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A Condition-Based Maintenance Policy for Multi-Component Systems with a High Maintenance Setup Cost

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Abstract

Condition-based maintenance (CBM) is becoming increasingly important due to the development of advanced sensor and ICT technology, so that the condition data can be collected remotely. We propose a new CBM policy for multi-component systems with continuous stochastic deteriorations. To reduce the high setup cost of maintenance, a joint maintenance interval is proposed. With the joint maintenance interval and control limits of components as decision variables, we develop a model for the minimization of the average long-run maintenance cost rate of the systems. Moreover, a numerical study on a case of a wind power farm consisting of a large number of non-identical components is performed, including a sensitivity analysis. At last, our policy is compared to a corrective-maintenance-only policy.

***keywords*:** Condition-based maintenance, Multi-component systems, Joint maintenance

1. Introduction

Condition-based maintenance (CBM) is a maintenance method that recommends maintenance decisions based on the condition of a component/system [23, 37]. CBM is becoming increasingly important, because (i) the development of advanced sensor and ICT technology makes the remote acquisition of condition monitoring data (e.g., temperature of engine, wearing of a brake) less costly; and (ii) condition data can improve diagnostics and prognostic of failures, which helps to reduce maintenance related costs further [23, 37]. Hence, considerable attention from researchers has been attracted to study CBM [37]. Compared with single-component systems, the maintenance optimization for multi-component systems in a CBM framework is much more complicated because of economic, structural or stochastic dependencies among the components [11, 12, 33, 40]. In this paper, we focus on economic dependency and propose a new CBM policy for multi-component systems with stochastic and continuous deteriorations. To reduce the setup cost of maintenance for multi-component systems, we propose a joint maintenance interval to synchronize the maintenance activities of all degrading components in a system. Maintenance strategies with static joint maintenance intervals are often applied in the industries of advance capital goods (e.g., aviation, oil-gas refinery, renewable energy and chemical process) due to the convenience of static intervals for the operations planning and coordination

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of maintenance resources (e.g., service engineers, maintenance equipments, spare parts) [12].

In a CBM framework, after several key steps, i.e., data acquisition, data processing, diagnostics and prognostic, maintenance policies will be optimized to minimize the operational costs or maximize the availability of systems [23]. The main difference between the conventional maintenance models and CBM models is the utilization of condition measurements [37]. Failures usually occur when the degradation level of a system reaches its failure threshold level, so that the condition monitoring data and stochastic models of the degradation processes are often necessary to estimate remaining useful lifetimes (RUL) or reliability functions. Si *et al.* [39] distinguished two types of probability models of RUL estimation: directly observed CBM models (e.g., regression-based models [27, 28], Wiener process [16, 17], Gamma processes [1, 45], Markovian-based models [24, 30]) and indirectly observed CBM models (e.g., stochastic filtering-based models [49], covariation-based hazard model [22, 47], hidden Markov model [8, 26]). In this paper, we consider systems with continuously observable degradation processes, which is a typical feature of systems in the industry of advance capital goods.

For single-component systems, based on the general random coefficient model [27], Wang [48] proposed a CBM model to determine the optimal control limit and the inspection interval in terms of costs, downtime or reliability. Gebraeel *et al.* [16, 17] extended the general degradation model to estimate the RUL distribution from sensor signals, by a Wiener process and Bayesian updating. Using this technique, a single-unit replacement problem is formulated as a Markov decision process to develop a structured replacement policy [14]. For monotonic stochastic deteriorations, a Gamma process can be used for condition-based maintenance optimization [1, 45]. The CBM models in this case were developed to have a single-level control limit [13, 35, 36] or a multi-level control limit [18] under the scenarios of periodic inspection [35], aperiodic inspection [13, 18] or continuous monitoring [25] [36]. If the degradation process can be modeled as discrete states, Markovian-based models were applied. The optimal replacement policies were derived from observable Markov processes [24, 30] or the evolution of the hidden states [8, 26]. Moreover, Proportional Hazards Models are also often used to relate the system's condition variables to the hazard function of a system [22, 47], so that the maintenance policies can be optimized with respect to the optimal risk value of the hazard function.

