Condition Based Maintenance Optimization for Multi-Component Systems Based on Neural Network Health Prediction

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Abstract

Condition Based Maintenance Optimization for Multi-Component Systems Based on Neural Network Health Prediction

Jialin Cheng

Condition-based maintenance (CBM) is an effective maintenance approach to prioritize and optimize maintenance resources based on condition monitoring information. A well established and effective CBM program can eliminate unnecessary maintenance actions, lower maintenance costs, reduce system downtime and minimize unexpected catastrophic failures. Most existing work reported in the literature only focuses on determining the optimal CBM policy for single units. Replacement and other maintenance decisions are made independently for each component, based on the component's age, condition monitoring data and the CBM policy.

In this thesis, a CBM optimization method is proposed for multi-component systems, where economic dependency exists among the components subject to condition monitoring. The proposed multi-component systems CBM policy is based on a method using artificial neural network (ANN) for remaining useful life (RUL) prediction which is proposed by Tian et al. (2009). Deterioration of a multi-component system is represented by a conditional failure probability value, which is calculated based on the predicted failure time distributions of components. The proposed CBM policy is defined by a two-level failure probability threshold. A simulation method is developed to obtain the optimal threshold values in order to minimize the long-term maintenance cost.

We conduct a case study using real-world vibration monitoring data to validate the proposed CBM approach. These data are collected from bearings on a group of Gould pumps at a Canadian Kraft pulp mill company and help to demonstrate the effectiveness of the proposed CBM approach for multi-component systems. The proposed CBM approach is also demonstrated using simulated degradation data for multi-component systems. The proposed maintenance policy can fulfill the requirements of a real plant environment where multiple components are under condition monitoring. By using the proposed CBM policy, maintenance managers can easily and quickly adjust the maintenance schedule according to the working condition of the system.

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Acronyms

CBM	Condition Based Maintenance
ANN	Artificial Neural Network
RUL	Remaining Useful Lifetime
FR	Failure Replacement
PR	Preventive Replacement
AI	Artificial Intelligent
ES	Expert Systems
FLS	Fuzzy Logic Systems
GA	Genetic Algorithm
MTBF	Mean Time between Failures
SBRP	Standard Block-replacement Policy
MBRP	Modified Block-replacement Policy

Chapter 1

Introduction

1.1 Introduction to Maintenance on Multi-Component Systems

Nowadays, the manufacturing industry is always looking for a way to achieve better quality and higher reliability. However, no matter how high quality the equipments have, they will deteriorate over time from operational wear. The Remaining Useful Lifetime (RUL) of the equipment is uncertain even when operating under certain load restrictions or within a specific environment. This will lower the reliability level of the system. Thus, maintenance has been introduced as an efficient approach to improve the reliability level during the useful life of a physical asset (Jardine et al. 2006). Condition-based maintenance (CBM) is an efficient maintenance approach to prioritize and optimize maintenance resources based on condition monitoring data.

The use of condition monitoring techniques has increased rapidly since the 1990s. With rising requirements for production performance, plants have increased cost and complexity while reducing downtime available for routine maintenance (preventive replacement, inspection and adjustment). Condition monitoring is seen as the appropriate technique for better maintenance in these circumstances (Nandi and Toliyat 1999, Wang et al. 2001, Wang et al. 2002, Saha 2003, Sabnavis et al. 2004). The greatest challenges for embedding condition monitoring techniques in decision models are the limited availability of failure histories for monitored components and quantifying the costs and benefits. The costs of data collection need to be balanced against the expected gains as a result of operating a maintenance policy with near-optimum cost (Baker and Scarf 1995). So when we talk about CBM on a component, that component should be under condition monitoring and allowed to fail before it is replaced by a new one. Take a manufacturing plant as an example. There are a great amount of production units containing many moving (rotation) parts such as motors, pumps, gear boxes and valves inside. These units are often in series and when one of the units fails, it can cause the entire system fails, resulting in a great loss in productivity. Various types of deterioration are suitable for CBM analysis, such as a ball bearing wear in a machine (Huang et al. 2007) and gearing wear in a laboratory gearbox experimental system (Tian and Zou 2009). Examples of CBM are the use of information obtained from oil analysis, vibration analysis, fuel consumption, environmental condition, etc. (Benjevic et al. 2001). Through condition monitoring, damage can be identified before failure occurs and unexpected shutdown of the entire system can be effectively prevented by taking preventive maintenance.

Most existing work reported CBM policy only focuses on single unit maintenance. Replacement and other maintenance decisions are made independently on each component, based on the individual component's age, deterioration, condition monitoring data and CBM policy. However, during the past three decades, there has been a growing interest in the modeling and optimization of maintenance of systems that consist of multiple components. The advantages are obvious. First, more complex systems can be investigated at the same time based on the development on analytical techniques and the availability of fast computers. Secondly, interactions, like economic dependency, between components in a system can be taken into account when making maintenance decisions. Economic dependency is common in most continuous operating systems, such as aircraft, ships, power plants, telecommunication systems, chemical processing facilities, and mass production lines (Cho and Parlar 1991). For these types of systems, the costs of system unavailability (e.g. onetime shut-downs) may be much higher than maintenance costs. Therefore, there is often great potential for cost savings by implementing preventive maintenance on multiple components.

Recently several articles address the maintenance of multi-component systems. Cho et al. (1991) reported a survey of maintenance models for multi-unit systems from 1976 to 1991, most of which used time-based model. The most basic time-based replacement policy for multi-component systems is group maintenance policy. Under this policy, some existing literature consider fixed groups of components, which is also known as block-replacement policy (Berg and Epstein 1976, Sheu 1991, Archibald and Dekker 1996); while some consider indirect grouping policy to find optimal possible groupings (Dekker et al. 1997, Van Dijkhuizen 2000). The overview of multi-component maintenance models with economic dependence are summarized by Dekker et al. (1997), including stationary grouping models and dynamic grouping models. The downtime of a system or failure of a component is often an opportunity to combine preventive and corrective maintenance. Berg (1977) proposed an opportunistic maintenance policy for a machine with two identical components. When the failed unit has to be replaced immediately at failure point, the second unit is also replaced by a new one if its age exceeds a predetermined control limit L. The opportunistic maintenance policy can be extended to a multi-level control-limit rule replacement policy, in which several thresholds are defined for performing inspections, preventive and corrective replacements, and opportunistic maintenance (Zheng and Fard 1991, Van der Duyn Schouten and Vanneste 1993, Pham and Wang 2000, Gürler and Kaya 2002). Most of the existing multi-component maintenance models allow groupings of maintenance tasks, but fewer of them are proposed in context of condition-based maintenance. Castanier et al. (2005) consider a condition-based maintenance policy for a two-unit series system. The fixed-cost for inspecting or replacing a component is charged only once if the maintenance actions are taken on both components. Four thresholds for each component are defined for performing inspections, preventive and corrective replacements (individual/joint maintenance). Gupta (2006) analyze strategically optimal maintenance actions for an n-component system whose deterioration is observed through a CBM monitoring system and a simulation-based optimization heuristic is developed to obtain the critical threshold value in order to minimize the long-term maintenance cost.

1.2 Research Motivations

Every inspection or replacement entails a fixed cost and a component-specific unit cost, but if maintenance actions on more than one component are combined, the fixed cost is charged only once. Since the maintenance of systems has become more and more complex, it is sometime worthwhile to replace similar components simultaneously rather than individually. Replacement costs can be saved when several components are jointly maintained instead of separately, that is, economies of scale can be achieved. The motivation for investigating this method is to reduce unit fixed replacement costs, such as sending a maintenance team and equipment to the site, for both failure replacement and preventive replacement. Thus, by considering the fixed replacement cost, it would be more economical to replace multiple components simultaneously instead of replacing one component at a time.

1.3 Research Contributions

A parametric CBM decision framework is proposed to coordinate failure/ preventive replacements on multiple components, and minimize long-run replacement cost of the system. The suggested methodology which allows evaluating the degradation of the multi-component system is based on an artificial neural network (ANN) method for predicting remaining useful life (RUL) which is proposed by Tian et al. (2009).

A simulation model is first introduced by considering a non-repairable single component subjected to stochastic degradation. Then the simulation model is generalized to multiple identical components. The cost optimization procedure is performed to find the optimal degradation thresholds of maintenance decision policy. Simulation results imply that the proposed policy for multi-component systems is more economical than the policy that maintains the system units separately.

A case study is conducted using real-world vibration monitoring data, which are collected from bearings on a group of Gould pumps at a Canadian kraft pulp mill company. This case study demonstrates the effectiveness of the proposed CBM policy for multi-component systems. Besides, a set of simulated degradation data for multi-component systems is also used to demonstrate the proposed CBM policy.

1.4 Thesis Organization

The rest of this thesis is organized as follows:

In Chapter 2, we conduct a detailed literature review on existing maintenance methods for multi-component systems; brief introduction to CBM and ANN prediction models are also given.

In Chapter 3, based on neural network health condition prediction, we propose a CBM optimization method for multi-component systems, where economic dependency exists among the components subject to condition monitoring. Details of the proposed CBM policy for multi-component systems will be discussed and a simulation method is used to obtain the decision variables of the proposed policy.

In Chapter 4, we conduct a case study using real-world vibration monitoring data and use a set of simulated degradation data for multi-component systems to demonstrate the proposed CBM policy for multi-component systems.

Finally, conclusions from our research and several direction of future work are presented in Chapter 5.

Chapter 2

Literature Review on CBM Optimization for Multi-component Systems and ANN RUL Prediction

In this Chapter, before we review the existing maintenance methods for multi-component systems, brief introduction to CBM and ANN prediction models are given.

2.1 Basic Concept and Applications of CBM

In the past several decades, maintenance on deteriorating systems has been extensively investigated in the literature. When maintenance becomes more and more important, there is a growing interest in developing and implementing optimal maintenance strategies, leading to higher system reliability, lower maintenance costs and limited occurrence of unexpected system failures.

2.1.1 Introduction of CBM

Nearly 99% of machine failures are preceded by some indicators (Bloch and Geitner 1983), which means most damage can be identified before failure occurs. Therefore, Condition-Based Maintenance (CBM) is an efficient maintenance approach for prioritizing and optimizing maintenance resources based on condition monitoring data. A well established and effective CBM program will prompt the maintenance personnel to perform necessary maintenance actions at the appropriated time, lower maintenance costs, reduce system downtime and minimize unexpected catastrophic failures. Also important from a psychological point of view, condition monitoring can reduce the uncertainty about the current operation state of the plant by providing knowledge about the vibration levels of a certain critical component, such as a bearing or any other components.

The use of condition monitoring techniques has increased rapidly since the 1990s. In order to achieve rising requirements for production performance, plants have increased cost and complexity, squeezed downtime which are required for routine maintenance (preventive replacement, inspection and adjustment). Condition monitoring is seen as the appropriate maintenance technique which can be used to balance maintenance cost and productivities. CBM can help a company save over 50-80 percent in maintenance costs and improve the profits of a plant by 20-60 percent (Rao 1996). Martin (1994) summarized the history of development and application of maintenance techniques and fault diagnosis of machine tools, from unplanned (breakdown) maintenance to planned maintenance, and the extension of this into condition based maintenance (CBM) and the necessity for condition monitoring. There have been lots of papers reviewing or providing overviews of the research on mechanical systems implementing CBM with an emphasis on models, algorithms and technologies in different fields of application (Nandi and Toliyat 1999, Wang et al. 2001, Wang et al. 2002, Saha 2003, Sabnavis et al. 2004).

No matter what the objective of a CBM program is, a typical CBM program consists of three key steps (Lee et al. 2004):

1. Data acquisition (information collecting), to obtain useful data from targeted physical assets.
2. Data processing (information handling), to analyze the data collected from step 1.

3. Maintenance decision making, to develop efficient maintenance policies for purpose of CBM.

Figure 1 Three steps of CBM program (Lee et al. 2004)

The challenge for embedding condition monitoring techniques in decision models is to quantify the cost and the benefit from implementing a CBM policy; on the other hand, the limited availability of failure histories for monitored components makes more difficult to develop truly condition based maintenance. The costs of data collection need to be balanced against the expected gains as a result of operating a maintenance policy with near-optimum cost (Baker and Scarf 1995), and that is the reason why the first generation of CBM in the oil and gas industry has only focused on vibration in heavy rotating equipment.

2.1.2 Diagnostics and prognostics approaches

As shown in Figure 1, maintenance decision-making is the last step of a CBM program. Diagnostics and prognostics are two main techniques for maintenance decision support in a CBM program. Diagnostics aim at fault detection, isolation and identification when a failure occurs on a component. Prognostics aim at fault prediction before a failure occurs. In another word, diagnostics are posterior event analysis and prognostics are prior event analysis. A CBM program can be applied to perform diagnostics or prognostics, or both. Jardine et al. (2006) review the recent research on diagnostics and prognostics of mechanical systems implementing CBM with an emphasis on models, algorithms and technologies for data processing and maintenance decision support.

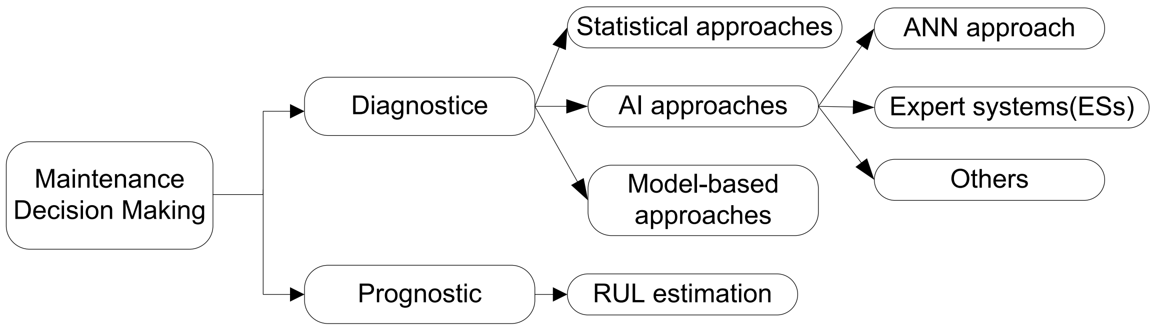

Figure 2 Main techniques for maintenance decision support

Form the definition of prognostics and diagnostics, it is obvious that prognostics is superior to diagnostics in the terms of prognostics can prevent unexpected faults or failures, and thus extra unplanned maintenance cost can be saved by preparing spare parts and planning human resources in advance. However, prognostics, like any other prediction techniques, cannot achieve 100% accuracy of faults and failures prediction, since there are always unpredictable faults and failures, so prognostics cannot completely replace diagnostics. In some practical cases, diagnostics can be a complementary tool for providing maintenance decision support (Wang and Sharp 2002). In addition, diagnostic information can be used as important feedback data for system redesign and helps to improve the accuracy of prognostics or to build better CBM model for prognostics by preparing more accurate event data. Similar to diagnosis, the approaches to prognosis also fall into three main categories: statistical approaches, artificial intelligent approaches and model-based approaches.

2.1.3 ANN approaches for diagnostic

Artificial neural networks (ANNs) is one of the popular artificial intelligence (AI) techniques which have been increasingly applied to machine diagnosis and have shown better performance than other diagnostic approaches. Siddique et al. (2003) review recent developments in applications of AI techniques for induction machine stator fault diagnostics, including Expert Systems (ES), Artificial Neural Networks (ANN), Fuzzy Logic Systems (FLS) and Genetic Algorithm (GA). They also point out that ANN modeling techniques for fault diagnosis sometimes do not provide satisfactory results mainly because of the noise present in the signals, usage of an inaccurate feature set and the local convergence problem. But a multi-layer feed forward ANN can be trained with GA as a global search technique to overcome the problem.

