\right)=0$ otherwise. Similarly, $I\left(t_{PR}(t_n)\geq t_m\right)=1$ if $t_{PR}(t_n)\geq t_m$, and $I\left(t_{PR}(t_n)\geq t_m\right)=0$ otherwise. Equation (4-8) gives the expected preventive replacement time while Equation (4-9) gives the expected failure replacement time. The expected total replacement time, $T_T(t_m)$, can be calculated as follows:

$$T_T(t_m)=T_{TP}(t_m)+T_{TF}(t_m) \tag{4-7}$$

$$T_{TP}(t_m)=\int_0^{\infty}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{t_n-t_m}{\sigma}\right)^2}\cdot t_{PR}(t_n)\cdot I\left(t_{PR}(t_n)<t_m\right)dt_n \tag{4-8}$$

$$T_{TF}(t_m)=\int_0^{\infty}\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{t_n-t_m}{\sigma}\right)^2}\cdot t_m\cdot I\left(t_{PR}(t_n)\geq t_m\right)dt_n \tag{4-9}$$

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

$$C_{TA} = \int_0^{\infty} \frac{\beta}{\alpha}\left(\frac{t_m}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t_m}{\alpha}\right)^{\beta}\right] \times C_T(t_m)dt_m \tag{4-10}$$

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

$$T_{TA} = \int_0^{\infty} \frac{\beta}{\alpha}\left(\frac{t_m}{\alpha}\right)^{\beta-1} \exp\left[-\left(\frac{t_m}{\alpha}\right)^{\beta}\right] \times T_T(t_m)dt_m \tag{4-11}$$

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:

$$C_{\mathrm{exp}ected}(\mathrm{Pr}) = \frac{C_{TA}}{T_{TA}} \tag{4-12}$$

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:

$$\begin{aligned} &\min \ C_{\mathrm{exp}ected}(\mathrm{Pr}) \\ &\text{s.t.} \\ &\qquad \mathrm{Pr} > 0 \end{aligned} \tag{4-13}$$

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*.

4.2.4. Implementation of the Optimal CBM Policy

This section corresponds to Phase 3 in the proposed CBM approach shown in Figure 3-4. 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 $T_p \sim N(t/p_t - \mu, \sigma^2)$, 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}. Step 5: Make replacement decisions. If a failure occurs during the previous inspection interval, perform failure replacement. If the failure probability Pr_{con} during 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 interval.

4.3. 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 (Stevens, 2006).

4.3.1. Numerical Examples

In this numerical example, simulated degradation signals are generated using the degradation model presented in Lu and Meeker (1993) and Gebraeel et al. (2005). The degradation model can be expressed as follows (Gebraeel et al., 2005):

$$S(t) = \phi + \theta \exp(\beta' t + \varepsilon(t) - \frac{\sigma'^2 t}{2}) \tag{4-14}$$

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, $L(t)$:

$$L(t) = \ln\theta + \left(\beta' - \frac{\sigma'^2}{2}\right)t + \varepsilon(t) \tag{4-15}$$

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 (3-14) can be simplified as

$$L(t) = \theta' + \beta'' t + \varepsilon(t) \tag{4-16}$$

4.3.1.1. Simulated Degradation Set 1

We set the parameters in Equation (3-16) 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 Figure 4-3.

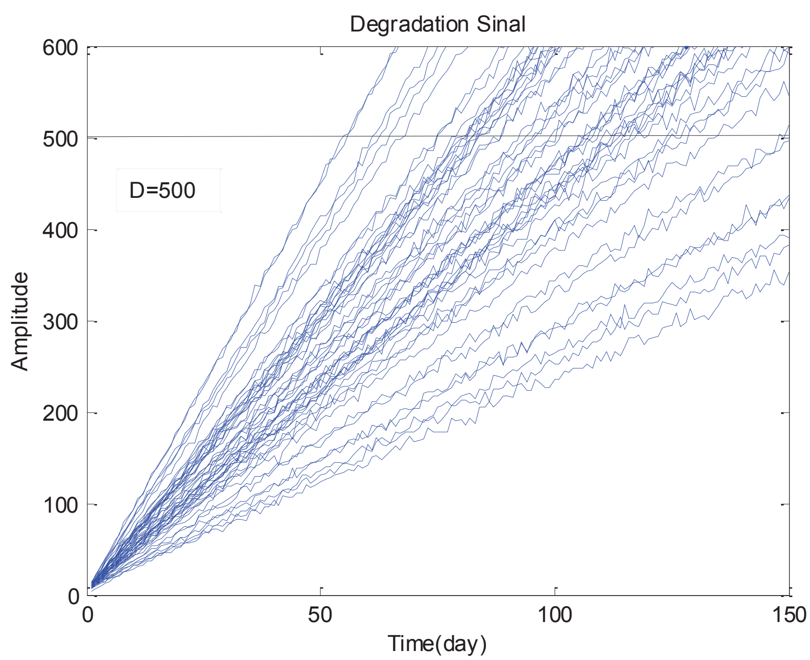

Figure 4-3 Plot of 50 generated degradation paths in the simulated degradation set 1