Although many CBM models have been proposed for single-component systems, they cannot be applied directly for multi-component systems because one has to deal with the economic dependency among the components. In our model, we consider the economic dependence incurred by the high setup cost of maintenance activities, such as sending maintenance personnel and equipment to a remote site. In the literature within this category, many maintenance models are developed based on failure time data (known as "age/time-based model") instead of condition monitoring data. For example, Radner and Jorgenson [38] introduced an (n, N) policy with a proof of optimality. They distinguished two types of components, 0 and 1, where n is the age threshold for opportunistic replacements of component 0 when component 1 fails and N is the preventive replacement threshold of component 0 when component 1 is good. Some numerical evidence [46] showed that (n, N) policy is near optimality with respect to a wide range of cost parameters. Some exact methods [21, 34] (e.g., via Markovian framework) for finding the optimal solution are intractable for systems with large amounts of components, due to the exponentially increasing state spaces. Hence, various heuristics were proposed to reduce the computational complexity [4, 43, 44]. To reduce the high setup cost, Dekker and Wilderman developed a maintenance clustering method to coordinate maintenance tasks at the system level considering the penalty cost of deviating maintenance schedule from the optimal maintenance interval of individual components. The proof of optimality by assuming the s-expected deterioration cost function based on a Weibull process [12, 51] reduced the complexity of the large-scale optimization problem from $O(2^n)$ to $O(n^2)$.

Contrary to age-based maintenance models, there are only a few condition-based maintenance models proposed for multi-component systems. Wijnmalen and Hontelez [50] used a heuristic algorithm for computing upper and lower control limits for component repair in systems, which is formulated under Markov decision framework. Barata *et al.* [5] proposed a maintenance policy for continuously monitored deteriorating systems to minimize the s-expected maintenance cost over a given mission duration by using Monte Carlo simulation. Marseguerra *et al.* [32] formulated an optimization model with two objectives (availability and net profit) based on a Markov degradation model and solved it by embedding Monte Carlo simulation in genetic algorithms. Both models did not include joint maintenance setup costs at system level. Considering the joint setup costs, Bouvard *et al.* [7] converted a condition-based maintenance problem into an age-based maintenance clustering problem, which yielded a schedule with a dynamic optimal maintenance interval. Castanier *et al.* [10] introduced a parametric maintenance decision framework to coordinate inspection/replacement of a two-component system and minimize the long-run maintenance cost. However, the solution becomes intractable when extending this model to multi-component systems. Tian and Liao proposed two maintenance policies for multi-component systems using Proportional Hazard Model [42] and Artificial Neural Network [41].

Our contribution is that we develop a new mathematical model to optimize the condition-based maintenance policy for systems with a large number of identical/non-identical components subject to high setup costs. To reduce the high setup costs, our model coordinates the maintenance tasks at the system level by introducing a static joint maintenance interval. The components are jointly maintained at the next upcoming maintenance time point if their physical conditions exceed the specified control limits, which can be easily implemented in the industries of advance capital goods. Under this structure, we develop a nested enumeration approach to evaluate and minimize the average long-run cost rate by specifying the control limits of degrading components and the static joint maintenance interval. This model is capable of dealing with systems consisting of a large number of identical/non-identical components, because the optimal joint maintenance interval and control limits can be determined sequentially: (i) for a given maintenance interval, the control limits of components are optimized by decomposing the optimization problems for the whole system into the optimization problems of each individual component (ii) next, one can optimize the static joint maintenance interval by including the setup cost at the system level in the total cost function. Notice that our model is not only adaptable for components with different degradation processes (e.g., random coefficient models, Wiener processes and Gamma processes), but also applicable to systems composed of components with different types of maintenance policies (e.g., age-based maintenance or periodic inspections).