An ANN is a mathematical model that tries to approximate a complex relationship between inputs and outputs or to find patterns in data. Modern neural networks are non-linear statistical data modeling tools. Their learning mechanism is modeled on the human brain's adjustments of its neural connections. An ANN model consists of a network of simple processing elements (neurons). Each processing element comprises a node and a weight. By adjusting its weights with observations of inputs and outputs, ANN learns the unknown function and this process is usually called the training of an ANN. Figure 3 shows the two-layer perceptron structure of a neural network model. The inputs form the input nodes of the network; the outputs are taken from the output nodes. The middle layer of nodes is termed the hidden layer, and unlike the input and output layers, its size is not fixed. The algorithm and the functionality can be found in D. Michie's book (Michie et al. 1994)

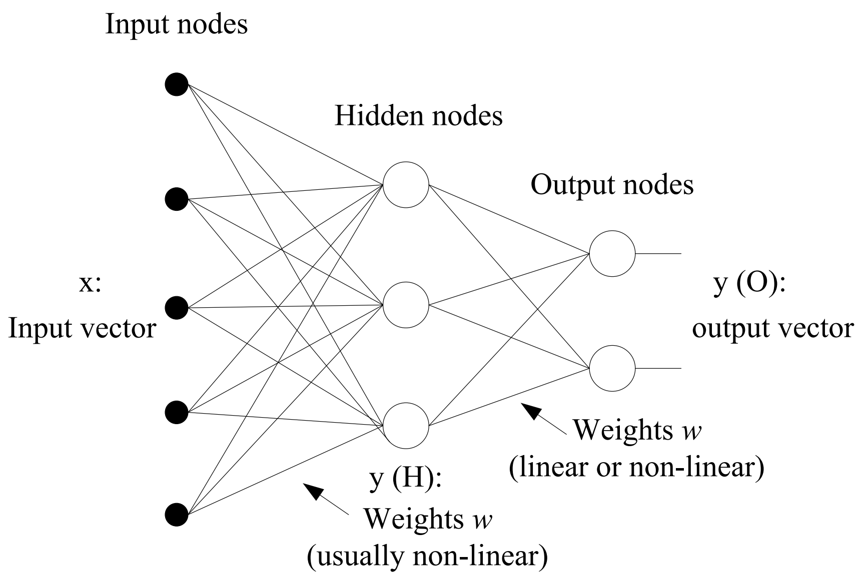

Figure 3 Structure of neural network model (Michie et al. 1994)

Artificial neural networks (ANNs) have also been considered to be very promising tools for predicting machine condition trends due to their adaptability, nonlinearity and arbitrary function approximation ability, and the details can be referred to session 2.2.

2.1.4 RUL estimation

RUL estimation is the major prediction types in machine prognostics. Remaining Useful Life (RUL), also called remaining service life, refers to the time left before a component and/or system of components experiencing a failure. The most widely used prognostics are used to predict the remaining useful life of a physical asset given the current machine condition and previous operation information. RUL can be defined as the conditional random variable (Jardine et al. 2006):

$$T - t | T > t, Z(t), \tag{2-1}$$

where T denotes the random variable of time to failure, t is the current age and $Z(t)$ is the condition profile from past to current time. In the literature, the term "RUL estimation" has two meanings. In some cases, it means finding the distribution of RUL; and in other some, it means the expectation of RUL, i.e.,

$$E[T - t|T > t, Z(t)]. \tag{2-2}$$

Jardine et al. (2006) summarize current AI techniques applied to RUL estimation in their review, including the use of neural networks to estimate the residual life of a bearing system (Zhang and Ganesan 1997), and to predict the machine condition trend (Yam et al. 2001).

2.1.5 Optimal maintenance policies

Maintenance aims to improve system availability and Mean Time Between Failures (MTBF), to reduce failure frequency and downtime. However, sometimes the maintenance required to achieve satisfactory system availability is very costly, so it is also necessary to consider how to reduce maintenance cost. Most research in maintenance involves the study of stochastic behavior of systems under various maintenance policies, in order to determine optimal system maintenance policies. The stochastic behavior of systems usually can be represented by system maintenance cost measures: maintenance cost per unit time, discounted cost rate, and the system reliability measures: availability, MTBF and failure frequency, etc. Generally, an optimal maintenance policy may have at least one or more of the objectives below (Wang 2002):

i. Minimize system maintenance cost rate,
ii. Maximize the system reliability measures,
iii. Minimize system maintenance cost rate while the system reliability requirements are satisfied,

iv. Maximize the system reliability measures when the requirements for the system maintenance cost are satisfied.

An optimal maintenance schedule may properly consider or incorporate various maintenance policies (like age replacement policy; block replacement policy; repair/failure limit; sequential), system configurations, shut-off rules, maintenance restoration degrees, correlated failures and repairs, failure dependence, economic dependence, non-negligible maintenance time, etc. In a series system there exists some shut-off rules. For example, while a failed component in a series system is in repair, all other components remain in ‘‘suspended animation’’ (they do not age and do not fail). After the repair is completed, the system is returned to operation. At that instant, the components in ‘‘suspended animation’’ are as good as they were when the system stopped operating (Barlow and Proshan 1975). Such a shut-off rule is practical and can be applied in other system configurations. Wang (2002) summarize a few shut-off rules and the following points are worthwhile to mention:

i. Because components are building blocks for multi-component systems, it is necessary and worthwhile to develop effective methods for modeling reliability measures and maintenance cost rates of a single-unit system. Analysis of multi-component systems will base on the developed methods for single-unit systems.
ii. Most optimal maintenance models in the literature use the optimization criterion: minimizing the system maintenance cost rate but ignoring reliability performance. However, maintenance aims to improve system reliability performance. Therefore, the optimal maintenance policy must be based on not only the cost rate but also system reliability levels. It is important to note that for multi-component

systems, minimizing system maintenance cost rate may not imply maximizing system reliability measures. Sometimes when the maintenance cost rate is minimized the system reliability measures are so low that they are not acceptable in practice. This is because various components in the system may have different life-time distributions, different maintenance costs and different reliability importance in the system (Wang and Pham, 1997). Therefore, an optimal maintenance policy needs to consider both maintenance cost and reliability measures simultaneously to achieve the best operating performance.

iii. The structure of a system must be considered to obtain optimal maintenance policy and optimal system reliability performance. For example, once a subsystem of a series system fails it is necessary to repair it at once. Otherwise, the system will have longer downtime and worse reliability performance. Meanwhile, when a subsystem of a parallel system fails, the system will still function even if the subsystem is not repaired immediately. In some practical case, repair of the subsystem can be delayed until it is time to perform preventive maintenance on the whole system by taking advantage of economic dependence; or when all subsystems have failed and thus the system fails, if the system failure during actual operation is not critical (Wang et al. 2001).

2.2 ANN RUL Prediction Model

Lots of existing literature proposed the ANN methods that utilized for component or equipment health condition prognostics and remaining life prediction. Lee et al. (2006) shows neural network methods are very intelligent prognostics tools for health condition prediction. A major application of ANN in the mechanical area is prediction of machine deterioration, like health condition prognostics of gears (Tian and zuo 2009), RUL predictions for ball bearings (Huang et al. 2007). Gebraeel et al. (2004, 2008) proposed the ball bearing remaining life prediction methods using vibration-based degradation signals, the output of the ANN models was a condition monitoring measurement, such as overall vibration magnitude.

Tian (2009) developed an artificial neural network (ANN) model based on Wu's method (Wu et al. 2007) and achieved a more accurate remaining useful life (RUL) prediction of equipment subject to condition monitoring. The prediction error is mainly improved by two aspects, one is reducing the effects of noise factors that are irrelevant to the equipment degradation, and another one is utilizing the validation mechanism in the ANN training process. Based on experiments by comparing the option of using two time points and using three time points, Tian et al. found that ANN using two time points is able to produces slightly more accurate prediction results and is more computationally efficient to calculate.

Later, Tian et al. (2009) also developed a neural network approach for RUL prediction utilizing both failure histories and suspension histories. Failure history refers to failure replacement; it means the component is ended with failure. Suspension history refers to preventive replacement, meaning the component ended with suspension and was preventively replaced. The ANN model in this paper takes the age and the condition monitoring measurements values at the current and previous inspection point as input data while the life time percentage of the inspected component at the current inspection point is output data.

2.3 Maintenance for Multi-Component Systems

Since the 1970s, there has been a growing interest in the modeling and optimization of maintenance of systems that consist of multiple components. The advantages are obviously. The developed analytical techniques and the availability of faster computers give promising to investigate more complex systems simultaneously. On the other hand, interactions between components in a system can be taken into account in maintenance decisions. In early maintenance literature, there are three types of interaction between components which are: economic dependence, structural dependence and stochastic dependence (Thomas 1986). That implies a multi-component system consist of several units of machines or many pieces of equipment, which may or may not depend on each other (Cho and Parlar 1991). Economic dependence implies that maintenance costs can be saved when several component are jointly maintained instead of separately, that is economies of scale can be obtained, in another point of view maintenance can be spread over time with simultaneous downtime of components. Structural dependence means if components structurally form a part, one failed component implies maintenance of other components as well. Stochastic dependence also referred to as failure interaction or probabilistic dependence, occurs when the state of a component influences the lifetime distribution of other components. Most multi-component maintenance models only consider economic dependence or structural dependence, since combining them makes the models too complicated to analyze. In this literature review, we will pay more attention to economic dependence because economic dependency is common in most continuous operating systems, such as aircraft, ships, power plants, telecommunication systems, chemical processing facilities, and mass production lines. For this type of system, the cost of system unavailability (e.g. onetime shut-down) may be much higher than maintenance costs. Therefore, there is often a great potential for cost savings by implementing preventive maintenance on multiple components.

Recently several articles address the maintenance of multi-component systems. Cho et al. (1991) reported a survey of maintenance models for multiunit systems from 1976 to 1991, most of which were time-based model. Dekker et al. (1996) gives a good overview of the multi-component maintenance models with economic dependence up to 1997, including stationary grouping models, where a long-term stable situation is assumed, and dynamic grouping models, which can take information into account that becomes available only in the short term. Wang H. (2002) gives a survey of maintenance policies of deteriorating systems. The maintenance policies for single component system are emphasized in this survey, but one section is devoted to opportunistic maintenance policies for multi-component systems. Some optimal maintenance planning for systems consisting of components that interact to each other were summarized in Nocolai and Dekker (2006).

Since the maintenance of systems has become more and more complex, it is sometime worthwhile to replace similar components simultaneous rather than singly. Replacement costs can be reduced when several components are jointly maintained instead of separately, that is economies of scales can be obtained. In the following section, we will review different multi-component system models based on different maintenance or replacement policies.

2.3.1 Group maintenance policy (block replacement)

Group maintenance policy is the most basic multi-component time-based replacement policy. Earlier group maintenance only consider grouping corrective maintenance, that is, components are only correctively maintained and a failed component can be left in the failed state until its corrective maintenance is carried out jointly with other failed components. Grouping of corrective maintenance is applicable for systems in which some kind of redundancy is available. Maintenance policies of this type are motivated by the existence of economies of scale through simultaneous repair of a number of (identical) components. Although leaving components in a failed condition for an extended period can increase the risk of costly production losses, modern management methods make it possible to achieve satisfactory system reliability with lower redundancy. For more detail of grouping corrective maintenance see (Dekker et al. 1997).

The main advantage of preventive maintenance is that its predictability. This is important when work preparation can conducted in advance, for example, new components can be ordered in time and enough maintenance crew are available at the planned maintenance execution times. Set-up cost can be saved by executing preventive maintenance simultaneously, and unexpected failures can be prevented.

An important class of group maintenance policy is block replacement policy. Under this policy, a component is maintained or replaced preventively at fixed intervals, regardless of the events occurring within such an interval. In that case, the average costs $c(T)$ are equal to $c(T) = (s + M(T))/T$, where T is a block interval of length; $M(T)$ expresses the expected costs due to failures (minimal repairs and operating costs over the interval), and s denotes the cost of preventive replacement. When this block replacement applied to a group of components while using the same interval, we have $c(T) = (s_G + \sum_{i=1}^{n} M_i(T))/T$ for maintaining a group of n components preventively at a cost of s_G each time. Sheu (1991) deals with a multiple components system considering minimal repairs and failure replacements within the interval. Notice that the block replacement policy allows the coordination of the replacement of components, but does not react to any event within the interval, such as failure replacement on one of the components.

Archibald and Dekker (1996) extend the modified block-replacement policy (MBRP) from Berg and Epstein (1976) in two ways; 1) a discrete time framework which allows the use of any discrete lifetime distribution, and 2) multi-component systems. In MBRP, components are replaced immediately on failure, and preventive maintenance (PM) is performed at regular intervals. During PM every component whose age is greater than a fixed threshold age is replaced. Unlike many models for multi-component systems, this policy is structured. MBRP results in a lower average cost-rate by replacing components selectively during PM by comparing to the standard block-replacement policy (SBRP) even thought in both of them PM is performed at regular intervals and so can be planned in advance. They also find that compared to the age-replacement policy the MBRP is easier to compute and characterize for multi-component systems.

Similar to block-replacement policies, there are other group maintenance policies for indirect grouping problems. While block-replacement policy considers a fixed group, indirect grouping policy consider the optimization over the possible groupings. This makes the problems more difficult, because of the combinatorial aspects that are involved.

In the standard indirect-grouping models: every T time units an occasion for preventive maintenance is created, and component i is preventively maintained at the integer multiple k_iT of T. For example, if T equal to one month, and $k_1 = 1$, $k_2 = 3$, then component 1 is preventively maintained every month, and component 2 every three months. After preventive maintenance a component is considered as good as new. So we get the total average costs $c(T)$ are equal to $\frac{S}{T} + \sum_{i=1}^{n} \frac{s_i + M_i(k_iT)}{k_iT}$, where the function $M_i(x)$ denoting the expected cumulative deterioration costs of component i (due to failures, repairs, operating costs, etc.), x time units after its latest preventive maintenance; S is the set-up cost incurred each time an occasion for preventive maintenance is created, and s_i is the extra cost of maintaining component i preventively on an occasion. Finding optimal values for T and k_i is a mixed continuous-integer programming problem and in general such problems are difficult to solve. However, since the $c(T)$ function is separable in the vector $k = (k_1, \dots, k_n)$, several fast (heuristic) solution methods can be developed (Dekker et al. 1997).

An extension of the standard-indirect grouping problem is studied by Van Dijkhuizen (2000). The author attempts to build a maintenance model with a hierarchical set-up structure, so preventive maintenance can be clustered in a multiple set-up multi-component system. Each component is maintained preventively at an integer multiple of a certain basic interval, and corrective maintenance is carried out in between whenever necessary. So, every component has its own maintenance frequency which is based on the optimal maintenance planning for single components. In this model, set-up activities may be combined when several components are maintained at the same time. The difficulty is in finding the optimal maintenance frequencies that minimize the average cost per unit of time.

The problem of establishing group maintenance policies, which are best from the view of the system's reliability or operational cost, has received significant attention in the maintenance literature. In Wang's (2002) opinion, there are three classes of problem for group maintenance. One class of problem has been to establish categories of units that should be replaced when a failure occurs. This is particularly important when there are varying access costs associated with disassembly and reassembly, and simultaneous PM of categories of parts may be more appropriate. A second class of group replacement studies has been concerned with reducing costs by including redundant parts into systems design. The third class of papers has been concerned with establishing group maintenance policies for systems of independently operating machines, all of which are subject to stochastic failures from the same distribution. In Popova and Wilson's studies (1999), there are three existing group maintenance policies for the third class of problems which are m-failure, T-age and (m,T) failure group policies for a system of identical components operating in parallel. They assume that downtime costs are incurred when failed components are not repaired or replaced. When the components are left in a failed condition, with the intention to group corrective maintenance, downtime costs are incurred. In the maintenance policies a trade-off between the downtime costs and the advantages of grouping (corrective) maintenance is made.

A T-age group replacement policy (Okumoto and Elsayed 1983), calls for a group replacement when the system is of age T. The m-failure policy (Assaf and Shanthikumar 1987) calls for replacing the system after m failures have occurred. The (m,T) failure group policies (Ritchken and Wilson 1990) combine the advantages of the m-failure and T-age policies. This policy calls for a group replacement when the system reaches the age of T, or when m failures have occurred, whichever comes first. In the *(m,T)* policy, the failure times for each machine are considered as Weibull with cumulative distribution:

$$F(t) = 1 - e^{-(\lambda t)^{\alpha}} \quad \text{for } t > 0, \; and \qquad \lambda, \alpha > 0. \tag{2-3}$$

m and T are the policy decision variables that can minimize the total expected cost which is given by:

$$\min_{m,T} K(m,T) = \frac{C_0 + E(K_s) + E(K_r) + E(K_d)}{E(\tau)} \tag{2-4}$$

which C_0 is the fixed cost of inspecting the machines; $E(K_s)$ is the expected cost of servicing (during the time of operation); $E(K_r)$ is the expected replacement cost; $E(K_d)$ is total expected downtime cost and $E(\tau)$ is expected time between successive renewals, that is, $E(\tau) = E(\min\{T, T_m\})$. The *(m, T)* group replacement policy requires inspection at either the fixed age *T* or the time when m machines have failed, whichever comes first. At an inspection, all failed units are replaced with new ones and all functioning units are serviced so that they become as good as new.