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 (Jardine and Tsang, 2006), 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 developed algorithm, the optimal threshold probability Pr* is found to be 0.009 and the corresponding expected total replacement cost per unit of time is \$35.09/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 35.28$/day, which is very close to the optimal replacement cost value 35.09 $/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 (Rausch and Liao, 2010). 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 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, 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 and for the constant interval replacement policy, the optimal replacement interval is found to be 58 days and the expected total replacement cost is 65.18 $/day. For the age-based replacement policy, the optimal replacement age is determined to be 59.9 days and the average total maintenance cost is

63.07 \$/day. The results are listed in Table 4-1, 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 35.09 \$/day. It costs 46.16% less than constant interval replacement policy and 44.35% less than aged-based replacement policy, as shown in Table 4-1.

Table 4-1 CBM optimization results comparison using the simulated data set 1

Maintenance Policy	**Expected Total Replacement Cost per Unit of Time (\$/Day)**	**Optimal Replacement Time (Days)**
Constant interval replacement policy	65.18	58.0
Age-based replacement policy	63.07	59.9
The proposed CBM approach	35.09	

4.3.1.2. 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 Figure 4-4. 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 38.17 $/day.

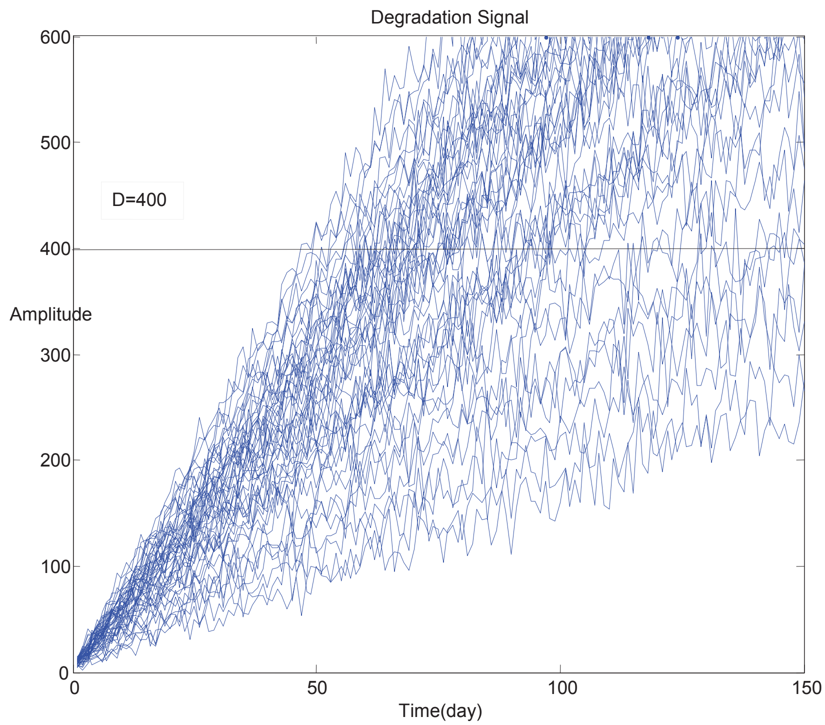

Figure 4-4 Plot of 50 generated degradation paths in the simulated degradation set 2

In Table 4-2, we can see the expected total replacement cost for the proposed CBM approach is still the lowest, which is 38.17 $/day. It saves 43.03% comparing to the constant interval replacement policy, and 40.24% comparing to the aged-based replacement policy.

Table 4-2 CBM optimization results comparison using the simulated data set 2

Maintenance Policy	Expected Total Replacement Cost per Unit of Time ($/Day)	Optimal Replacement Time (Days)
Constant interval replacement policy	67.00	63.0
Age-based replacement policy	63.87	59.7
The proposed CBM approach	38.17	

4.3.2. Case Study

4.3.2.1. Case Study Introduction

The proposed CBM approach is demonstrated using the real-world condition monitoring data collected from bearings on a group of Gould pumps at a Canadian Kraft Mill company (Stevens, 2006) which is introduced in Chapter 3. Based on the ANN approach developed in Tian et al. (2010), 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 another 10 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.