The outline of this paper is as follows. The description of the system and the assumptions are given in Section 2. The details of the mathematical model are explained in Section 3. In Section 4, a numerical case of a wind power farm maintenance problem is studied. In this section, our optimal policy is also compared with an optimal corrective-maintenance-only policy. Moreover, in Section 5, a sensitivity analysis is performed. Finally, the conclusions are stated in Section 6.

2. System Description

Consider an overall system consisting of m systems. $J = \{1, 2..., m\}$ denotes the set of systems as shown in Figure 1. System $j \in J$ consists of l_j components. For the overall system, all components of all systems are numbered from 1 to k and $I = \{1, 2, ..., k\}$ denotes the set of components, where $k = \sum_{j \in J} l_j$.

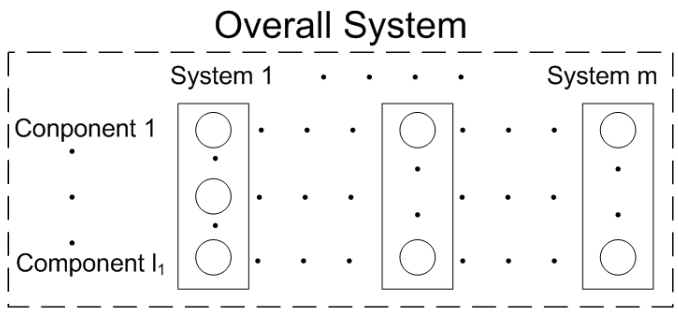

Figure 1: Structure of a typical multi-component system

When maintenance actions are taken, a maintenance crew and equipment have to be sent to the field and the operation of the system is interrupted. Consequently, a high fixed setup cost S is charged on the overall system for maintenance actions on its components. Hence, it is economically beneficial to perform maintenance actions of multiple components simultaneously. Due to the convenience of implementation, maintenance policies with a *fixed interval* are commonly adopted in practice. For example, the maintenance of an offshore wind power farm (the overall system) with multiple wind turbines (the systems) is based on a regular schedule [31], so that the maintenance crew and equipments are only sent to the field at fixed time points. We consider such a policy with a *static maintenance interval* τ (a decision variable). Namely, it is possible to set up maintenance actions only at time points $n\tau$, $n \in \mathbb{N}$. In practice, the maintenance interval (in terms of days or weeks) is small compared with the long life cycles (from 10 to 40 years) of complex systems. Hence, an infinite time horizon is assumed in this paper.

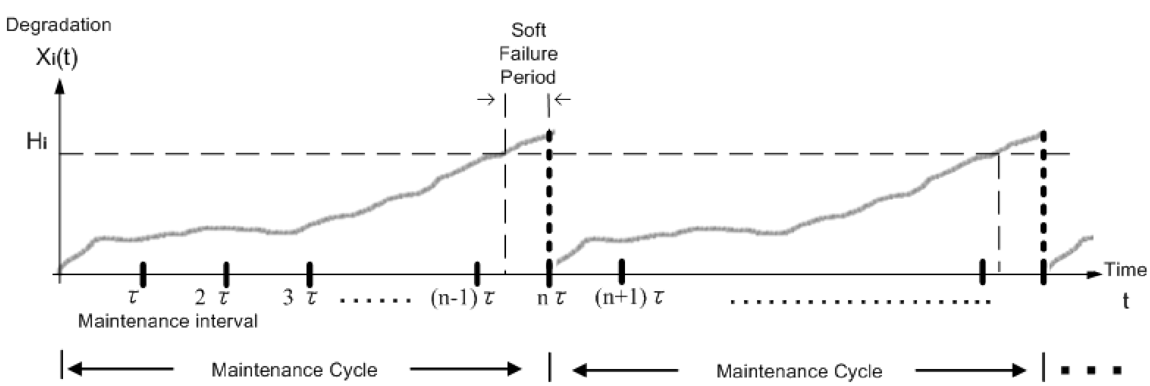

Figure 2: Condition-based maintenance of single components with corrective maintenance only