Gertsbakh (1984) introduces a group maintenance policy in an n identical units system. Each unit has exponential lifetimes, and is repaired when the number of failed units reaches the prescribed number *k*, the policy decision variable. Vergin and Scriabin (1977) propose a *(n,N)* policy. Under this group maintenance policy, a unit undergoes preventive replacement if it has operated for *N* periods, and undergoes a group replacement if it has operated n periods and if either another unit fails or another unit reaches its preventive replacement age (where $n < N$). Sheu and Jhang (1997) propose a 2-phase group maintenance policy for a group of identical repairable units. The first phase is the time interval $(0; T]$, and the second time phase is the time interval $(T; T + W]$. Individual units have two types of failures. Type I failures are removed by minimal repairs, whereas Type II failures are removed by replacements or are left idle. A group of maintenance is conducted at time $T+ W$ or upon the kth idle, whichever comes first. The policy decision variables are T, W, and k.

Many maintenance models consider the grouping of maintenance activities on a long-term basis with an infinite horizon. Wildeman et al. (1997) propose a rolling-horizon approach that takes a long-term tentative plan as a basis for a subsequent adaptation according to information that becomes available on the short term, and it yields to a dynamic grouping policy. Costs are minimized since only one set-up is utilized in the execution of a group of activities. This policy makes it easy to incorporate with many preventive maintenance optimization models such as block replacement, inspection and efficiency models and age-replacement models.

2.3.2 Opportunistic maintenance policy

The downtime of a system or failure of a component is often an opportunity to combine preventive and corrective maintenance. Especially in the case of series systems, a single failure results in a breakdown of the system. Of course, non-failed components should not be replaced when they are in a good condition, because useful lifetime would be wasted. The condition of a multi-component system depends on the condition of each component. From the view of minimize maintenance cost, economies of scale are incorporated when maintenance activities are combined. For example, S is a fixed cost that is incurred for any maintenance operation (preventive, corrective or combined), while s_i, c_i are additionally individual cost incurred when component i is subject to preventive or corrective maintenance. We assume that all repairs are supposed to be instantaneous and to result in components which are as good as new. When a corrective maintenance action on component i is combined with preventive maintenance of component k, the associated costs equal to $S + s_i + c_k$, which is S cheaper than in the case of separate actions. The maintenance policies proposed in the articles discussed below use the opportunistic maintenance policy.

Berg (1976, 1977, 1978), suggests a preventive replacement policy for a machine with two identical components which are subject to exponential lifetime distribution. Failure of either of the units causes a failure of the machine and the failed unit has to be replaced immediately. Under this policy, at failure point, the second unit is also replaced by a new one if its age exceeds a predetermined control limit L. Later, Berg (1978) extends it to a trigger-off policy: both units are replaced in one of the following circumstance:

I. When one of the two units fails and the age of the other unit exceeds the critical control limit *L*, both units are replaced;
II. When any of them reaches a predetermined critical age *S*, both units are replaced.

One unit is replaced at age *T* or at failure, whichever occurs first. Control limits *L* and critical ages *S* are the policy parameters to minimize the total expected costs per unit time in the long run.

Van der Duyn Schouten et al. (1998) investigate a maintenance solution for replacing light bulbs in traffic control signals. Each installation consists of three compartments for the green, red, and yellow lights. Maintenance action for light bulbs means replacement, either correctively or preventively. First, economic dependence is present in the form of set-up cost, because each replacement action requires a fixed cost in the form of transportation of manpower and equipment. Second, the failure of individual bulbs is an opportunity for doing preventive maintenance on other bulbs, thus can be saved fixed costs. The authors apply two types of maintenance policies in this article. In the first policy, also known as the standard indirect-grouping strategy (introduced in maintenance by Goyal and Kusy 1985), corrective and preventive replacements are strictly separated. Economies of scale are achieved by combining preventive replacements on various classes of bulbs. The second policy type is opportunistic age-based grouping policy. Upon failure of a light bulb, the failed bulbs and all other bulbs older than a certain age are replaced.

Another extension application of opportunistic maintenance policy is in k-out-of-n system. If $k = 1$, then it is a parallel system; if $k = n$, then it is a series system. One problem of optimizing (age-based) maintenance in k-out-of-n systems is to determine downtime costs when a failure of a component does not directly result in system failure. Smith and Dekker (1997) derive the uptime, downtime and costs of maintenance in a 1-out-of-n system with cold standby, which means that the redundant machines cannot fail while they are waiting and failed units can be replaced by spare units in order to reduce the system downtime. But in general it is very difficult to assess the availability and the downtime costs of a k-out-of-n system. In this article, the authors optimize the following age-based replacement policy. A machine is taken out for preventive maintenance and replaced by a standby one, if its age has reached a certain value, T_{pm}. The maximum long-term economy can be obtained by determining the value T_{pm} and the number of redundant components needed in the system.

Also consider in a k-out-of-n system, the opportunistic maintenance policies proposed in the following article is age-based and also contain a threshold for the number of failures. A modified strategy of maintenance the light-standards is studied in Dekker et al. (1998). A light standard consists of n independent and identical lamps screwed on a lamp assembly. The lamps are subject to stochastic failures and are replaced if the number of failed lamps reaches a pre-specified number m in order to achieve a minimum luminance. That means the replacement of a failed lamp can be postponed till the number of failed lamps reaches a certain number at which the luminance becomes unacceptably low. The set-up activity is an opportunity to combine corrective and preventive maintenance. In this paper, several opportunistic age-based variants of the m-failure group replacement policy are considered and in particular, an age-criterion to indicate which non-failed lamps should be preventively replaced at the same time. A simulation optimization is used to determine the optimal opportunistic age threshold.

2.3.3 Multi-level control-limit rule replacement policy

This kind of maintenance policy is actually an extension of opportunistic maintenance policy. In multi-level control-limit rule replacement policy several thresholds are defined for doing inspections, preventive and corrective replacements, and opportunistic maintenance. These thresholds are maintenance decision variables. Most articles on this type of models only consider single components, when few articles apply this model on multi-component systems.

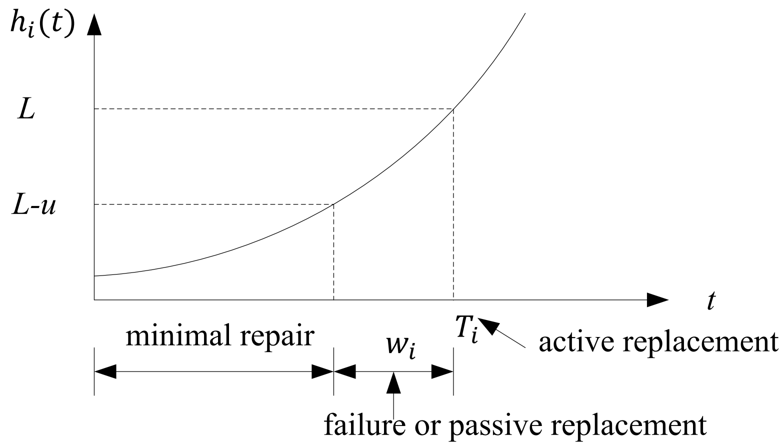

Figure 4 Replacement and repair interval as function of hazard rate (Zheng & Fard 1991)

Zheng and Fard (1991) examine an opportunistic hazard rate replacement policy based on failure rate tolerance for a repairable system with several types of units. A unit is subject to minimal repair at failure when the hazard rate falls in interval $(0, L - U)$, see figure 4. A unit is replaced by a new one either when the hazard rate reaches L or at failure with the failure rate in a predetermined interval $(L - U, L)$. An operating unit is replaced when its hazard rate reaches L. When a unit is replaced due to the hazard rate reaching L, all operating units with their hazard rates falling in $(L - U, L)$ are replaced at the same time. Optimal L and U are obtained to minimize the total maintenance cost rate. Later, Zheng (1995) develops an all opportunity-triggered replacement policy for a non-repairable system with n identical units. In this policy, both failure replacement and active replacement create the opportunities to replace other units preventively. A unit is replaced at failure or when the age of a unit exceeds T, whichever occurs first. When a unit is replaced, all the operating units with their age in the interval $(T - w, T)$ are replaced simultaneously. Optimal T and w are obtained to minimize the mean total replacement cost rate.

Pham and Wang (2000) introduce optimal (τ; T) opportunistic maintenance of a k-out-of-n system with imperfect PM and partial failure. It is a two-stage opportunistic maintenance policy for the system and in the first stage only minimal repairs are performed on failed components before time τ. During time τ to time T, the corrective maintenance (CM) of all failed components are combined with PM of all functioning but deteriorated components when m components have failed; if the system survives to time T without perfect maintenance, it will be subject to PM at time T (see figure 5). Application to aircraft engine maintenance is presented as an example in this article. Based on this policy, Wang et al. (2001) investigate opportunistic preparedness maintenance of multi-unit systems with $(n+1)$ subsystems considering imperfect maintenance and economic dependency.

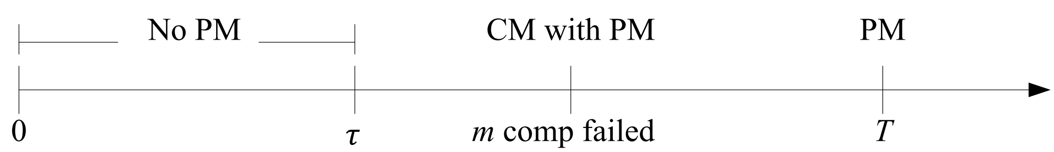

Figure 5 (τ; T) opportunistic maintenance policy (Pham and Wang 2000)

Lots of articles in the maintenance field reveal that the detailed age information on component level should be used in making maintenance decisions. Gürler and Kaya (2002) propose an opportunistic maintenance policy for a series system with identical items, which is an extension work by Van der Duyn Schouten and Vanneste (1993). In their model, the lifetime stature of the components is described by several stages, which are classified as good, doubtful, preventive maintenance (PM) due and failed. The proposed policy is of the control-limit type. Components which are PM due or failed are preventively or correctively replaced immediately. The entire system is replaced when a component is PM due or failed and the number of components in doubtful states is at least N. Here, N is a policy decision variable that achieves significant savings in this policy.

2.3.4 CBM optimization method for multi-component maintenance

In condition-based maintenance, the maintaining decision is taken based on the observed condition of the system. Cost and other system resource can be saved by taking preventive maintenance only when necessary. So far, most published research on condition based maintenance deals with simple one-unit systems, fewer of them subject to multi-component systems.

Fran Barbera et al. (1999) built a condition based maintenance model with exponential failures and fixed inspection intervals for a two-unit system in series, which introduced in Ozekici (1988) first, in order to minimize the long-run average cost of maintenance actions and failures. For identical unit, Fran's policy can be simplified and summarized as follows:

- Decision A: Repair only Unit 1 when $X_{t2} \leq a$ & $X_{t1} \geq b$ $(a < b)$;
- Decision B: Repair only Unit 2 when $X_{t1} \leq a$ & $X_{t2} \geq b$ $(a < b)$;
- Decision C: Overhaul the system when $X_{t1} + X_{t2} \geq c$ & $X_{t1} > a$ & $X_{t2} > a$ $(a < b < c)$;
- Decision D: Do nothing otherwise.

X_{ti} $(i = 1{,}2)$ is the state (condition) of unit i at the end of period t. So X_{0i} is assumed as an initial state value of unit i and $X_{0i} = 0$. a, b, c $(a < b < c)$ is the optimal numerical solution to the dynamic programming equation which is the minimum cumulative cost. The optimum cumulative future cost from period t on is denoted as $f_t(X_{t1}, X_{t2})$, and is equal to the minimum of the cost of period t plus the optimum cumulative future cost at period $t + 1$ $(\text{i.e.}, f_{t+1}(X_{t+1,1}, X_{t+1,2}))$.

$$f_t(X_{t1}, X_{t2}) = \min_{\delta_1,\delta_2}(K_1\delta_1(1 - \delta_2) + K_2\delta_2(1 - \delta_1) + K\delta_1\delta_2 + H(X_{t1}^*, X_{t2}^*) + f_{t+1}(X_{t+1,1}, X_{t+1,2})) \quad (2\text{-}5)$$

where $\delta_i = \begin{cases} 0 & \text{if no maintenance action is initiated on unit } i \\ 1 & \text{if a maintenance action is initiated on unit } i \end{cases}$

and $X_{ti}^* = X_{ti} - [X_{ti} - X_{0i}]\delta_i$. $H(X_{t1}^*, X_{t2}^*)$ is the conditional expected cost of failure at the end of period t.

Barata et al. (2002) investigate the use of Monte Carlo (MC) simulation for modeling continuously monitored deterioration systems and finding the optimal degradation threshold of ‘on condition’ maintenance strategy that minimizes the expected total system cost over a given mission time by a direct search. A non-repairable single component subjected to stochastic degradation was first considered in this paper and then the degradation model was generalized to multi-component repairable systems. As a result of that, a two-component series system has a higher total expected cost than one-component repairable system due to the greater degradation rate of the second component which leads to more preventive maintenance actions, failures and replacements.

Marseguerra et al. (2002) proposed an approach which combined the Monte Carlo simulation method, for a more realistic modeling of the degradation process, and Genetic Algorithms (GAs), for searching the optimal thresholds (a degradation level) which can simultaneously optimizing two typical objectives of interest, profit and availability.

The objective function of the maintenance optimization model usually consists of a fixed-cost (the set-up cost) and variable cost. Castanier et al. (2005) consider a condition-based maintenance policy for a two-unit series system. The fixed-cost for inspecting or replacing a component is charged only once if the maintenance actions are taken on both components. That means joint maintenance of two components saves costs. In this article the condition of the components is modeled by a stochastic process and it is monitored by non-periodic inspection. Four thresholds for each component are defined for doing inspections, preventive and corrective replacements (individual/joint maintenance). A cost model based on the long-term average operating cost per unit of time is proposed to optimize the performance of the multi-threshold policy. The cumulative operating cost up to time t is:

$$C(t) = C_{INSP}(t) + \sum_{i=1}^{2} C_{PREV}^{(i)}(t) + \sum_{i=1}^{2} C_{CORR}^{(i)}(t) - c_s N_{SR}(t) + C_{FU}(t) \quad (2\text{-}6)$$

where:

- $C_{INSP}(t)$ is the cumulative cost associated with the system inspections on a horizon of length t;

- $\sum_{i=1}^{2} C_{PREV}^{(i)}(t)$ is the cumulative cost associated with the preventive replacements of the component i independently on the operation performed on the component j (i.e. it includes the cumulative set-up costs);
- $\sum_{i=1}^{2} C_{CORR}^{(i)}(t)$ is the cumulative cost associated with the corrective replacements of the component i independently on the operation performed on the component j (i.e. it includes the cumulative set-up costs);
- c_s is set-up cost and $N_{SR}(t)$ is the total number of complete system replacements performed between 0 and t;
- $C_{FU}(t)$ is the cumulative cost incurred by the time elapsed by the system in the failed state (i.e. when at least one component has failed).

So the long-run average operating cost per unit time is defined as: $C_{\infty} = \lim_{t\to\infty} \frac{\boldsymbol{E}(C(t))}{t}$.

Gupta (2006) aims to analyze strategically optimal maintenance actions for an n-component system whose deterioration is observed through a monitoring system set in place to support CBM. Deterioration of a multi-component system is modeled by a continuous-time jump diffusion model which incorporates interaction between the components of the system. Under this policy, A decision maker can create an option to maintain a system and/or its components if the deterioration of the system and/or its components exceeds a critical threshold level, ${D^{th}}_{sys}$ or ${D^{th}}_{i}$, respectively, $i \in \{1, \ldots, N\}$. A component fails if its deterioration level exceeds the maximum deterioration level: ${D^{th}}_{i} \geq {D^{max}}_{i}, i \in \{1, \ldots, N\}$. The whole system fails when ${D^{th}}_{sys} \geq {D^{max}}_{sys}$. A simulation-based optimization heuristic is developed to obtain the critical threshold value in order to minimize the long-term maintenance cost.