4.3.2.2. 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 for 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 developed algorithm, 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 3.88\$/day, as shown in Figure 4-5.

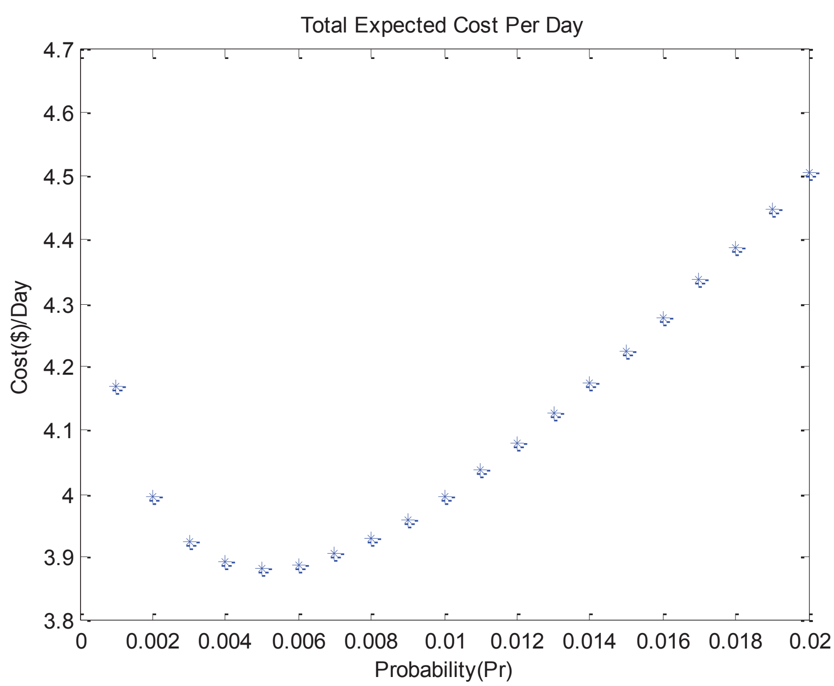

Figure 4-5 Expected replacement cost with different threshold failure probability values

4.3.2.3. Maintenance Cost Calculation Verification Using the Simulation Method

Simulation is an important way to verify the performance of maintenance policies (Wang and Pham, 1997). 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 the previous section, 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.

4.3.2.4. 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. We will use 10 test histories to illustrate the implementation of the optimal maintenance policy.

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 418.8 days. Based on Equation (3-1), the predicted lifetime is adjusted to be 665.6 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 $t_n = 665.6$ days, and $\sigma = 204.4521$ days. Using Equation (3-3), 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 Figure 4-6. So, the operation of the component can be continued at the age of 147 days and no replacements should be performed.

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 4-3, where the replacement time 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.