At the component level, we can continuously monitor the degradation of a certain physical parameter (e.g., the temperature of an engine, the wearing of a braking system, the cracks of a stringer). For each component $i \in I$, $X_i(t)$ is the degradation path over time $t \in [0, \infty)$ (see Figure 2). In this paper, we assume a *soft failure*, which means that a component continues functioning with a lower performance when its degradation exceeds its soft failure threshold H_i (i.e., $X_i(t) > H_i$). Such soft failures usually happen to components with mechanical degradation [9]. For example, the bearing of a wind turbine is not able to deliver satisfactory performance after a certain percentage of the house thickness is worn [31], which is considered as a soft failure. When $X_i(t)$ exceeds H_i and a soft failure is observed between two maintenance points $(n-1)\tau$ and $n\tau$, a corrective maintenance (CM) action (with a cost $C_{CM,i}$) on the failed component is taken at the maintenance point $n\tau$. The period from the time point when the soft failure occurs till the maintenance point $n\tau$ is the *soft failure period* (see Figure 2). Such soft failures can cause quality loss in production or lower performance in operation with a cost rate $C_{p,i}$. For instance, if a wind turbine does not function properly due to a worn bearing, the aerodynamic power generation from mechanical torque will be less efficient, which is considered as revenue loss due to the soft failure [31]. The quality loss/low performance cost is equal to the length of soft failure period times $C_{p,i}$.

In order to avoid a high corrective maintenance cost $C_{CM,i}$ and quality loss costs when $X_i(t)$ exceeds H_i, it is economically beneficial to take maintenance actions pro-actively, which is known as preventive maintenance (PM), with a lower cost $C_{PM,i}$ ($C_{PM,i} < C_{CM,i}$). Thus, for each component, we introduce a control limit C_i to trigger PM actions at the next closest maintenance point, before its degradation exceeds H_i ($C_i < H_i$), as shown in Figure 3. When the stochastic degradation increases fast and exceeds both C_i and H_i at the next closest maintenance point $n\tau$, a CM action will be taken (see Figure 3 (B)). Nevertheless, if the stochastic degradation increases slow and the degradation level is between C_i and H_i at the next closest maintenance point $n\tau$, a PM action with a lower cost will be taken (see Figure 3 (A)). Therefore, both τ and C_i, $i \in I$, are the decision variables of the optimization model. After a maintenance action is taken, the condition of the component is restored to the original degradation level (also known as "Repair-As-New") and the component continues its operation till the next maintenance action is taken. This process will repeat throughout the infinite time horizon. The period between two consecutive maintenance actions for a component is defined as a *maintenance cycle* (see Figure 2) and the beginning of each cycle is a so-called renewal point. According to renewal theory, the average cost rate over an infinite time horizon is equal to the average cost rate over one maintenance (renewal) cycle, $Z_i(\tau, C_i)$. The s-expected maintenance cost per cycle and the s-expected maintenance cycle length are derived in Section 3.2.

To solve the maintenance problem for systems with a large number of components, we propose a nested approach. We first decompose the optimization of the overall system into the optimization problems at individual component level to find the optimal control limit of each component C_i^* for a given τ by minimizing the average cost rate of each component . Afterwards, we can find the optimal τ by minimizing the average maintenance cost rate of the overall system $Z_{syst}(\tau)$. Notice that we assume the components in the overall system are independent of each other. Hence, the analysis of the overall system can be fully decomposed into the analysis of individual components. Moreover, we assume that the overall system is composed of a large number of systems, so that the probability of no component failure within one maintenance interval is negligible. Hence, a setup of maintenance actions is always needed at each static maintenance point. Therefore, the average setup cost rate can be modeled as $\frac{S}{\tau}$. Consequently, the minimum average cost rate