Zhou et al. (2006) introduce a condition-based predictive maintenance (CBPM) model for continuously monitored multi-unit series system. First, they applied CBPM model for a single-unit: PM is performed whenever the reliability of unit i reaches the thresholdR_i. Then by introducing the "set-up cost" concept, a dynamic opportunistic maintenance (OM) policy for multi-unit system was developed. The substance of the OM policy is to determine the optimal combination $G^*$of the n component system by maximizing the cost saving. For example, in a three-unit system, there are four possible combination candidates. If G^* is $\{(1, 2), 3\}$, it means when unit 1 reaches its reliability threshold, only unit 2 is performed a PM action together with unit 1.

Tian and Liao (2010) investigate a multi-component system CBM policy based on proportional hazards model (PHM), where economic dependency exists among different components subject to condition monitoring. The fixed preventive replacement cost only incurred once when multiple components preventively replace simultaneously. In their proposed policy, component i is preventively replaced if $K \cdot h_i > d_1$, where K is a constant, h_i is the hazard value of component i. A preventive replacement on one component offers the opportunity to combine preventive maintenance on other components. So if preventive replacement is performed on any component in the system, perform preventive replacement on component j if $K \cdot h_j > d_2$, d_1, d_2 $(d_1 \geq d_2 \geq 0)$ are the level-1 and level-2 on condition risk threshold and which are the PHM based CBM policy decision variables to minimize the long-term expected replacement cost.

Chapter 3

CBM Optimization for Multi-Component Systems Based on ANN RUL Prediction

Condition-based maintenance optimization is a process that attempts to balance the maintenance requirements (cost, system reliability, etc.) and the maintenance resources (manpower, equipment, facilities, etc.), based on the condition monitoring data. The objective of this process is to select the appropriate maintenance strategy for the multi-component systems and identifying the optimum time for replacement of components before failure in order to achieve high system reliability and low replacement costs. The maintenance optimization process will effectively improve system reliability and reduce overall maintenance costs.

The optimal CBM policy for multi-component systems directs the maintenance actions using the information collected through condition monitoring. In this Chapter, we illustrate the methodology of CBM Optimization for Multi-Component Systems based on ANN health condition prediction. A simulation method for cost evaluation will be illustrated and we will see how the optimal CBM policy can achieve a lower maintenance cost.

Deterioration of multi-component systems in this paper is represented by a condition failure probability value. The CBM policy we proposed is defined by a two-level failure probability thresholds and simulation optimization is used to determine the failure probability thresholds. Systems consisting of multiple identical components are referred to multi-component systems when we consider there will be economic dependency existence among the components.

Notations:

μ, σ	Parameters of the normal distribution;
α, β	Parameters of the weibull distribution;
Pr_1^*	Level 1 failure probability threshold;
Pr_2^*	Level 2 failure probability threshold;
C_f	The cost of performing a failure replacement;
C_p	The variable cost of performing a preventive replacement;
C_{p0}	The fixed cost of performing a preventive replacement;
N	The number of components in the multi-component systems;
L	The constant inspection interval;
C_r	Total expected replacement cost per unit time;
PT_i	Predicted failure time of component i;
FT_i	Actual failure time of component i;

3.1 The methodology of CBM policy

Regarding the multi-component systems under discussion, we make several assumptions as follows:

- The components in the system are identical, and are independent in their degradation and failure process.
- The components in the system are economically dependent. That means, a fixed preventive replacement cost, denoted by C_{p0}, is incurred when preventive replacement takes place on any component. If preventive replacement is performed on multiple components simultaneously, the fixed preventive cost is incurred only once.
- Inspection points of the monitoring system are discrete and equally spaced, that is, between each inspection point, there is a fixed interval.
- The condition of the component is monitored and predicted continuously. Each preventive or failure replacement will always restore the component to an "as good as new" condition.
- The costs of failure replacement are much higher than those associated with preventive replacement since an unexpected failure may cause unnecessary delays, long downtime of the system or damage to other equipment.

In our research work, the predicted failure time distribution can be obtained by ANN health prediction model at each inspection point, and the degradation of a component is denoted by Pr, which is the condition failure probability from current to the next inspection time. By performing CBM optimization, an optimal threshold failure probability value can be obtained, which is denoted by Pr^*. At each inspection point, Pr^* is a threshold value that helps to make maintenance decisions on each component whether it should be replaced (preventive replacement or failure replacement) or should continue its normal operation.

As pointed out in Chapter 2, maintenance of multi-component systems differs from that of single unit system because (economic/ structural/ stochastic) dependency exists. Therefore, when considering economic dependency among the components, if certain criteria we set are met, performing preventive replacements for multiple components simultaneously can significantly reduce the overall long-run replacement cost. In the following section, we illustrate the methodology of CBM optimization for both single unit and multi-component systems.

The CBM policy for single unit

The CBM policy for single unit based on ANN RUL prediction method is summarized as follows:

1) Inspect a component which is subjected to condition-based monitoring in a fixed interval. At each inspection time, calculate the predicted failure probability Pr of the component based on ANN RUL prediction method.
2) When a component's Pr exceeds the threshold value Pr^*, preventively replace the component. Otherwise, the operation can continue.
3) When a component fails, perform failure replacement.

Thus, the CBM policy for single unit is defined by the failure probability threshold value, denoted by Pr^*, there is only one decision variable in the single unit CBM policy.

The proposed CBM policy for multi-component systems

In multi-component systems, Pr^* is used to determine not only when and also which components should be preventively replaced at each inspection time. The ANN RUL prediction based CBM policy for multi-component systems are proposed as below:

1) Inspect these components which subjected to condition-based monitoring in a fixed interval. Calculate the predictive failure probability of each component at each inspection time based on ANN RUL prediction method.
2) When a component's predicted failure probability Pr exceeds the level-1 threshold value Pr_1^*, preventively replace the component.
3) When a component fails, perform failure replacement.
4) When there is a preventive replacement or a failure replacement performed on any component in the system, simultaneously replace other components if their Pr values exceed the level-2 threshold value Pr_2^*.

At each inspection time, one of the following events takes place exclusively for each component i:

1. Component i reaches Pr_1^* $\rightarrow$ a preventive replacement is performed on i.
2. Component i reaches Pr_2^* if there is a failure replacement or a preventive replacement that needs to be performed on one of the components in the multi-component systems $\rightarrow$ preventively replace component i simultaneously.
3. Component i fails $\rightarrow$ a failure replacement is performed, the component is replaced by a new one.
4. None of the above $\rightarrow$ component i continues its normal operation.

3.2 Calculation of predictive failure probability

The predictive failure probability is decision variable in our proposed CBM policy. Calculation of this value is based on a predicted Remaining Useful Lifetime (RUL) of a component using ANN prognostic approach. Therefore, the predicted accuracy will influence the feasibility of the CBM policy. Support vector machines (SVMs) are another promising machine learning tools, which are widely used in statistical classification and regression analysis. In our research, we compared the predicted accuracy between ANN and SVMs, and the comparative results are shown in table 1.

Table 1 The RUL prediction result

	Mean Prediction Errors (%)	Standard Deviation of Errors (%)
SVMs approach for RUL prediction	38.5%	43.4%
ANN approach for RUL prediction	13.8%	14.3%

Although some research show that SVMs have great learning performance and generalization ability in failure prognosis (Khawaja and Vachtsevanos 2009, Saha et al. 2009), it still has its limitation and is unsuitable for long-term predictions in some case. Based on our experience, ANN approach for RUL prediction achieves a more accuracy and is more adaptive in our case. Tian's ANN prediction model (2009) is used in this research, and the output of this model is a predicted failure time or a RUL of a component which subject to condition monitoring. Although there is only one output, the uncertainties associated with the predicted failure time still exist, which we called the ANN life percentage prediction errors. We obtain these errors during the ANN training and testing processes and use them to construct the predicted failure time distribution.

As shown in Figure 6, during the ANN training process, both failure histories and suspension histories are used for training the ANN model. The inputs include the component's age data and two condition monitoring measurements at the current and previous inspection point. The output of the ANN training model is the life percentage of the inspected component in the current inspection time. The ANN training process is actually a process of searching minimum training error which corresponding to an optimal training model that would be used in the testing process in the next step. Different weights and bias are adjusted to minimize the training error which denoted by the difference between predicted life percentage and the actual life percentage. The best performing ANN training model which has the minimum training error is used for ANN testing. Therefore, the ANN prediction error is defined as the difference between the ANN predicted value and the actual life percentage value at any inspection point in the test histories. For example, the age of the component at a certain inspection point is 400 days and the ANN predictive life percentage value is 78.3%, that means the predicted failure time is 400/78.3% = 511 days. The actual failure time of the component is 540 days. As a result, the ANN prediction error is $\left|\frac{511-540}{540}\right| \times 100\% = 5.37\%$. Since there are many inspection points in each test histories (both failure and suspension histories), a set of ANN life percentage prediction errors can be obtained by using several inspection histories for ANN testing.

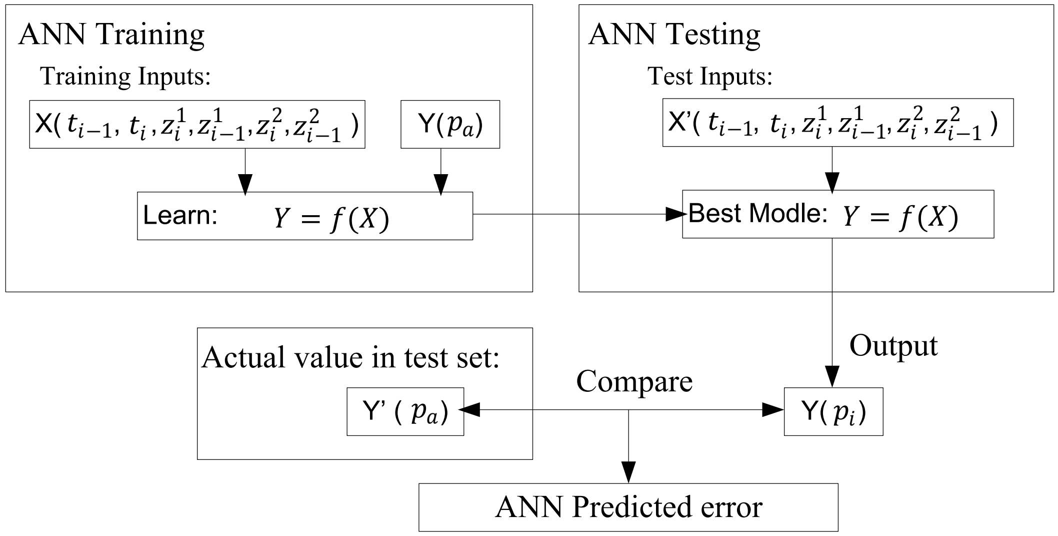

Figure 6 Structure of the ANN model for RUL prediction

After analyzing these ANN prediction errors, we assume that these values follow a normal distribution $N(\mu_p, \sigma_p^2)$, and we can estimate the mean μ_p and standard deviation σ_p. Assuming that the ANN life predicted percentage is P_t at the inspection point t, so the mean of the predicted life percentage is $(P_t - \mu_p)$, and the standard deviation is σ_p, if t also represents the current age of the component, then the mean predicted life time is $t/(P_t - \mu_p)$, and the corresponding standard deviation is $\sigma_p \cdot t/(P_t - \mu_p)$. So we can conclude that the predicted life time/ failure time FT_p follows the normal distribution:

$$FT_p \sim N\left(\frac{t}{P_t - \mu_p}, \left(\frac{\sigma_p \cdot t}{P_t - \mu_p}\right)^2\right) \tag{3-1}$$

Thus, we consider the same circumstance in a multi-component system. For example, we suppose there are 3 components under condition monitoring, all of their predictive lifetime distribution follow normal distribution (3-1) (see Figure 7), the distribution mean,

$\mu = \frac{t}{P_t - \mu_p}$, is predicted failure time of each component and $\sigma = \frac{\sigma_p \cdot t}{P_t - \mu_p}$ is the time prediction error standard deviation.

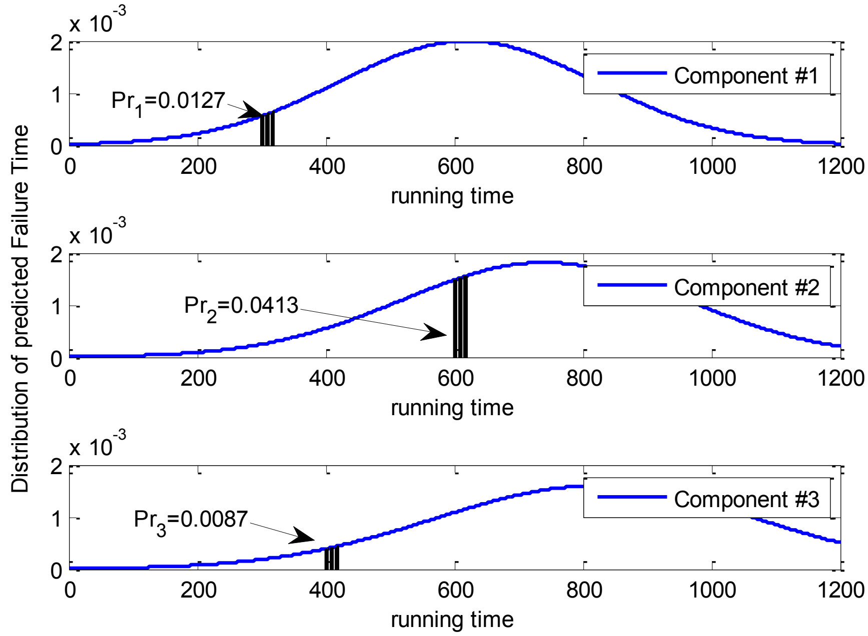

Figure 7 Calculation of failure probability for 3 components

The conditional failure probability during the next inspection time can be calculated through the following equation:

$$Pr_i = \frac{\int_{t_i}^{t_i+L} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt}{\int_{t_i}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt} \tag{3-2}$$

where t_i is the inspection time of component i, L is the constant inspection interval, μ is the predicted failure time using ANN RUL prediction, and σ is the time prediction error standard deviation. As showed in figure 7, the failure probability according to each component during the next inspection interval is equal to the area of shadow region divided by the right side area starting from the current inspection point of time. P_r indicate the probability that a component operates with a fail until next inspection interval.

3.3 CBM Optimization model

Pr_1^* and Pr_2^* are the decision variables in our proposed CBM policy for multi-component systems. By setting these two variables in different values, we can obtain different maintenance strategies and different corresponding expected replacement cost. The objective of the CBM optimization is to identify the most optimum time for replacement of components before failure in order to minimize the long-run expected replacement cost. In another word, the optimal failure probability thresholds indicate when and which component we perform failure/ preventive replacement can achieve the minimum long-run expected replacement cost. The optimization model can be formulated as below:

$$\min C_r(Pr_1^*, Pr_2^*) \tag{3-3}$$

$$s.t.$$

$$C_r \leq C_0\,, 1 \geq Pr_1^* \geq Pr_2^* \geq 0$$

where C_0 is the cost constraint value, Pr_1^* and Pr_2^* are Level-1 and Level-2 failure probability threshold values and also are the policy decision variables.

3.4 Simulation method for cost evaluation

In our research, a simulation method is used to model a real-life situation in Matlab to calculate total expected replacement costs. By changing two level conditional failure probability thresholds, Pr_1^* and Pr_2^*, we can obtain different expected replacement costs results. After the simulation process, we can determine the optimal condition failure probability threshold value which corresponds to the minimum expected replacement cost. At the beginning of this section, we will explain the simulation method of cost evaluation for single component. Then, following the same rule, a simulation method used for cost estimation for multi-component systems will be further described.

3.4.1 Simulation method for single unit component

The procedure of the simulation method for one component is given as follows.