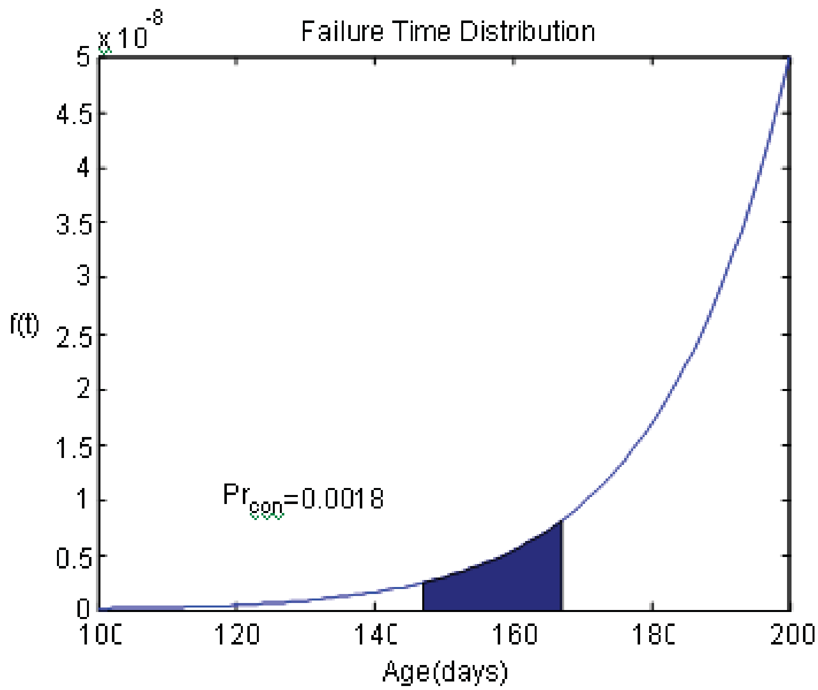

Figure 4-6 Failure probability value at age 147 days

Table 4-3 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

4.3.2.5. Comparison between Proposed Approach and Benchmark Replacement Policies

Firstly, we 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 777 days, and the corresponding expected cost is 10.46 \$/day. For the age-based replacement policy, the optimal replacement age is found to be 715.4 days, and the corresponding expected replacement cost is 9.94 \$/day. As discussed previously, the optimal expected cost using the proposed CBM approach is 3.88 \$/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 4-4.

Table 4-4 CBM optimization results comparison using bearing condition monitoring data

Maintenance policy	**Expected Total Replacement Cost per Unit of Time (\$/day)**	**Optimal Replacement Time (days)**
Constant interval replacement policy	10.46	777.0
Age-based replacement policy	9.94	715.4
The proposed CBM approach	3.88	

The comparison performed above is based on the maintenance optimization results. Next we apply the three optimal maintenance policies to the 10 test histories respectively, and investigate how they perform when applying to real condition monitoring and replacement histories. The results are shown in Table 4-5, 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.

Table 4-5 CBM optimization results comparison when applying to the 10 test histories

No.	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.

We also compare the proposed CBM approach with the widely used PHM method (Banjevic et al., 2001) 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 test 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.

4.4. Concluding Remarks

In this research, we develop a CBM optimization approach based on ANN remaining life prediction information, in which 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. Secondly, a numerical method is developed to more accurately and efficiently evaluate the cost of the CBM policy, which provides clear advantages 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.

This research has been organized into a journal paper and has been accepted (Wu et al., 2012).

CHAPTER 5 CBM OPTIMIZATION CONSIDERING IMPROVING PREDICTION ACCURACY

Nomenclature

$T_{n,t}$: predicted failure time at time *t*

$e_{n,t}$: prediction error at time *t*

$\mu_{e_{n,t}}$: mean of $e_{n,t}$

a_μ : function coefficient

b_μ : function coefficient

T_a : adjusted predicted failure time

$\sigma_{n,t}^p$: standard deviation of the life prediction percentage error

$\sigma_{n,t}$: standard deviation of $e_{n,t}$

a_σ : function coefficient

b_σ : function coefficient

5.1. Motivation

In our previous research in Chapter 4 (Wu et al, 2012), the proposed ANN based replacement policy uses prediction error to estimate the prediction uncertainty. 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. Therefore, we attempt to 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.

5.2. 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. This approach makes vital improvements based on the approach proposed in Chapter 4 (Wu et al, 2012). The key differences are that the prediction accuracy improvement is considered, and the predicted failure time distribution quantification is different. The procedure of the proposed CBM method is shown in Figure 5-1. Compared with the procedure in the proposed approach in Chapter 4 (Wu et al, 2012), the improvements are mainly shown in phase one.