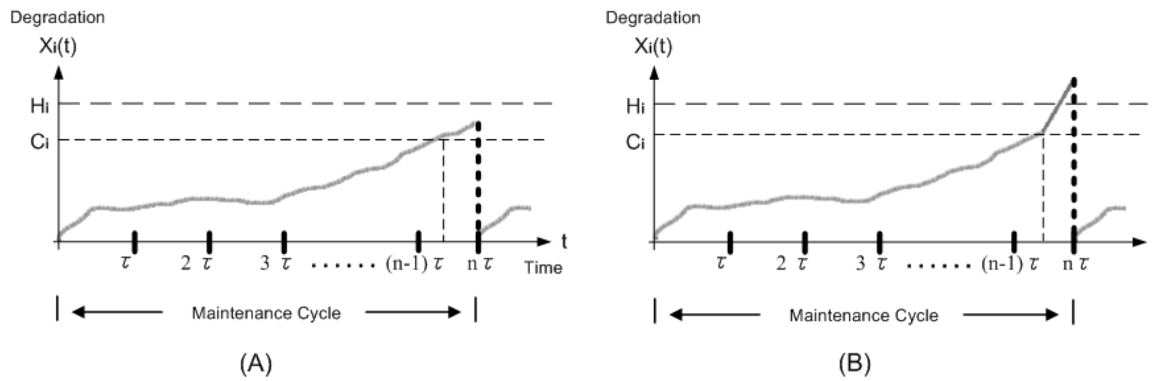

Figure 3: Condition-based maintenance of single components with preventive and corrective maintenance: (A) a PM action is taken at the next maintenance point if $H_i \geq X_i(t) > C_i$; (B) a CM action is taken at the next maintenance point if $X_i(t) > H_i$

on the overall system level for a given τ is

$$Z_{syst}(\tau) = \frac{S}{\tau} + \sum_{i \in I} Z_i^*(\tau)$$

where $Z_i^*(\tau) = Z_i(\tau, C_i^*)$, which is the minimum average cost rate for each component with optimal control limit C_i^* for a given τ.

2.1 Notation:

i : index of components in the overall system
n : index of maintenance intervals over the planning horizon
$X_i(t)$: degradation of component i on a physical condition
τ : maintenance interval at the system level (decision variable)
C_i : control limit on the degradation level of component i (decision variable)
H_i : soft failure threshold on the degradation level of component i
Z_i : average cost rate of component i(without setup costs)
Z_{syst} : average cost rate of the overall system
$C_{PM,i}$: cost per PM action taken on component i
$C_{CM,i}$: cost per CM action taken on component i
$C_{p,i}$: soft failure cost rate on component i
S : cost per set-up action taken at the system level

2.2 Assumptions

1) The components in the overall system are independent of each other.
2) The time horizon is infinite
3) Maintenance actions are set up at fixed maintenance points $n\tau, n \in \mathbb{N}$.
4) The system continues its operation with a lower performance when the degradation of components exceeds the failure thresholds (also known as "soft failure").

5) The overall system is composed of a large number of components.
6) Maintenance actions restore the conditions of components back to their initial degradation levels. (also known as "repair-as-new").

3. Model Formulation and Analysis

In this section, the degradation model of components within a single maintenance cycle is introduced in Subsection 3.1. The optimization model is formulated both at the component and system level in Subsection 3.2.

3.1 Degradation Model

As mentioned in the literature in Section 1, there are several approaches to model the stochastic degradation paths of components (e.g., Random Coefficient Model, Gamma process, Brownian Motion or Markov Process). In this paper, we use the Random Coefficient Model [27], because it is relatively flexible and convenient for describing the degradation pathes derived from physics of failures, such as law of physics and material science. According to the Random Coefficient Model, $X_i(\hat{t};\Phi_i,\Theta_i)$, the degradation level of component i at time $\hat{t}\in[0,\infty)$ in a single maintenance cycle, is a random variable, given a set of constant parameters $\Phi_i=\{\phi_{i,1},...,\phi_{i,Q}\}, Q\in\mathbb{N}$; and a set of random parameters, $\Theta_i=\{\theta_{i,1},...,\theta_{i,V}\}, V\in\mathbb{N}$, following certain probability distributions. The probability that the degradation at time $\hat{t}$ does not exceed a threshold χ is equal to the probability that the passage time T_χ of the threshold χ is less than time $\hat{t}$