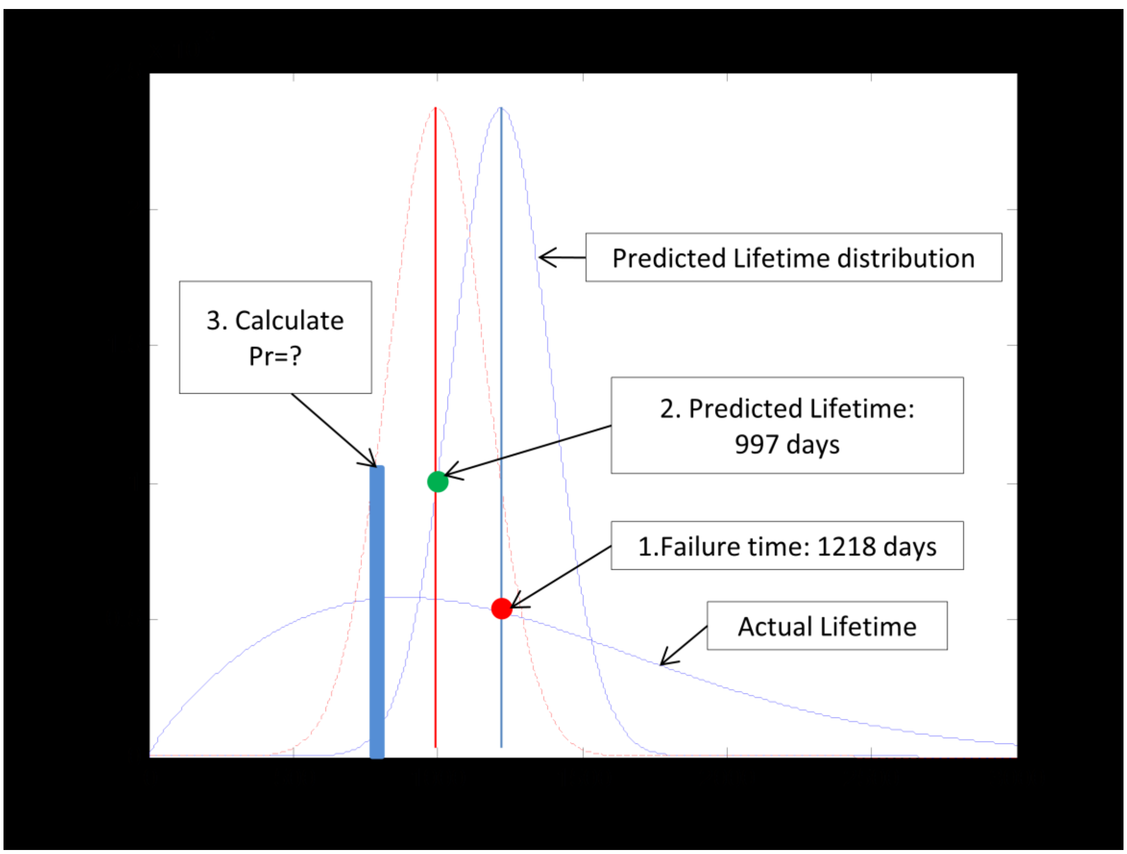

Figure 8 The procedure of simulation for calculating Pr

Step 1: Define the maximum simulation iteration.

Set the maximum simulation iteration NT, for example, 100,000 inspection points. It means we start from inspection point 0 and end with inspection points 100,000. Between each inspection point, there is a fixed inspection interval L, like 20 days. In general, the more iteration we set, the more accurate the simulation result can be achieved.

Step 2: Generate a random failure time as the actual failure time of a component.

Weibull analysis is a promising method of analyzing and predicting failures and malfunctions of all type (Jardine and Tsang 2006). In general, distribution of data on product life time can be modeled by a Weibull function with distribution parameters α, β.

$$f(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1} \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right] \qquad \text{for } t \geq 0 \tag{3-4}$$

Thus, the lifetime distribution of a component can be obtained with the available failure and suspension histories subject to condition monitoring. The maximum likelihood method bellow can help us to estimate the lifetime distribution parameters α and β.

$$L = \prod_{i=1}^{n_E} f(t_i;\ \theta) \cdot \prod_{j=1}^{n_R} R(t_j^{+};\ \theta) \tag{3-5}$$

The first part of the likelihood function is the probability density function of the distribution of the exact failure data. The second part is the reliability function distribution of the suspension data. $n_E$and n_R are the total numbers of failure and suspension histories; θ is the parameters need to be estimated. In order to simplify the calculation process, we take logarithm on both side of equation (3-5). In our case, Matlab optimization function is performed to find the optimal parameters which can maximize the objective function lnL. Details of how to using the maximum likelihood function is given in Chapter 4.

After a component was replaced (failure / preventively) by a new one, a new life cycle begins. At the starting point of a new cycle, we generate a random failure time, FT, of the component which follows Weibull distribution (3-4) with the parameters α, β. See Figure 8, label 1. The value of FT is defined as the actual lift time of the component in our case.

Step 3: Generate a random predicted failure time of a component.

We supposed the objective component was under condition monitoring and regularly inspect. In inspection point k ($k = 0, \ldots, NT$), generate a predicted failure time,PT_k, of the component by random, based on ANN RUL prediction error (See Figure 8, label 2). This predicted lifetime distribution follows normal distribution:

$$PT_k \sim N(\mu, \sigma^2) \tag{3-6}$$

By considering there is a prediction error exist, in our case: $\mu = FT$, $\sigma = \sigma_p \cdot FT$, σ_p is standard deviation of ANN RUL prediction error.

Step 4: calculation of predicted failure probability.

During a lifetime of the component, calculate predicted failure probability Pr in each inspection point by using equation below (see figure 8, label 3):

$$Pr_k = \frac{\int_t^{t+L} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t-PT_k)^2/2\sigma^2} dt}{\int_t^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t-PT_k)^2/2\sigma^2} dt} \quad (k = 0, \ldots, NT) \tag{3-7}$$

Where t is the inspection time in one life circle at inspection point k, L is the constant inspection interval, and $\sigma = \sigma_p \times FT$, σ_p is standard deviation of ANN RUL prediction error.

If Pr_k is greater than the failure probability threshold P_r^*, preventively replace the component at inspection point k. When t exceeds FT and there is no preventive replacement performs during the lifetime of a component, perform failure replacement at the inspection point just behind the generated failure time FT.

In order to calculate the total replacement cost, we introduce two variables to represent the stature of a component:

$$\Delta_{pk} = \begin{cases} 1 & \text{The component is preventively replaced at the point of time } k; \\ 0 & \text{No preventive replacement on the component at the point of time } k. \end{cases}$$

$$\Delta_{fk} = \begin{cases} 1 & \text{The component fails and is replaced by a new one at the point of time } k; \\ 0 & \text{No failure replacement on the component at the point of time } k \end{cases}$$

If $\Delta_{pk} = 0$ & $\Delta_{fk} = 0$, the component continues its normal operation.

Step 5: New life cycle start.

Start a new life cycle of the component after a preventive replacement or a failure replacement took place, back to *Step 2*. The iteration would not stop until maximum simulation inspection point is reached.

Step 6: Estimate total expected replacement cost.

After the maximum simulation inspection point is reached, we can calculate the total expected replacement cost by the following formula:

$$C_r = \frac{Cost\_total}{Time\_total} = \frac{\sum_{k=0}^{NT}\left((C_{po} + C_p) \cdot \Delta_{pk} + C_f \cdot \Delta_{fk}\right)}{NT \times L} (\$/day) \tag{3-8}$$

where C_{po} and C_p are the fixed and variable cost of preventive replacement that occur in inspection point k, C_f is the failure replacement cost. NT is the total inspection point in the simulation process, L is the inspection interval.

Step 7: Determine the optimal CBM policy.

The predicted failure probability threshold is decision variable in the single unit CBM policy. The minimum calculated cost corresponding to the optimal predicted failure probability threshold value P_r^*. So once P_r^* is determined, the optimal CBM policy is determined and the optimization model as follow can be satisfied.

$$\min C_r(P_r^*) \qquad s.t. \quad C \leq C_0 \, , P_r^* \geq 0 \tag{3-9}$$

3.4.2 The proposed CBM policy cost evaluation

We assume that there are N components in the multi-component systems. The procedure of the simulation method for CBM policy cost evaluation is shown in Figure 9, and is discussed in details as follows:

Step 1: Define the maximum simulation iteration.

Set the maximum simulation iteration NT, for example, 100,000 inspection points. It means we start from inspection point 0 and end with inspection points 100,000. Between each inspection point, there is a fixed inspection interval L, like 20 days.

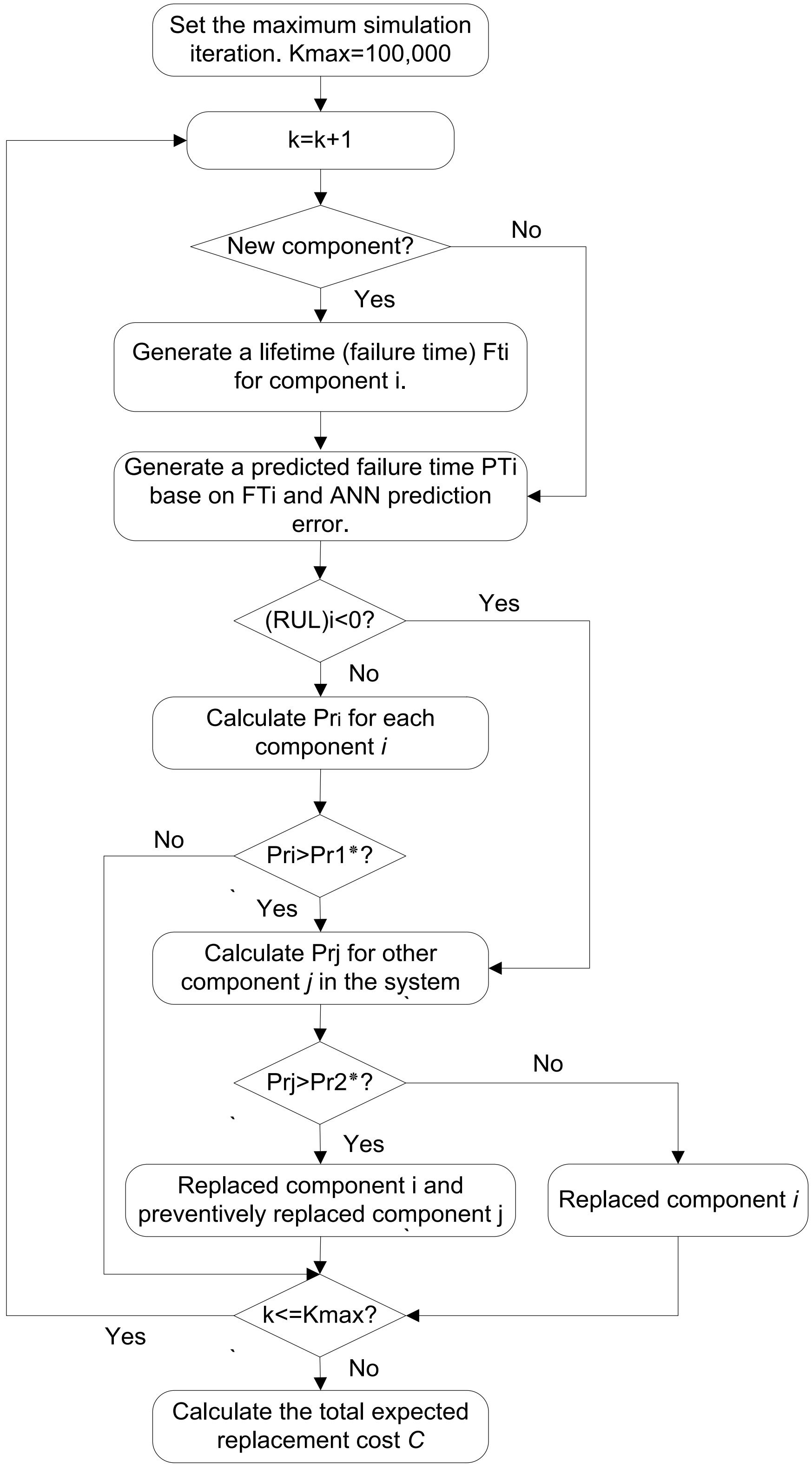

Figure 9 The procedure of the simulation method for cost evaluation in multi-component system

Step 2: Generate a random failure time as the actual failure time of each component.

At the starting point of a new life cycle of component i, generate a random failure time, FT_i, which follows Weibull distribution (3-4) with the parameters α, β.

Step 3: Generate a random predicted failure time of a component.

In inspection point k $(k = 0, \dots, NT)$, generate a random predicted failure time for component i based on ANN RUL prediction error. In a simulation process, this random predicted failure time simulate the predicted result based on ANN model using condition monitoring data at each inspection time. The predicted lifetime is denoted by PT_{ki} and follows normal distribution:

$$PT_{ki} \sim N(\mu, \sigma^2) \qquad (k = 0, \dots, NT; i = 1, \dots, N) \tag{3-10}$$

where $\mu = FT_i$, $\sigma = \sigma_p \times FT_i$, σ_p is standard deviation of ANN RUL prediction error.

Step 4: calculation of predicted failure probability.

During a lifetime of component i, calculate conditional failure probability $P_{r_{ki}}$ in each inspection point by using equation below:

$$P_{r_{ki}} = \frac{\int_{t_i}^{t_i+L} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt}{\int_{t_i}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{-(t_i-\mu)^2/2\sigma^2} dt} \quad (k = 0, \dots, NT; i = 1, \dots, N) \tag{3-11}$$

Where t_i is cumulated inspection time of component i in one life cycle, L is the constant inspection interval, μ is the predicted failure time of different component at different inspection point of time PT_{ki}, and $\sigma = \sigma_p \times FT_i$, σ_p is standard deviation of ANN RUL prediction error.

If Pr_{ki} is greater than the level-1 condition failure probability threshold Pr_1^*, preventively replace the component at inspection point k. If there is no preventive replacement performs during a lifetime of the component i, perform failure replacement at the inspection point just past the generated failure time FT_i. When there is a preventive replacement or a failure replace took place at inspection time k, check other components in the system, if Pr_{kj} $(j = 1, \ldots, N)$ is greater than the level-2 failure probability threshold Pr_2^* , perform preventive replacement on component j simultaneously.

We also introduce two variables to represent the stature of the component i in the multi-component systems:

$$\Delta_{pki} = \begin{cases} 1 & \text{Component } i \text{ is preventively replace at the point of time } k; \\ 0 & \text{No preventive replacement on component } i \text{ at the point of time } k. \end{cases}$$

$$\Delta_{fki} = \begin{cases} 1 & \text{Component } i \text{ is preventively replace at the point of time } k; \\ 0 & \text{No failure replacement on component } i \text{ at the point of time } k. \end{cases}$$

If $\Delta_{pki} = 0$ & $\Delta_{fki} = 0$, the component i continues its normal operation.

Step 5: New life cycle starts.

Start a new life cycle of component i after a preventive or a failure replacement takes place, back to *Step 2* and set the cumulated inspection time, t_i, equals to 0. The iteration would not stop until maximum simulation iteration is reached.

Step 6: Estimate total expected replacement cost.

Similar to cost calculation method for single component, the expected replacement cost for multi-component system can be obtained by the following equation:

(3-12)

$$C_r = \frac{Cost\_total}{Time\_total} = \frac{\sum_{k=0}^{NT} \boldsymbol{C_k}}{NT \times L} \ (\$/day)$$

where $\boldsymbol{C_k}$ is the total cost occurs at inspection point k which calculated by formula (3-13), NT is the total inspection point of the simulation process, and L is the inspection interval.

$$\boldsymbol{C_k} = C_f \cdot \sum_{i=1}^{N} \Delta_{fki} + C_p \cdot \sum_{i=1}^{N} \Delta_{pki} + I(\Delta_{pki}) \cdot C_{p0} \tag{3-13}$$

where $I\left(\Delta_{pki}\right) = 1$, when $\sum_{i=1}^{N} \Delta_{pki} \geq 1$ & $\sum_{i=1}^{N} \Delta_{fki} = 0$; otherwise $I\left(\Delta_{pki}\right) = 0$. N is number of components under condition monitoring, C_{p0} is fixed preventive replacement cost and C_p is variable preventive replacement cost, C_f is failure replacement cost at a time.