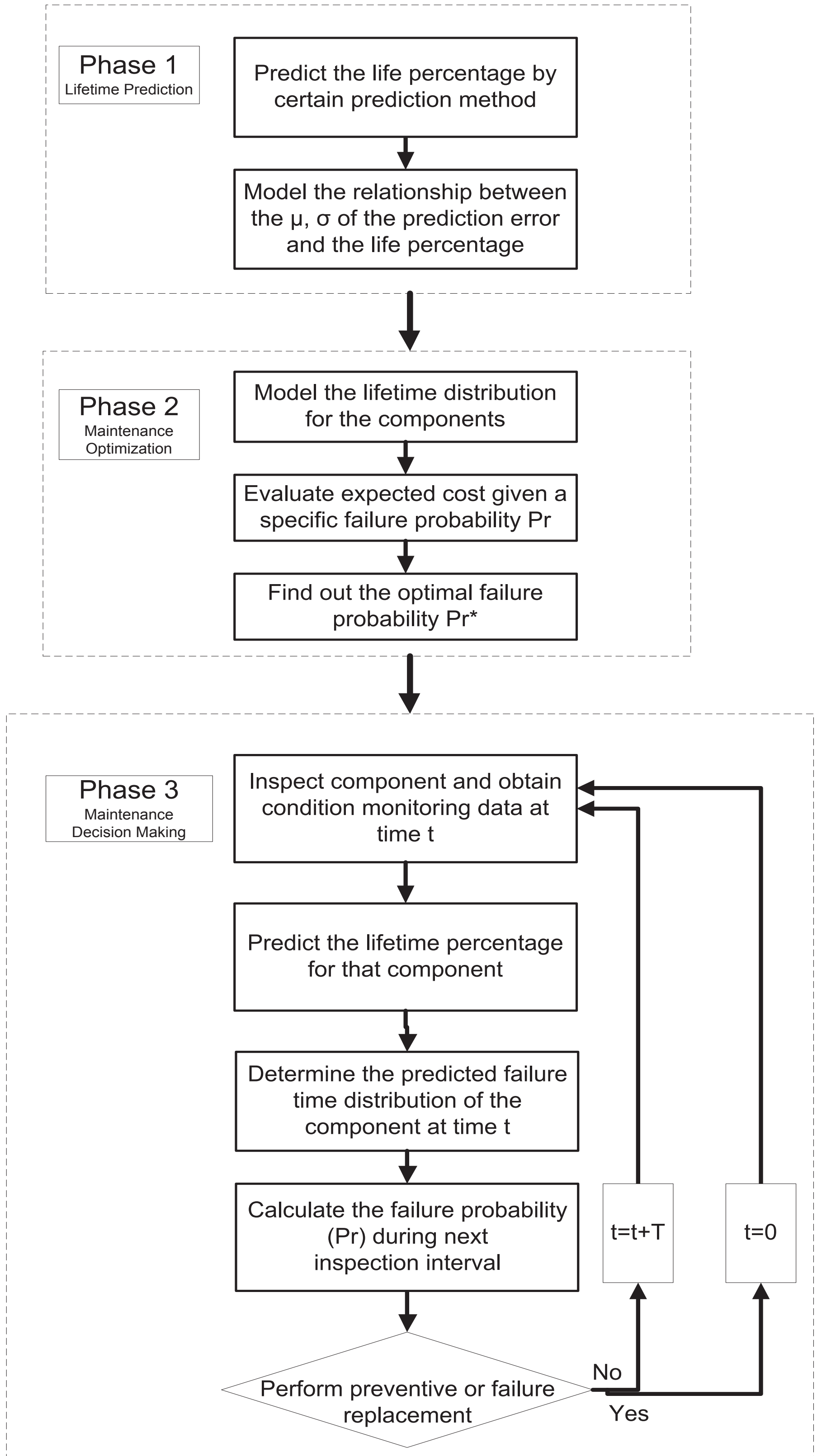

Figure 5-1 Procedure of the proposed CBM approach

Since the CBM decision process and cost evaluation and optimization are similar with the proposed approach in Chapter 4 (Wu et al, 2012), in this chapter we mainly focus on the prediction accuracy and uncertainty modeling.

Suppose at a certain inspection point t, the predicted failure time is $T_{n,t}$. Here "n" is used to indicate that it is the "predicted" failure time value. As mentioned previously, the actual failure time of the component is t_m. Thus the prediction error at time t is defined 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 research 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, denoted by $\mu_{e_{n,t}}$, can be calculated as:

$$\mu_{e_{n,t}} = a_\mu \cdot p_t + b_\mu, \tag{5-1}$$

where a_μ and b_μ are function coefficients. 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 (5-1), we have:

$$\frac{T_{n,t}-T_a}{T_a} = a_\mu \cdot \left(\frac{t}{T_a}\right) + b_\mu, \tag{5-2}$$

and thus

$$T_a = \frac{T_{n,t}-t \cdot a_\mu}{1+b_\mu}. \tag{5-3}$$

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:

$$\sigma_{n,t}^{p} = a_\sigma \cdot p_t + b_\sigma, \tag{5-4}$$

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

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

$$T_{n,t} \sim N\left(T_a, \sigma_{n,t}^2\right). \tag{5-6}$$

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 review (Kacprzynski et al, 2002, Marble and Morton, 2006, Gebraeel, 2006).

5.3. 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.

5.3.1. Case Study

The proposed CBM optimization approach is demonstrated using a real-world case. This condition monitoring data was collected from bearings on a group of Gould pumps at the Canadian Kraft Mill company (Stevens, 2006), as introduced in Chapter 3. In this case, 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).