$$Pr\{T_\chi\leq\hat{t}\}=Pr\{X(\hat{t};\Phi_i,\Theta_i)\geq\chi\},\qquad\forall i\in I. \tag{1}$$

EXAMPLE 1: In order to clarify the model, a simple example is given. Consider a component i in the system with a degradation path $X_i(t;\Phi_i,\Theta_i)=\phi_{i,1}+\theta_{i,1}t^{\phi_{i,2}}$ where $\Phi_i=\{\phi_{i,1},\phi_{i,2}\}$ and $\Theta_i=\{\theta_{i,1}\}$. Equation (1) can be written in terms of $F_{\theta_{i,1}}$ (the cumulative density function of random variable $\theta_{i,1}$, $\theta_{i,1}\geq 0$):

$$\begin{aligned}Pr\{T_\chi\leq\hat{t}\} &= Pr\{\phi_{i,1}+\theta_{i,1}\hat{t}^{\phi_{i,2}}\geq\chi\}\\ &= Pr\{\theta_{i,1}\geq\frac{\chi-\phi_{i,1}}{\hat{t}^{\phi_{i,2}}}\}\\ &= 1-F_{\theta_{i,1}}\Big(\frac{\chi-\phi_{i,1}}{\hat{t}^{\phi_{i,2}}}\Big)\end{aligned} \tag{2}$$

♢

For component i, the cumulative distribution functions of passage time T_{C_i} and T_{H_i} (when the degradation level exceeds C_i and H_i) can be derived based on Equation (1) given the degradation path function $X_i(\hat{t};\Phi_i,\Theta_i)$ and the probability distributions of Θ_i. Recalling the proposed policy explained in section 2 (see Figure 3), maintenance actions are taken at fixed time points. Hence, the probability that the control limit C_i is reached between time point $(n-1)\tau$ and $n\tau$ can be expressed as

$$Pr\{X_i\big((n-1)\tau;\Phi_i,\Theta_i\big)\leq C_i<X_i(n\tau;\Phi_i,\Theta_i)\}=Pr\{(n-1)\tau\leq T_{C_i}<n\tau\}\qquad\forall n\in\mathbb{N},\quad i\in I \tag{3}$$

The probability that soft failure threshold H_i is reached before time point $n\tau$ can be expressed as

$$Pr\{X_i(n\tau;\Phi_i,\Theta_i) > H_i\} = Pr\{T_{H_i} < n\tau\} \qquad \forall n \in \mathbb{N}, \quad i \in I \tag{4}$$

where $C_i < H_i$ and $T_{C_i} \leq T_{H_i}$. After C_i is reached between $(n-1)\tau$ and $n\tau$, there are two possibilities for the maintenance action at $n\tau$ as mentioned in Section 2: preventive maintenance (PM) if $C_i \leq X_i(n\tau) < H_i$ and corrective maintenance (CM) if $X_i(n\tau) \geq H_i$. Thus, the probability that either PM or CM occurs at time $n\tau$ after the degradation level of component i has reached its control limit C_i between time $(n-1)\tau$ and $n\tau$ can be derived based on Equations (1), (3) and (4):

$$Pr\{PM\ at\ n\tau\} = Pr\{T_{H_i} > n\tau,\ (n-1)\tau \leq T_{C_i} < n\tau\} \tag{5}$$

$$Pr\{CM\ at\ n\tau\} = Pr\{T_{H_i} \leq n\tau,\ (n-1)\tau \leq T_{C_i} < n\tau\} \tag{6}$$