At inspection point k, $\boldsymbol{C_k}$ can be in one of three possible circumstances as follows:

1) $\boldsymbol{C_k} = C_{po} + nC_p, (1 \leq n \leq N)$, there is at least one preventive replacement needed but no failure replacement;
2) $\boldsymbol{C_k} = mC_f + nC_p, (1 \leq m \leq N, 0 \leq n \leq N-1)$, there are at least one failure replacement and n preventive replacement perform;
3) $\boldsymbol{C_k} = 0$, there is neither preventive replacement nor failure replacement needed.

Step 7: Determine the optimal CBM policy for multi-component systems.

Similar to the single unit CBM policy, the two level predicted failure probability are decision variables in the CBM policy for multi-component systems. The minimum calculated replacement cost corresponding to the predicted failure probability threshold value P_{r1}^* and P_{r2}^*. So once P_{r1}^* and P_{r2}^* are determined, the optimal CBM policy is determined and the optimization model (3-3) can be satisfied.

3.5 Implementation of the Optimal CBM Policy for Multi-component System

The optimal CBM policy is determined once the level-1 and level-2 predicted failure probability thresholds are determined, and the maintenance policy can be implemented as follows:

1. Define a multi-component system and determine the total number of components in such a system. The components in the system are identical, and are independent in their degradation and failure process.
2. Obtain the significant condition monitoring data like oil analysis data or vibration data, at each inspection point, and between each inspection time there is a constant interval L.
3. For component i, at each inspection point t, predict a lifetime percentage value P_{ti}, based on the ANN RUL prediction method by using condition monitoring data. Corresponding to each P_{ti}, a predicted failure time distribution as below can be built.

$$FT_{pi} \sim N\left(\frac{t}{P_{ti} - \mu_p}, \left(\frac{\sigma_p \cdot t}{P_{ti} - \mu_p}\right)^2\right) \quad (3\text{-}14)$$

   where μ_p and σ_p are the mean and standard deviation of the ANN life percentage prediction error. For each component, calculate the predicted failure probability during next inspection interval, Pr_i, using Equation (3-11).

4. Maintenance decision making.

   - Decision 1: Perform failure replacement if a failure occurs on any component in the current inspection interval.
   - Decision 2: No failure occurs on any component in the current inspection interval. Check the calculated failure probability of each components, if $Pr_i > Pr_1^*$, which is the level-1 failure probability threshold, preventive replace component i.
   - Decision 3: If preventive replacement or failure replacement is performed on any component in the system, perform preventive replacement on component j if $Pr_j > Pr_2^*$, where Pr_2^* is the level-2 failure probability threshold. And noted that j can be any other components in the multi-component systems.
   - Decision 4: If there is no failure or preventive replacement performs on any component at current inspection point, all the components continue their normal operation to the next inspection.

Chapter 4

Case Studies

In this Chapter, we use two examples to illustrate the proposed multi-component CBM policy, and the simulation method for the cost evaluation. Comparative studies between the CBM policy for multi-component systems and that for single unit are given to demonstrate the advantages of the proposed multi-component CBM policy.

4.1 Case Study of Canadian Kraft pulp Mill Company

In this case, we consider the multi-component systems consisting of five bearings under vibration monitoring. The bearing vibration monitoring data used in this case were collected from bearings on a group of Gould pumps at a Canadian kraft pulp mill company (Stevens 2006).

4.1.1 Case introduction

Kraft Mill is a large producer that manufactures over 300,000 tons of kraft pulp each year. By facing the competition stress of the market pricing for pulp and paper, key objective of Kraft Mill is reducing costs while keeping production in a high level. Management of this mill was seeking a way to balance the normal production pressure to keep running versus the cost of a failure, as well as eliminating or substantially reducing the frequency of pump failure. In Stevens' case studies (2006), an advanced failure prediction software package EXAKT, developed by OMDEC Inc., helps them to fix the problem.

The production process of kraft pulp is showed in Figure 10. The domain process is pulping, which reduces the wood to a fibrous mass for onward processing into paper and board products. The pulp they produce is transferred to the converting mill and then put on the market as lightweight publication grades of paper, tissues and paper relative products. During the pulping process, high incidence of unpredicted failures among a small group of Gould pumps are the major cause of breakdown facing by Kraft Mill.

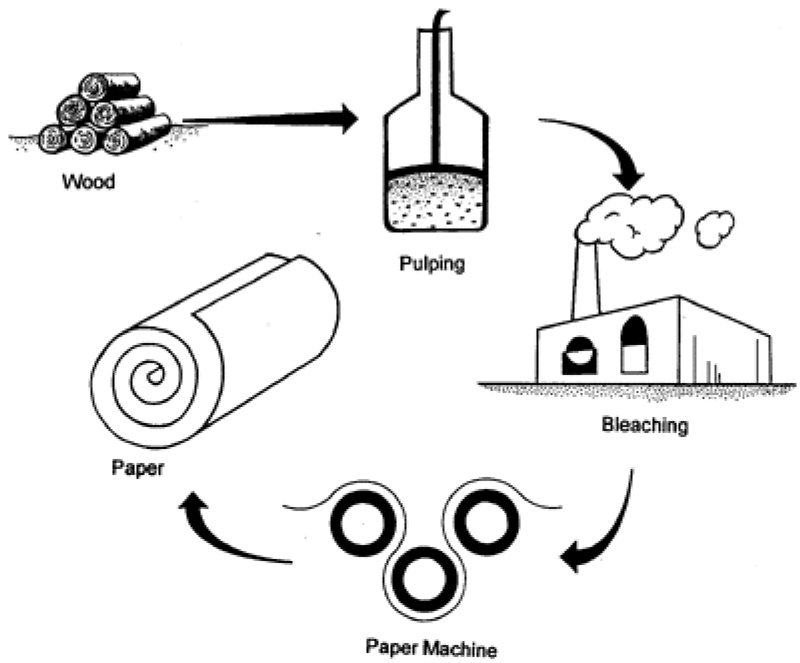

Figure 10 Production process of Kraft Pulp (Johnston et al. 1996)

In this case, the examined units were Gould 3175L pumps which were used 24*7 for pulping process in Kraft Mill. When the pumps were run below their best efficiency point by throttling the discharge flow, it causes excessive load on the thrust bearings (see Figure 11). Although a thrust bearing is designed to support a high axial load while permitting rotation between parts like other rotary bearing, the failure of a thrust bearing is still the significant cause of the failure of the pumps. Three main causes of thrust bearing failures are: poor crankshaft surface finish, misalignment of the thrust bearing and crankshaft, and overloading (Carley 2003). One kind of thrust bearing failures is shown in Figure 12, when the bearing load exceeds the designed load, the raceways "spall," eventually failing from fatigue stress. The spalling on the surface of a ball increases wear to the raceway, noise, and bearing vibration. By analyzing the pump failure histories, EXAKT can accurately predict whether a pump could continue to run or not until the next shutdown (Stevens 2006).

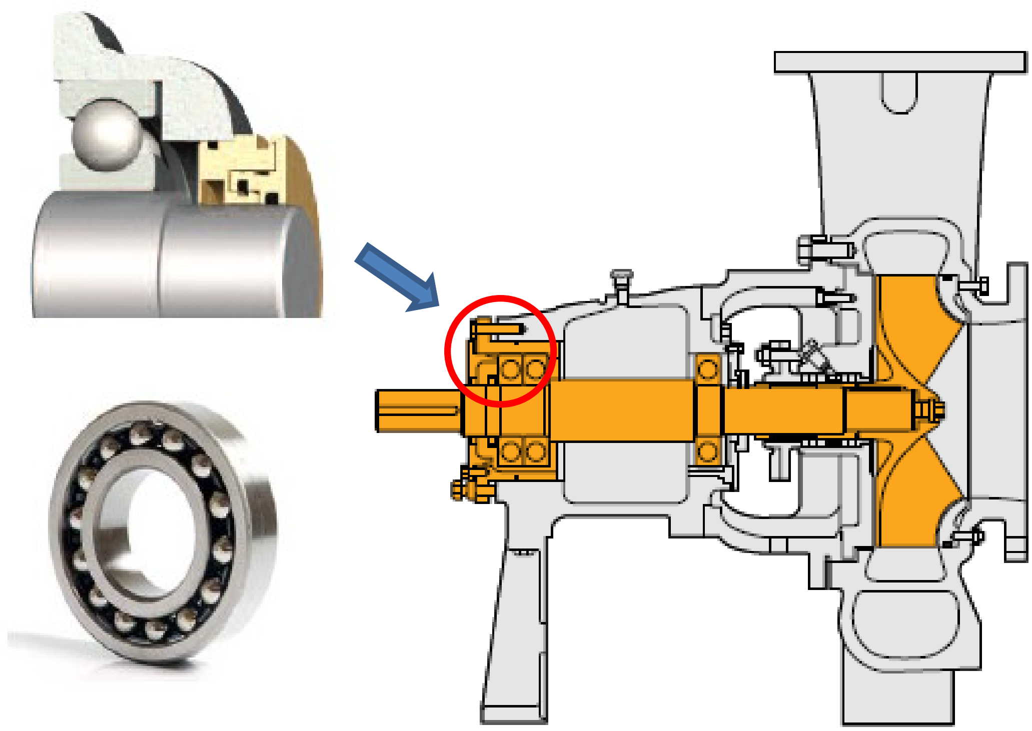

Figure 11 Gould 3175L pumps bearings (Stevens 2006)

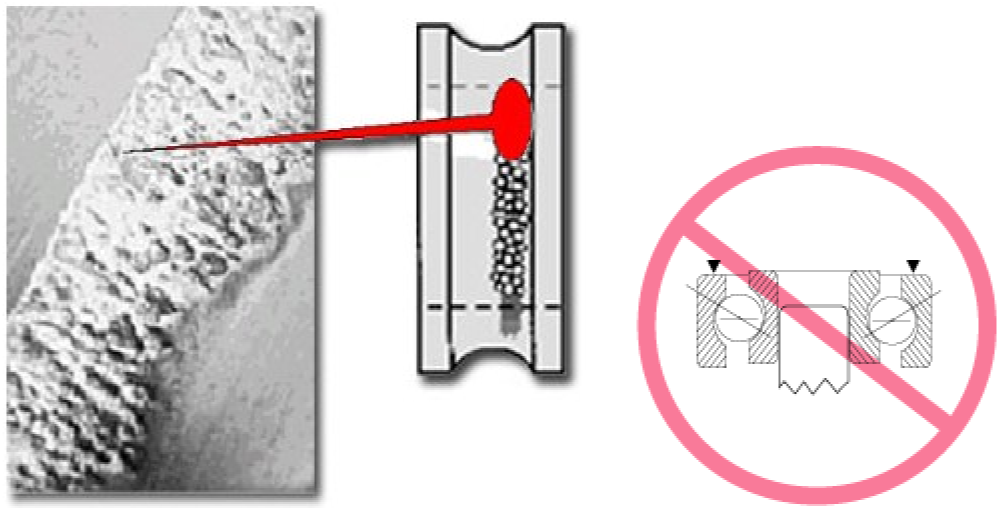

Figure 12 Sample failure of pump thrust bearing (Dynaroll website 2010)

In our case study, we use totally 24 bearing histories which were examined in 8 pump locations, embracing 10 bearing failure histories and 14 suspension histories. For each location, seven types of measurements were recorded: five different vibration frequency bands $(8 * 5)$, and the overall vibration reading $(8 * 1)$ plus the bearing's acceleration data $(8 * 1)$. So the original inspection data includes 56 $(8 * 5 + 8 * 1 + 8 * 1)$ vibration measurements at each time.

An EXAKT Weibull Proportional Hazard model (Stevens 2006) was used to do the significance analysis for the 56 vibration measurements. As the result show in Table 2, only two of the variables were identified as significant influence on the health of bearings, which are P1H_Par5 (band 5 vibration frequency in Pump location P1H), and P1V_Par5 (band 5 vibration frequency in Pump location P1V). Then we use these two measurements and the age time of the component as the inputs of the ANN RUL prediction model. 5 failure histories and 10 suspension histories are used as training ANN inputs and the other 5 failure histories are used as test inputs. After comparing the predicted lifetime to the actual lifetime, we found that the prediction error follow the normal distribution, as shown in Figure 13, the mean of prediction error is 0.1385 and the standard deviation is 0.1429.

Table 2 Significant analysis for Kraft Mill pump bearing measurement

Parameter	Estimate	Sign. (*)	Standard Error	Wald	DF	p - Value	Exp of Estimate	95 % CI	
								Lower	Upper
Scale	2707	-	507.3	-	-	-	-	1713	3702
Shape	2.879	Y	0.6196	9.195	1	0.002426	-	1.664	4.093
P1H_Par5	24.87	Y	6.405	15.07	1	0.0001034	6.311e+010	12.31	37.42
P1V_Par5	42.56	Y	13.67	9.689	1	0.001854	3.039e+018	15.76	69.36

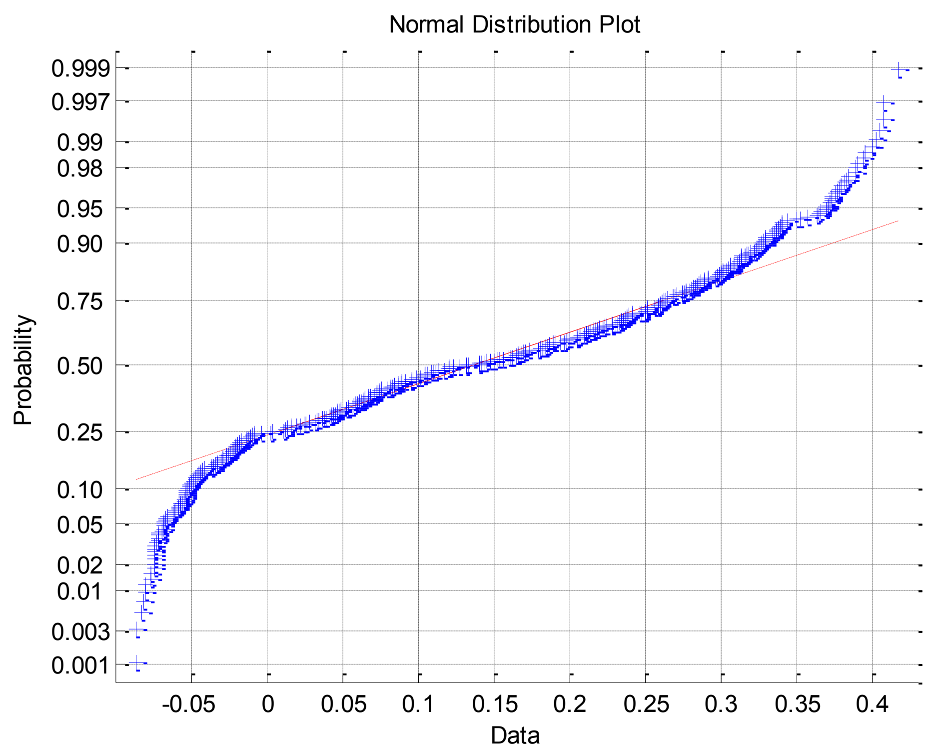

Figure 13 Normal distribution plot of ANN RUL prediction error

In this case, no account was taken of the time required to perform failure or preventive replacement since they were considered to be very short (hours or days), compared to the mean time between replacement of an item, which may be measured in weeks or months.

Any cost that are incurred due to replacement stoppages need to be included as part of C_{p0}, the total fixed cost of a preventive replacement, and C_f, the total cost of a failure replacement. In this case, C_f is estimated to be \$16,000, the fix preventive replacement cost C_{p0} is \$3,000, and the variable preventive replacement cost C_p is \$1,800. That means, the total preventive replacement cost is estimated to be: $C_{p\_total} = \$3{,}000 + n \times \$1{,}800$, n is the number of components needed to be preventively replaced in one maintenance action.