5.3.1.1. 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 Equation (4-1), the relationship between mean value of prediction error and the life percentage can be modeled as:

$$\mu_{e_{n,t}} = 0.7371p_t - 0.6765 \tag{5-7}$$

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:

$$\sigma_{n,t}^{p} = -0.1076 p_t + 0.1440 \tag{5-8}$$

5.3.1.2. 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 Chapter 4. Based on Equations (4-10) and (4-11), 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. By performing optimization, 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 5-2.

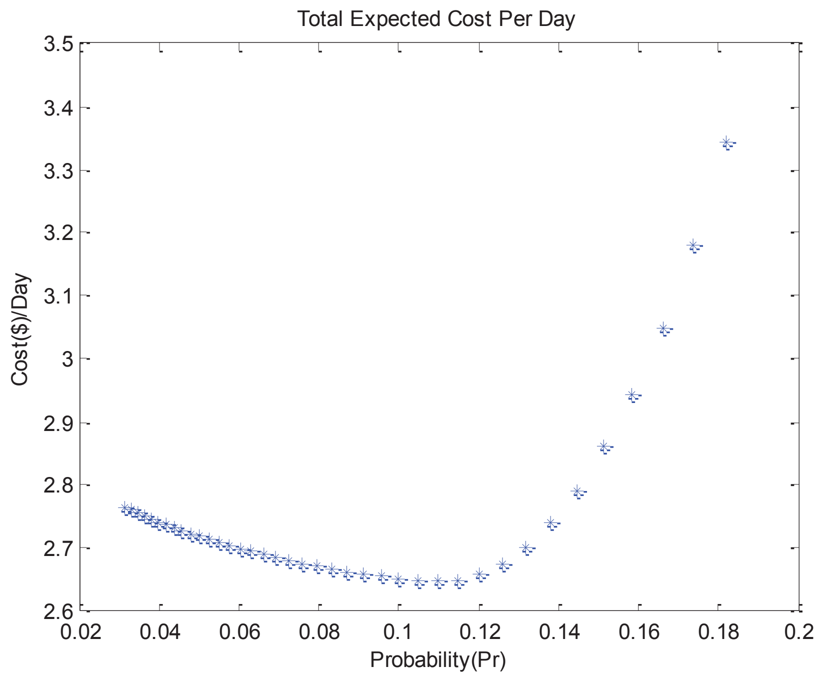

Figure 5-2 Expected replacement cost corresponding to different threshold values

5.3.1.3. 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 567^{th} 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 545^{th} day and the current inspection point 567^{th} 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 (5-2) and (5-3). And using Equation (5-4) and (5-5), the standard deviation of the lifetime prediction error is calculated as 26.03 days. Thus, at inspection point 567^{th} day, the predicted failure time follows the following normal distribution:

$$T_p \sim N\left(612.57, 26.03^2\right) \tag{5-9}$$

So the failure probability during the next inspection interval can be obtained as 0.1329, as shown in Figure 5-3. 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.

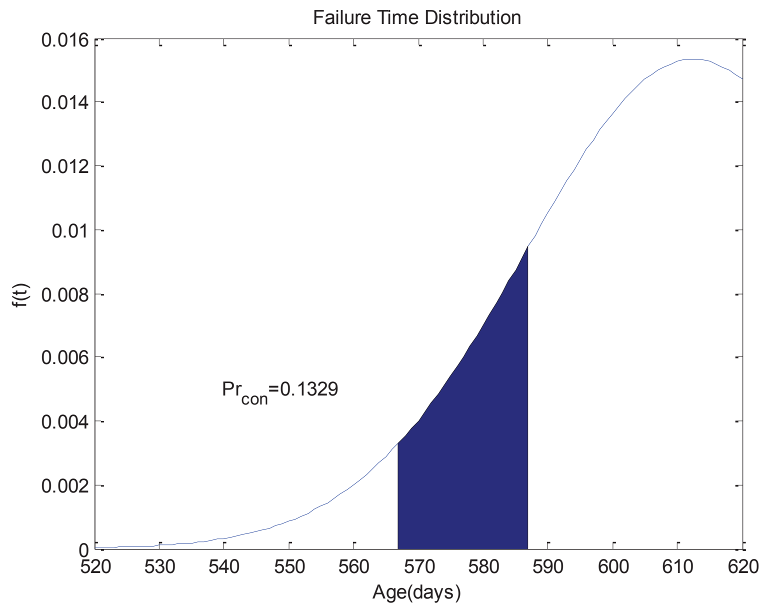

Figure 5-3 Failure probability value at age 567 days

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 5-1. 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 5-1 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

5.3.1.4. 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 5.3.1.2., 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 5-2.