EXAMPLE 1 (continued): According to Equations (2) and (3), the probability of reaching the control limit C_i between $(n-1)\tau$ and $n\tau$ can be obtained as

$$Pr\{(n-1)\tau \leq T_{C_i} < n\tau\} = F_{\theta_{i,1}}\Big(\frac{C_i - \phi_{i,1}}{\big((n-1)\tau\big)^{\phi_{i,2}}}\Big) - F_{\theta_{i,1}}\Big(\frac{C_i - \phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big), \qquad \forall n \in \mathbb{N}, \quad i \in I \tag{7}$$

For component i, the probability that either PM or CM occurs at time point $n\tau$ after the degradation reaches C_i between $(n-1)\tau$ and $n\tau$ can be derived from Equations (5) and (6):

$$\begin{aligned} Pr\{PM\ at\ n\tau\} &= Pr\Big\{\theta_{i,1} < \frac{H_i - \phi_{i,1}}{(n\tau)^{\phi_{i,2}}},\ \frac{C_i - \phi_{i,1}}{\big((n-1)\tau\big)^{\phi_{i,2}}} \geq \theta_{i,1} > \frac{C_i - \phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big\} \\ &= \begin{cases} F_{\theta_{i,1}}\Big(\frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}}\Big) - F_{\theta_{i,1}}\Big(\frac{C_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big) & \textit{if } \frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}} > \frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}} \\ F_{\theta_{i,1}}\Big(\frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big) - F_{\theta_{i,1}}\Big(\frac{C_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big) & \textit{if } \frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}} \leq \frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}} \end{cases} \end{aligned} \tag{8}$$

and

$$\begin{aligned} Pr\{CM\ at\ n\tau\} &= Pr\Big\{\theta_{i,1} \geq \frac{H_i - \phi_{i,1}}{(n\tau)^{\phi_{i,2}}},\ \frac{C_i - \phi_{i,1}}{\big((n-1)\tau\big)^{\phi_{i,2}}} \geq \theta_{i,1} > \frac{C_i - \phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big\} \\ &= \begin{cases} 0 & \textit{if } \frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}} > \frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}} \\ F_{\theta_{i,1}}\Big(\frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}}\Big) - F_{\theta_{i,1}}\Big(\frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}}\Big) & \textit{if } \frac{H_i-\phi_{i,1}}{(n\tau)^{\phi_{i,2}}} \leq \frac{C_i-\phi_{i,1}}{((n-1)\tau)^{\phi_{i,2}}} \end{cases} \end{aligned} \tag{9}$$

Regardless of the distribution of $\theta_{i,1}$, the sum of the probabilities of PM and CM in the interval of $n\tau$ is equal to the probability of reaching C_i between $(n-1)\tau$ and $n\tau$, as derived in Equation (7) . $\diamondsuit$

3.2 Evaluation and Optimization

As mentioned in Section 2, we propose a nested approach to find the optimal maintenance policy (i.e., the control limits C_i of all components and the maintenance interval τ) by minimizing the average long-run cost rate of the overall system.

Evaluation and optimization for each component

We evaluate the average long-run maintenance cost rate for component $i \in I$ incurred by preventive maintenance, corrective maintenance and soft failure. According to the Renewal Theory, the average long-run cost $Z_i(\tau, C_i)$ is equal to the s-expected maintenance cost per cycle $\mathbb{E}\Big[K_i(\tau, C_i)\Big]$ divided by the s-expected cycle length $\mathbb{E}\Big[L_i(\tau, C_i)\Big]$. The s-expected maintenance cost per cycle $\mathbb{E}\Big[K_i(\tau, C_i)\Big]$ is given as

$$\mathbb{E}\Big[K_i(\tau, C_i)\Big] = \sum_{n \in \mathbb{N}} \Bigg[Pr\{PM\ at\ n\tau\}C_{PM,i} + Pr\{CM\ at\ n\tau\}C_{CM,i}\Bigg] + \mathbb{E}\Big[D_i(\tau, C_i)\Big]C_{p,i} \tag{10}$$