As mentioned before, the lifetime of bearing follows a Weibull distribution. We take total 15 suspension histories (including 5 failure histories and 10 suspension histories) into maximum likelihood method function (3-5), and we got:

$$L = \prod_{i=1}^{5} f(t_i;\ \theta) \cdot \prod_{j=1}^{10} R(t_j^{+};\ \theta) \tag{4-1}$$

$$\Rightarrow L = \prod_{i=1}^{5} \frac{\beta}{\alpha} (\frac{t_i}{\alpha})^{\beta-1} \exp\left[-\left(\frac{t_i}{\alpha}\right)^{\beta}\right] \cdot \prod_{j=1}^{10} \exp\left[-\left(\frac{t_j}{\alpha}\right)^{\beta}\right]$$

where $i = 1, \dots, 5$ represents 5 failure histories under the estimate; $j = 1, \dots, 10$ represents 10 suspension histories under the estimate; t_i is the actual failure time in failure history i, and t_j is the actual suspension time in suspension history j.

In order to simplify the calculation, we take logarithm on both side of equation (4-1).

$$lnL = \ln\left(\frac{\beta}{\alpha}\right) + (\beta - 1) \sum_{i=1}^{5} \ln\left(\frac{t_i}{\alpha}\right) + \sum_{i=1}^{5} \left[-\left(\frac{t_i}{\alpha}\right)^{\beta}\right] + \sum_{j=1}^{10} \left[-\left(\frac{t_j}{\alpha}\right)^{\beta}\right] \tag{4-2}$$

By setting the objective function is equal to (4-2) and applying Matlab optimization function to analysis both the failure and suspension data, we obtain the lifetime distribution parameters α and β : $\alpha = 1386.3$, $\beta = 1.8$, thus we get the lifetime distribution as bellow:

$$f(t) = \frac{\beta}{\alpha}(\frac{t}{\alpha})^{\beta-1} \exp\left[-\left(\frac{t}{\alpha}\right)^{\beta}\right] \qquad \text{for } t \geq 0 \qquad (4\text{-}3)$$

$$\Rightarrow f(t) = \frac{1.8}{1386.3}(\frac{t}{1386.3})^{0.8} \exp\left[-\left(\frac{t}{1386.3}\right)^{1.8}\right] \qquad \text{for } t \geq 0$$

4.1.2 Expected cost calculation for single unit

In the CBM policy for single component, which is described in Chapter 3, the maintenance decision is made on components individually, and there is only one failure probability threshold value needed to be determined to minimize the long term replacement cost. By using the simulation method presented earlier, the cost of a certain CBM policy can be calculated by giving certain failure probability threshold, Pr^*. The failure replacement cost is set to be \$16,000, the same as in a multi-component system. Since the preventive replacement is performed on the components individually, the preventive replacement cost is $\$3{,}000 + 1 \times \$1{,}800 = \$4{,}800$, that means both the fixed cost and the variable cost is charged when a preventive replacement is performed. The steps of cost calculation using simulation method for single unit are as follow:

Step 1: Set the maximum simulation iteration is 100,000 inspection points. Between each inspection point, the fixed inspection interval, L equals 20 days.

Step 2: At the starting point of each iteration, generate a random failure time, FT, for the component which follows Weibull distribution (4-3).

Step 3: In inspection point k ($k = 0, \dots, 100{,}000$), generate a predicted failure time, PT_k, of the component by random, based on ANN RUL prediction error. PT_k follows a normal distribution (3-6). In this case: $\mu = FT$, $\sigma = \sigma_p \times FT$, σ_p is standard deviation of ANN RUL prediction error. Thus, we have

$$PT_k \sim N(\mu, \sigma^2) \Rightarrow PT_k \sim N(FT, (0.1429 \times FT)^2) \tag{4-4}$$

Step 4: During a lifetime of the component, calculate conditional failure probability Pr of each inspection point by using equation (3-7), thus we have:

$$Pr_k = \frac{\int_t^{t+20} \frac{1}{0.1429\sqrt{2\pi}} e^{-(t-PT_k)^2/2\times 0.1429^2} dt}{\int_t^{\infty} \frac{1}{0.1429\sqrt{2\pi}} e^{-(t-PT_k)^2/2\times 0.1429^2} dt} \quad (k = 0, \dots, 100{,}000; t \geq 0) \tag{4-5}$$

where t is the cumulated inspection time in one life circle.

If Pr_k is greater than the failure probability threshold Pr^* ($0 < Pr^* < 1$), preventively replace the component at that certain point. If there is no preventive replacement during a lifetime of the component, perform failure replacement at the inspection point just behind the generated failure time, FT.

Step 5: Start a new life circle of the component after a preventive replacement or a failure replacement took place, back to Step 2. The iteration would not stop until a maximum simulation inspection point 100,000 is reached.

Step 6: Then we estimate total expected replacement cost by equation (3-8), we got:

$$C_r = \frac{Cost\_total}{Time\_total} = \frac{\sum_{k=0}^{100,000}\left((3,000 + 1,800) \cdot \Delta_{pk} + 16,000 \cdot \Delta_{fk}\right)}{100,000 \times 20}(\$/day) \quad (4\text{-}6)$$

where

$$\Delta_{pk} = \begin{cases} 1 & \text{The component was preventively replaced at the point of time } k; \\ 0 & \text{No preventive replacement on the component at the point of time } k. \end{cases}$$

$$\Delta_{fk} = \begin{cases} 1 & \text{The component was failure and was replaced by a new one at time } k; \\ 0 & \text{No failure replacement on the component at the point of time } k \end{cases}$$

Step 7: find the optimal expected cost. This is the minimum cost rate value responding to the condition failure probability threshold value Pr^*. The expected replacement cost as function of failure probability for single unit is plot in Figure 14.

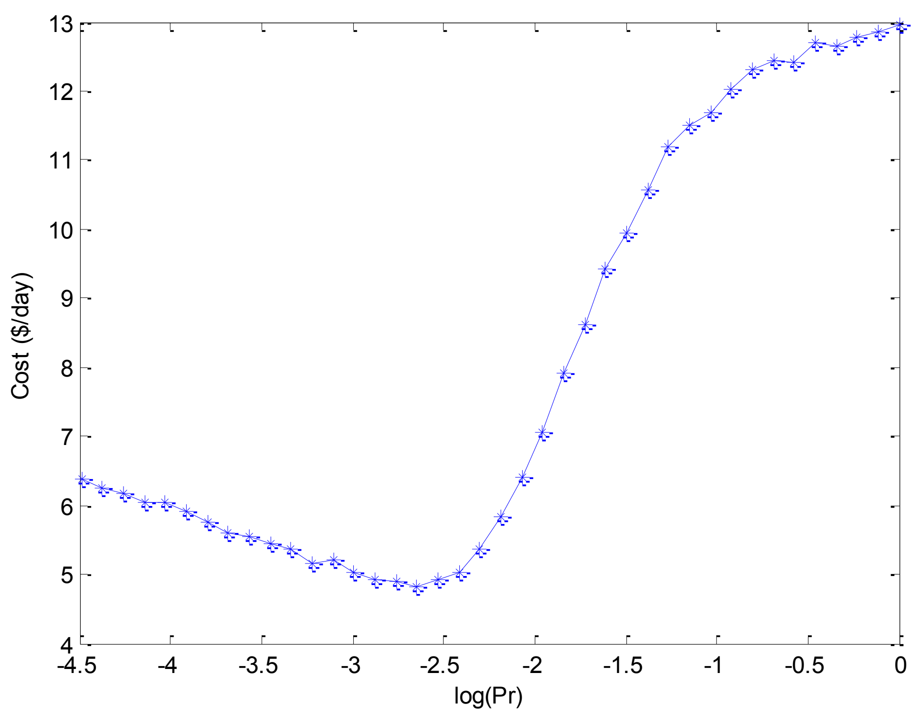

Figure 14 Cost versus failure probability threshold value for single-unit CBM policy

In Figure 14, there are totally 40 points of cost rate corresponding to different $\log(Pr^*)$ values from -4.5 to 0. From this figure, the optimal threshold value exists, which the lowest cost rate for single component is $4.8264/day and the corresponding threshold value $Pr^*$is 0.0708.

Thus, we can obtain the optimal CBM policy for the single unit as follows:

At a certain inspection point k, one of the following actions will be performed on the bearing:

1) If a bearing failed, perform failure replacement for the failed bearing;
2) Perform preventive replacement if the bearing is still working but the following condition is met:

$$Pr_k > Pr^* = 0.0708$$

4.1.3 Expected cost calculation for multi-component systems

For multi-component systems, level-1 and level-2 probability thresholds are two decision variables to determine the optimal CBM policy, therefore, the expected replacement cost of certain CBM policy can be evaluated by giving certain probability threshold values Pr_1^* and Pr_2^*. In our case, we consider the multi-component systems consisting of 5 identical bearings which are operating in parallel and which are subject to random failures. The lifetimes of the individual components are independent random variables and are identically distributed as Weibull distribution with parameters $\alpha = 1386.3$, $\beta = 1.8$.

The simulation procedure is as follows:

Step 1: Set the maximum simulation inspection point is 100,000, same as in single unit policy. Between each inspection point, the fixed inspection interval, L equals 20 days.

Step 2: At the starting point of each iteration for component i ($i = 1, \dots, 5$), set t_i equals 0, generate a random failure time, FT_i, of the component which follows Weibull distribution (4-3).

Step 3: At inspection point k ($k = 0, \dots, 100{,}000$), generate a random predicted failure time,PT_{ki}, of the component i, based on the ANN RUL prediction error. PT_{ki} follows a normal distribution (3-10). In this case: $\mu_i = FT_i$, $\sigma = \sigma_p \times FT_i$, σ_p is standard deviation of ANN RUL prediction error. Thus, we have

$$PT_{ki} \sim N(FT_i, (0.1429 \times FT_i)^2) \tag{4-7}$$

Step 4: During the lifetime of component i, calculate the conditional failure probability Pr_i of each inspection point by using equation (3-11), thus we have:

$$P_{r\,ki} = \frac{\int_{t_i}^{t_i+20} \frac{1}{0.1429\sqrt{2\pi}} e^{-\frac{(t_i - PT_{ki})^2}{2\times 0.1429^2}} dt_i}{\int_{t_i}^{\infty} \frac{1}{0.1429\sqrt{2\pi}} e^{-\frac{(t_i - PT_{ki})^2}{2\times 0.1429^2}} dt_i} \quad (k = 0, \dots, 100{,}000; i = 1, \dots, 5;\ t_i \geq 0) \tag{4-8}$$

where t_i is cumulated inspection time in one life circle for component i.

At each inspection point k, if Pr_{ki} ($i = 1, \dots, 5$) is greater than the given level-1 condition failure probability threshold Pr_1^* ($0 < Pr_1^* < 1$), preventively replace the component at time point k. If there is no preventive replacement during the lifetime of component i, perform failure replacement at the inspection point just behind FT_i. When there is a preventive/ failure replacement occurs in time k, check other components, if

Pr_{kj} ($j = 1, \ldots, 5$) is greater than the given level-2 failure probability threshold Pr_2^*, perform preventive replacement on component j simultaneously.

Step 5: When there is a preventive/ failure replacement took place on component i, start a new life circle of component i by setting $t_i = 0$, and back to Step 2. The iteration would not stop until k equals 100,000.

Step 6: Estimate cost rate. In this case, the fix preventive replacement cost C_{po} is 3,000 and the variable preventive replacement cost C_p is 1,800. By using formula (3-13), we have:

$$C_r = \frac{Cost\_total}{Time\_total} = \frac{\sum_{k=0}^{100,000} \boldsymbol{C_k}}{100,000 \times 20} \ (\$/day) \ \ (k = 0, \ldots, 100,000) \tag{4-9}$$

where

$$\boldsymbol{C_k} = C_f \cdot \sum_{i=1}^{N} \Delta_{fki} + C_p \cdot \sum_{i=1}^{N} \Delta_{pki} + I(\Delta_{pki}) \cdot C_{p0} \tag{4-10}$$

$$\Rightarrow \boldsymbol{C_k} = 16,000 \cdot \sum_{i=1}^{5} \Delta_{fki} + 1,8000 \cdot \sum_{i=1}^{5} \Delta_{pki} + 3,000 \cdot I(\Delta_{pki})$$

where

$$\Delta_{pki} = \begin{cases} 1 & \text{Component } i \text{ is preventively replace at the point of time } k; \\ 0 & \text{No preventive replacement on component } i \text{ at the point of time } k. \end{cases}$$

$$\Delta_{fki} = \begin{cases} 1 & \text{Component } i \text{ is preventively replace at the point of time } k; \\ 0 & \text{No failure replacement on component } i \text{ at the point of time } k. \end{cases}$$

If $\Delta_{pki} = 0$ & $\Delta_{fki} = 0$, the component i continues its normal operation.

$I(\Delta_{pki}) = 1$, if $\sum_{i=1}^{N} \Delta_{pki} \geq 1$ & $\sum_{i=1}^{N} \Delta_{fki} = 0$; otherwise $I(\Delta_{pki}) = 0$.

Step 7: find the optimal total expected replacement cost. By setting different value of Pr_1 and Pr_2, the corresponding total expected replacement cost can be evaluated.

The expected cost as a function of Pr_1^* and Pr_1^*/Pr_2^* is plotted in figure 15. The optimal failure probability threshold values can be observed from this figure, where the lowest expected cost exists.

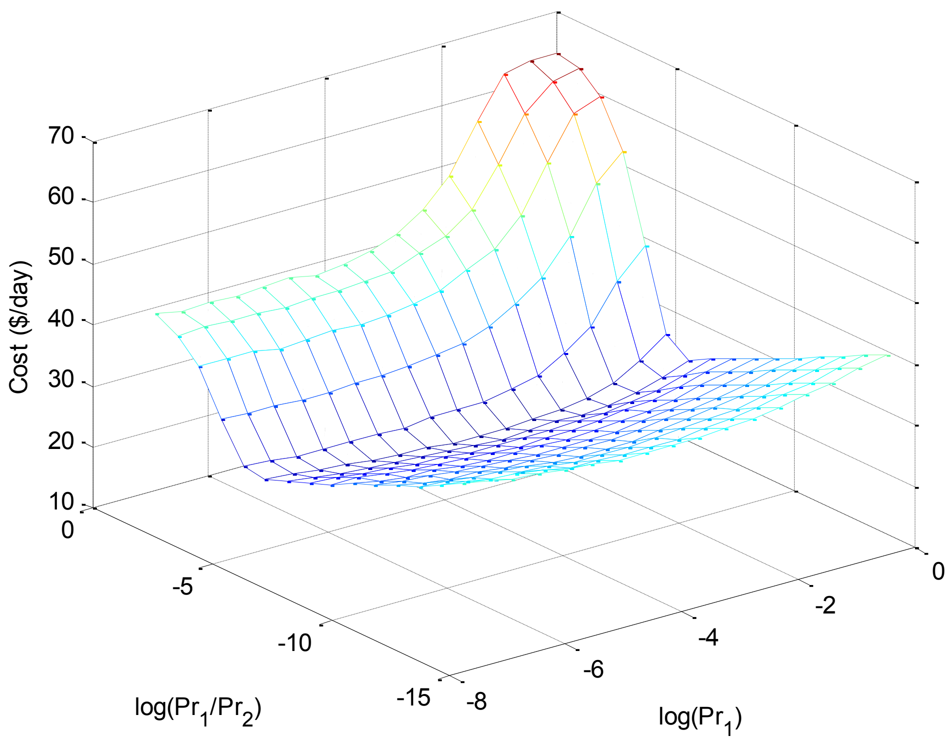

Figure 15 Cost versus two condition failure probability threshold values

As shown in Figure 15, the minimal expected cost for multi-component occurs when $Pr_1^* = 0.100259$ and $Pr_2^* = 4.0973 \times 10^{-4}$, the expected maintenance cost for the multi-component systems containing 5 components is $\$17.5651/day$.

The comparative results are showed in Table 3. Compare to the CBM policy for single component, the optimal cost is much lower when using multi-component CBM policy, cost savings in percentage is 27.21%.

Table 3 Comparison of cost between single unit and multi-component CBM policy

	Single Unit	**Multi-component systems (5 components)**
Cost ($/day)	4.8264	17.5651
Cost for each component($/day)	4.8264	3.513
Cost savings in percentage	27.21%	

This comparative study demonstrates that the proposed multi-component CBM policy can achieve a lower total expected replacement cost by taking advantage of economic dependency in the multi-component systems.