Table 5-2 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	715.4
ANN based replacement policy (Wu et al, 2012)	3.88	
The proposed CBM approach	2.65	

Next we will apply the three maintenance policies to 5 test histories respectively, and investigate how they perform when applying to real inspection histories. Using the same procedure illustrated in Section 5.3.1.3., the implementation results for the 5 histories are shown in Table 5-3. 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 5-3 CBM optimization results comparison when applying to the 5 test histories

No.	**Actual Failure Time**	**Age-based Replacement Policy**			**ANN based Replacement Policy (Wu et al, 2012)**			**The Proposed CBM Policy**		
		Time (days)	**Type**	**Cost ($)**	**Time (days)**	**Type**	**Cost ($)**	**Time (days)**	**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		

P: Preventive replacement.

5.3.2. Simulated Degradation Data Set

In this example, the simulated degradation data set is the same with the one in Section 4.3.1.2 in Chapter 4 (Wu et al, 2012) and (Gebraeel et al, 2005).

Same as the case study, ANN is selected as prediction method in this example. 20 failure histories and 10 failure histories are selected randomly from the 50 generated degradation paths as training histories and testing histories, respectively. Altogether there are 154 lifetime prediction error data points for the 10 test 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.

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:

$$\mu_{e_{n,t}} = a_1 p_t^4 + a_2 p_t^3 + a_3 p_t^2 + a_4 p_t + a_5 \tag{5-10}$$

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

$$\mu_{e_{n,t}} = 5.4775 p_t^4 - 11.5624 p_t^3 + 8.0164 p_t^2 - 1.9814 p_t + 0.1042 \tag{5-11}$$

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:

$$\sigma_{n,t}^{p} = -0.0382 p_t + 0.0748 \tag{5-12}$$

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 5-4.

By applying the two benchmark policies to the degradation signal data respectively, we can obtain the comparison results as shown in Table 5-4. 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.

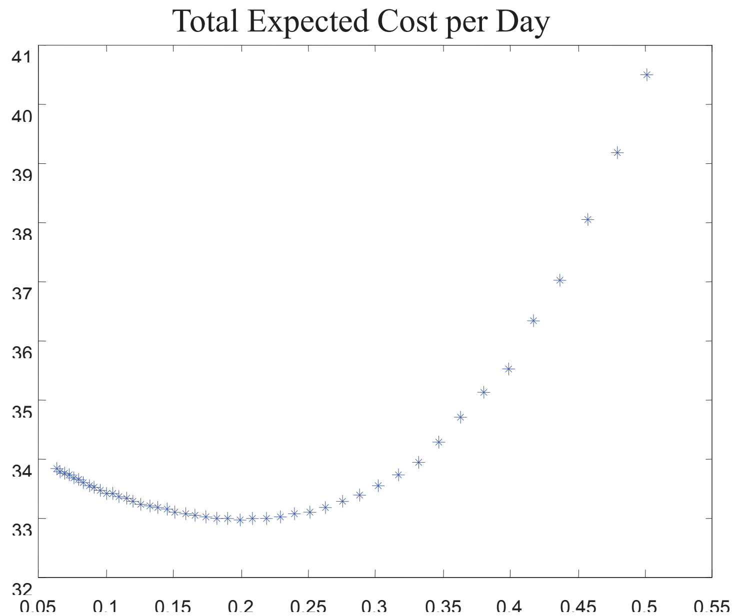

Figure 5-4: Expected replacement cost corresponding to different threshold values

Table 5-4 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	59.7
ANN based replacement policy (Wu et al, 2012)	38.17	
The proposed CBM approach	32.97	

Next we will apply the three maintenance policies to 10 test 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 5-5 is the practical implementation results for each maintenance policy.

Table 5-5 CBM optimization results comparison when applying to the 10 test histories

No.	**Actual Failure Time**	**Age-based Replacement Policy**			**ANN based Replacement Policy (Wu et al, 2012)**			**The Proposed CBM Policy**		
		Time (days)	**Type**	**Cost ($)**	**Time (days)**	**Type**	**Cost ($)**	**Time (days)**	**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		

P: Preventive replacement.

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.

5.4. Concluding Remarks

In this research, we propose a CBM optimization approach considering improved prediction accuracy. In this approach, we quantify the remaining life prediction uncertainty 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 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.

This research has been combined with another research and organized into a journal paper and this paper has been accepted (Tian et al., 2013).