We can obtain the optimal CBM policy for this case:

$$Pr_1^* = 0.1003 \,,\ Pr_2^* = 0.0004$$

Based on the proposed CBM policy for multi-component systems, at a certain inspection point k, one of the following actions will be performed on the bearing:

1) If a bearing failed, perform failure replacement for the failed bearing;
2) For bearing i ($i = 1, \dots, 5$), perform preventive replacement if the bearing is still working but the following condition is met:

$$Pr_i > Pr_1^* = 0.1003$$

where Pr_i is a predicted failure probability of component i calculated by ANN RUL prediction

3) If one bearing meets condition 1) or condition 2), the other bearings will be preventively replaced simultaneously when they are not failed but the following condition is met:

$$Pr_i > Pr_2^* = 0.0004$$

For Kraft Mill Company, as a result of executing the proposed CBM policy for multi-component systems, four key benefits can be obtained:

- Total downtime cause by replacement can be reduced, maintenance can be spread over time when simultaneous replace several components;
- Unexpected shutdown of the systems can be prevented. The simulation results (see Table 4) indicate that the incidence of failure replacement is 0.067% in total 100,000 inspection points of time.
- Compared to CBM single unit policy, the proposed CBM policy for multi-component systems can achieve cost saving of over 20%.
- Use of these approaches can easily extend to other key equipments in the Mill in order to reduce production cost.

Table 4 Times of replacement in total 100,000 inspection points

Bearing	#1	#2	#3	#4	#5	Average times
Times of PR	2223	2212	2216	2182	2210	2209
Times of FR	13	19	11	14	18	15
Incidence of failure replacement						0.067%

4.1.4 The extension of the case study

In this section, we would use real bearing lifetime data to further clarify the feasibility and effectiveness of the proposed CBM approaches. We consider there are 3 major bearing locations, #Lo_1, #Lo_2 and #Lo_3. In each location there is only one bearing under condition monitoring. We use 9 bearing failure histories in this case study and the actual failure times are list in Table 5. All these bearings are identical and were working in the same condition. We suppose all the 9 bearing are used in 3 locations following the sequence from 1 to 9, which means, at the beginning, Bearing 1, 2, 3 are working in location of #Lo_1, #Lo_2 and #Lo_3, Bearing 2 fails after 283 days and is replaced by Bearing 4 in day 284. So we have Bearing 1, 4, 3 works in location #Lo_1, #Lo_2 and #Lo_3 from then on. When Bearing 1 fails after 473 days, we replace it by Bearing 5. The process will stop until all these 9 bearing are used.

Table 5 Bearing failure histories

Bearing	1	2	3	4	5	6	7	8	9
Time to Fail (days)	473	283	601	511	692	986	1402	1246	964

By using the failure histories in Table 5, we compare the performance of the proposed CBM policy with two maintenance policies, and the results are list in Table 6. We can see that when using breakdown maintenance policy, the bearing will not be replaced by a new until it fails. Cost of failure replacement is very high because of the unpredictable shutdown and no scheduled maintenance activities. The corresponding replacement cost is \$20.117/day. If we implementing the single unit CBM policy which we illustrated in section 4.1.2 in these 3 location, we can obtain a lower expected replacement cost, which is \$7.248/day. Replacement cost is much lower than the breakdown maintenance policy and there is no failure replacement occurs under this policy. The expected replacement cost is \$5.417/day when we using the proposed CBM policy for multi-component systems. From Table 6, we can see that in the first round of multi-component CBM policy, bearings in location #1 and location #3 have same replacement age, which are 380 days, and they are preventive replaced at the same inspection point 19th. The fixed preventive replacement cost is charged only once, so the replacement cost occurs at the 19th inspection point is (\$3,000+\$1,800)+\$1,800=\$6,600. The proposed CBM policy for multi-component systems can achieve a cost saving of 25.26% compared to the single unit CBM policy, and 73.07% when taking breakdown maintenance policy.

Table 6 Comparison results between the proposed CBM policy and the other two maintenance policies

Location/Type	#Lo_1	Type	#Lo_2	Type	#Lo_3	Type	Replacement Cost (\$/day)
Breakdown maintenance	473	FR	283	FR	601	FR	$C_r = \frac{\sum Cost}{\sum Time} =$ \$20.117/day
	692	FR	511	FR	986	FR	
	1246	FR	1402	FR	964	FR	
Single Unit CBM Policy	280	PR(14)	140	PR(21)	520	PR(47)	$C_r = \frac{\sum Cost}{\sum Time} =$ \$7.248/day
	560	PR(69)	440	PR(97)	800	PR(137)	
	1180	PR(204)	1340	PR(263)	700	PR(298)	
Multi-component CBM Policy	380	PR(19)	240	PR(12)	380	PR*(19)	$C_r = \frac{\sum Cost}{\sum Time} =$ \$5.417/day
	620	PR(50)	480	PR(36)	620	PR*(50)	
	920	PR*(96)	1200	PR*(96)	920	PR(96)	

FR-Failure Replacement; PR/PR*- Preventive Replacement;
PR(14) means the bearing is preventive replaced at inspection point 14th ;
Cost Calculation: FR=\$16,000; PR=\$4,800: PR*=\$1,800

In the following part, we will investigate how the fixed replacement cost value affects the optimal CBM policy and the optimal total expected replacement cost. Suppose the total preventive replacement cost is fixed at \$4,800, including fixed and variable preventive replacement cost. When the fixed preventive replacement cost is set to 0, the multi-component CBM policy can be simplified as the single-unit CBM policy. Because the preventive replacement cost is fixed at \$4,800, joint maintenance or separate maintenance is at the same price. We use λ to denote the ratio between the fixed replacement cost and the total fixed and variable replacement cost. For example, when $\lambda = 0.625$, that means, the fixed preventive replacement cost is $\$4{,}800 \times 0.625 = \$3{,}000$, and the variable preventive replacement cost is $\$4{,}800 \times (1 - 0.625) = \$1{,}800$. By changing the proportion of the fixed cost in the total preventive replacement cost, we can obtain different condition failure probability thresholds that represent the optimal CBM policies.

Table 7 Cost versus fixed preventive replacement cost ratio λ for case study 1

ratio λ	Optimal CBM policy: $[Pr_1^*, Pr_2^*]$	Cost (\$/day)	Cost savings in percentage
0	[0.0737, 0.0737]	24.1695	0%
0.1	[0.0608, 0.0136]	22.9864	4.89%
0.2	[0.0743, 0.0273]	21.4912	11.08%
0.3	[0.0907, 0.0017]	21.3160	11.81%
0.4	[0.0907, 0.0074]	20.2336	16.29%
0.5	[0.0907, 0.0027]	19.2080	20.53%
0.6	[0.1108, 4.53×10^{-4}]	17.4176	27.94%
0.7	[0.1108, 1.01×10^{-4}]	15.8816	34.29%
0.8	[0.1108, 1.67×10^{-4}]	14.9712	38.06%
0.9	[0.1108, 1.01×10^{-4}]	12.7968	47.05%
1	[0.1108, 1.67×10^{-4}]	10.9520	54.69%

Table 7 lists the optimal cost values and the optimal CBM policies corresponding to different λ values. We can see that when ratio λ equals to 0, there is no fixed preventive replacement cost, the total expected replacement cost is the same as that for the single-unit CBM policy. There is no economic dependency shown in this case. When ratio λ is larger than 0, economic dependency appears and the optimal cost for the multi-component CBM policy is lower than that when λ equals 0. As shown in Table 7, when we increase ratio λ, the optimal cost become lower, and the resulting cost savings as a percentage becomes higher. When ration λ increase to 1, the cost saving in percentage rise to as much as 54.69%. In other words, when the proportion of the fixed preventive cost to the total preventive cost become lager, the higher economic benefits we can obtain, and the advantage of utilizing the multi-component CBM policy becomes more and more obvious.

4.2 A numerical example

In this section, we use a set of simulation degradation signals to demonstrate the proposed CBM policy. The simulated degradation signals can be generated by the degradation model presented in Gebraeel et al. (2005). Let $S(t)$ denote the degradation signal as a continuous stochastic process, continuous with respect to time t and the degradation model has the following expression:

$$S(t) = \emptyset + \theta \exp(\beta t + \varepsilon(t) - \frac{\sigma^2 t}{2}) \quad (4\text{-}11)$$

where $\emptyset$ is a constant, θ is a lognormal random variable, that means, $\ln\theta$ has mean μ_0 and variance σ_0^2, β is a normal random variable with mean μ_1 and variance σ_1^2, and $\varepsilon(t) = \sigma W(t)$ is a centered Brownian motion such that the mean of $\varepsilon(t)$ is zero and the variance of $\varepsilon(t)$ is $\sigma^2 t$. Gebraeel et al. assume θ, β and $\varepsilon(t)$ are mutually independent. Under these assumptions, it makes it more convenient to work with the logged degradation signal and the degradation model can be simplified as follow:

$$L(t) = \theta' + \beta' t + \varepsilon(t) \tag{4-12}$$

where $\theta' = \ln\theta$ is a normal random variable with mean μ_0 and variance σ_0^2, $\beta' = \beta - \frac{\sigma^2}{2}$.

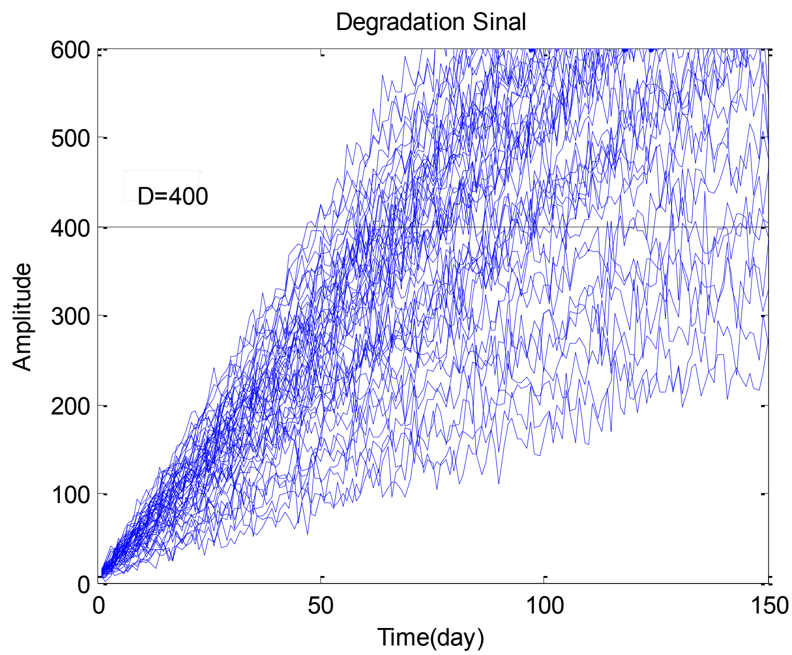

Figure 16 Plot of generated degradation paths

As showed in Figure 16, we generate 50 degradation paths by setting up the parameters in the simplified degradation model as $\mu_0 = 5$, $\sigma_0 = 1$, $\mu_1' = 5$, $\sigma_1' = 1.5$, $\sigma = 0.5$. D equals to 400, which is used to denote the critical level for the degradation path when the failure is assumed to have occurred. The failure time of each degradation path is defined as the time when the actual path cross the critical degradation level D. Among all these 50 degradation paths, we randomly choose 20 failure paths as the input to train ANN and another 10 failure paths as the test histories. After using ANN to train and test the generated data, we obtain the mean and the standard deviation of the ANN life percentage prediction errors are: $\mu_p = 0.0034$, $\sigma_p = 0.0349$. By applying the Maximum likelihood method, we can determine the lifetime of the components follow the Weibull distribution with the parameters of $\alpha = 106.9373, \beta = 4.7895$. Let total preventive replacement cost equal to \$4,000, including the fixed preventive replacement cost, which is \$2,400, and the variable preventive replacement cost, which is \$1,600. Failure replacement cost equal to \$12,000 and inspection interval L is 5days. As the result of the simulation method for single unit, the optimal failure probability threshold Pr^* is 0.0648 and the corresponding total expected replacement cost is \$44.98/day. Then, we also apply the simulation method for multi-component, through a numerical searching, the optimal failure probability threshold is found as: $Pr_1^* = 0.0648, Pr_2^* = 6.128 \times 10^{-5}$, and the corresponding lowest cost is \$174.66/day.

The comparative results are showed in Table 8. Compare to the CBM policy for single component, using multi-component CBM policy achieve a lower total expected replacement cost, cost savings in percentage is 22.33%.

Table 8 Comparative results in the numerical example

	Single Unit	**Multi-component systems (5components)**
Probability threshold	Pr^*=0.0648	$Pr_1^* = 0.1108, Pr_2^* = 6.128 \times 10^{-5}$
Cost Rate(\$/day)	44.9784	174.6640
Average Cost Rate(\$/day)	44.9784	34.9328
Cost savings in percentage	22.33%	

Now we investigate how the fixed replacement cost value affects the optimal CBM policy and the optimal total expected replacement cost. By applying the proposed CBM policy for multi-component systems we can find out how the economic dependency exists. Again, λ is used to denote the ratio between the fixed replacement cost and the total fixed and variable replacement cost, which is \$4,000. For example, if λ equals to 0.2, the fixed preventive replacement cost is $\$4{,}000 \times 0.2 = \$800$, and the variable preventive replacement cost is $\$4{,}000 \times (1-0.2) = \$3{,}200$. By performing the proposed simulation method for multi-component systems with respect to different λ values, the resulting optimal cost values and the optimal CBM policies can be obtain and are listed in Table 9.

Table 9 Cost versus fixed preventive replacement cost ratio λ for case study 2

ratio λ	Optimal CBM policy: $[Pr_1^*, Pr_2^*]$	Cost ($/day)	Cost savings in percentage
0	[0.0648, 0.0648]	224.892	0%
0.2	$[0.0907, 6.11 \times 10^{-4}]$	201.808	10.26%
0.4	$[0.0743, 2.49 \times 10^{-5}]$	188.614	16.13%
0.6	[0.0743, 0]	152.624	32.13%
0.8	[0.1108, 0]	104.944	53.34%

When $\lambda = 0$, the proposed multi-component CBM policy is the same as the single-unit policy, and the cost saving in percentage is 0%. When $\lambda > 0$, economic dependency exists, the optimal cost for the multi-component CBM policy decrease with the increase of λ value. When ration λ increase to 0.8, the cost saving in percentage rising to as much as 53.34%. The larger the proportion of the fixed preventive cost to the total preventive cost, the higher the cost savings in percentage. This example demonstrates again that for multi-component systems where economic dependency exists, the proposed multi-component CBM policy is more effective and can lead to lower total expected replacement cost.

Chapter 5

Conclusion and Future Work

In this Chapter, we conclude our research work and list some potential topics that are relevant to our work and that can be studied in the future.

5.1 Conclusion

Most existing reported CBM policies only focus on single unit maintenance. Replacement and other maintenance decisions are made independently on each component, based on the component's age, deterioration, condition monitoring data and the CBM policy. Since the maintenance of systems has become more and more complex, it is sometimes more economical to replace similar components simultaneously rather than singly. Replacement costs can be saved when several components are jointly maintained instead of separately, that is economies of scale can be obtained. In this work, we propose a multi-component system CBM policy based on ANN RUL prediction model. A simulation method is developed for the cost evaluation and searching for the optimal threshold to determine the CBM policy.

A case study using real-world vibration monitoring data and a numerical example demonstrate the effectiveness of the proposed CBM policy for multi-component systems- a lower total expected replacement cost compared to the single unit CBM policy is easily achieved. The proposed dynamic multi-component CBM policy can function in a real plant environment with multiple components under condition maintenance and can be modified to utilize information from other prognostics methods such as model-based and other data-driven methods, as long as the lifetime predicted error are known.

5.2 Future Work

Based on our work in this thesis, several further studies can be conducted as follows:

- Develop an algorithm for the exact cost evaluation of the multi-component CBM policy. The algorithm can provide an accurate total expected replacement cost, which is important for finding the trend of the cost as a function of the probability threshold values then determine the optimal CBM policy decision variables corresponding to the lowest cost.
- Because of the limited availability of failure data for monitored components, it is difficult to develop a truly condition-based maintenance. Applying the proposed approaches on a practical case can further eliminate the gap between theory and actual practice.
- Some existing maintenance models for multi-component systems address the failure interaction (also called stochastic dependence) between the components, as there is also economic dependence between components (Scarf and Deara 1998, 2003). We can further modify our proposed approach by taking failure interaction between the components into account.

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