CHAPTER 6 CONCLUSIONS AND FUTURE WORK

6.1. Conclusions

In CBM optimization, the effectiveness of the optimal maintenance policy greatly depends on the accuracy of the equipment health condition prediction. The reported health condition prediction methods can be roughly classified into model-based methods and data-driven methods. Our research mainly focuses on CBM optimization using data driven methods such as PHM and ANN.

In this thesis, we proposed three approaches: the data processing method for CBM using PHM, the CBM optimization using ANN based health condition prediction and the CBM optimization considering improving prediction accuracy.

The data processing method for CBM using PHM

In CBM optimization using PHM, to use actual condition monitoring measurement values directly as input may introduce external noise to the model. Therefore the built model may not accurately represent the health condition of the equipment or component and the optimal maintenance policy obtained based on the PHM model may not be really optimal. In this research, we propose an approach to remove the external noise and fit the inspection measurements before feeding them into the PHM model. The proposed approach is fitting the actual measurements using the Generalized Weibull-FR function.

Two case studies using real-world vibration monitoring data, collected from Gould pump bearing in a Canadian Kraft Mill company and from shear pump bearings in a food processing plant, respectively, are used to demonstrate the proposed approach. The validation result is that the proposed approach will save the average maintenance cost and increase the average replacement interval to make better use of remaining useful life.

The CBM optimization using ANN based health condition prediction

ANN based methods are believed to be very promising tools to predict equipment health condition and remaining useful life. Therefore, we develop a CBM optimization approach based on ANN remaining life prediction information and a numerical method for cost evaluation. The proposed approach can deal with 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.

The proposed approach has been demonstrated to be effective using two simulated degradation data sets, and a real-world condition monitoring data set collected from pump bearings. This approach can also be modified 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.

The CBM optimization considering improving prediction accuracy

It is observed that the prediction accuracy often improves with the increase of the age of the component. Therefore, we develop an approach to quantify the remaining life prediction uncertainty considering the prediction accuracy improvements. In this approach, we quantify the remaining life prediction uncertainty 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. An effective CBM optimization approach is also proposed to optimize the maintenance schedule.

The proposed approach is illustrated using vibration monitoring data collected from pump bearings in the field and another data set from simulated degradation. This approach is compared with two benchmark maintenance policies: age-based maintenance policy and the ANN based maintenance policy considering constant prediction accuracy, and it has been found to be more effective.

6.2. Future Work

Based on the researches elaborated in this thesis, further studies can be conducted in the following directions.

- Develop a CBM optimization approach using bi-variate PHM to determine the optimal maintenance policy for different types of components simultaneously. Currently in the research of CBM optimization using PHM, univariate PHM are often used to analyze the covariates and determine the optimal maintenance policy. In that case, only one variate is considered, that is, we only consider the affect that the covariate brings to one single type of component. And the maintenance policy is also determined for that specific type of component. But usually, a piece of equipment consists of many components and the covariate may have influence on most of the component. In the future, we may investigate to implement a bi-variate PHM using vector hazard rate in maintenance optimization. The influence that the covariates bring to two different types of the components, for example gear and bearing, will be incorporated in this model. The optimal maintenance policy for both components can be determined based on the bi-variate PHM.

- Investigate the application of Accelerated Life Testing (ALT) in CBM optimization due to the reason that it is very costly and time-consuming to conduct a lifetime test. In the application of maintenance optimization using data driven methods, a certain number of failure histories or suspension histories are required to determine the optimal maintenance policy. In practice it is very costly and time-consuming to conduct a lifetime test because of the long lifetimes of most of the components and the challenge of testing components that are used continuously under normal conditions. Accelerated life testing (ALT) is an effective approach to accelerate lifetime test and obtain failure or suspension data of a component or equipment in a much faster manner. By subjecting the tested component to conditions (stress, strain, temperatures etc.) in excess of its normal service parameters, faults and potential modes of failure will be revealed in a short amount of time. In the future research, we may try to apply ALT in maintenance optimization. By increasing the stress loading to the bearing we can accelerate the failure of the bearing and obtain a certain number of bearing failure histories. Based on the failure histories data we can determine the optimal maintenance policy for the bearing using accelerated life testing model.

- Conduct more experiments to further test the approaches proposed in this thesis, which are the data processing method for CBM using PHM, the CBM optimization using ANN based health condition prediction and the CBM optimization considering improving prediction accuracy.

- Apply the developed approaches to address CBM problems in various engineering systems, such as aircraft systems and wind energy systems.

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