where $Pr\{PM\ at\ n\tau\}$ and $Pr\{CM\ at\ n\tau\}$ can be obtained from Equations (5) and (6), $C_{PM,i}$ and $C_{CM,i}$ are the costs of preventive maintenance and corrective maintenance on component i respectively, excluding the setup cost. The soft failure cost in Equation (10) is evaluated by the product of the s-expected soft failure period $\mathbb{E}\Big[D_i(\tau, C_i)\Big]$ and the penalty cost rate $C_{p,i}$, as described in Section 2. The s-expected soft failure period $\mathbb{E}\Big[D_i(\tau, C_i)\Big]$ can be derived as

$$\mathbb{E}\Big[D_i(\tau, C_i)\Big] = \sum_{n \in \mathbb{N}} \int_{(n-1)\tau}^{n\tau} \left(\int_x^{n\tau} (n\tau - y) f_{T_{H_i}|T_{C_i}}(y|x)dy \right) f_{T_{C_i}}(x)dx, \quad \forall\ i \in I \tag{11}$$

where $f_{T_{C_i}}(x)$ is the probability density function of passage time T_{C_i} and $f_{T_{H_i}|T_{C_i}}(y|x)$ is the conditional probability density function of passage time T_{H_i}, given that $T_{C_i} = x$.

Moreover, the s-expected cycle length $\mathbb{E}\Big[L_i(\tau, C_i)\Big]$ is given as

$$\mathbb{E}\Big[L_i(\tau, C_i)\Big] = \sum_{n \in \mathbb{N}} n\tau Pr\{(n-1)\tau \leq T_{C_i} < n\tau\}, \qquad \forall i \in I \tag{12}$$

EXAMPLE 1 (continued): Assuming that the degradation rate $\theta_{i,1}$ follows a Weibull distribution with α_i and β_i, the distribution of passage time T_{C_i} can be derived as

$$f_{T_{C_i}}(x) = \phi_{i,2}\beta_i\Big(\frac{C_i - \phi_{i,1}}{\alpha_i}\Big)^{\beta_i} x^{-(\phi_{i,2}\beta_i+1)} exp\Big[-\Big(\frac{C - \phi_{i,1}}{\alpha_i x^{\phi_{i,2}}}\Big)^{\beta_i}\Big], \qquad \forall i \in I$$

And the s*-expected soft failure period can be derived according to Equation (11)*

$$\mathbb{E}\Big[D_i(\tau, C_i)\Big] = \sum_{n \in \mathbb{N}} \Bigg[\int_{(n-1)\tau}^{n\tau} \Big[n\tau - \Big(\frac{H_i - \phi_{i,1}}{C_i - \phi_{i,1}}\Big)^{(1/\phi_{i,2})} x\Big]^+ f_{T_{C_i}}(x)dx\Bigg], \quad \forall i \in I \tag{13}$$

$\diamondsuit$

Hence, the optimization for C_i is formulated as

$$\begin{aligned} \min_{C_i} \qquad & Z_i(\tau, C_i) = \frac{\mathbb{E}\Big[K_i(\tau, C_i)\Big]}{\mathbb{E}\Big[L_i(\tau, C_i)\Big]} \\ \text{s.t.} \qquad & 0 < C_i < H_i \qquad \forall i \in I \end{aligned}$$

Notice that the maintenance interval τ is treated as a given parameter instead of a decision variable in this suboptimization problem, so that the optimal control limit $C_i^*(\tau)$ can be obtained for each component for a given τ.

Evaluation and optimization of the overall system

Since each τ value has its corresponding $C_i^*(\tau)$ and $Z_i^*(\tau)$, the average long-run cost rate of the overall system $Z_{syst}(\tau)$ can be minimized by enumerating τ. $Z_{syst}(\tau)$ includes not only the sum of the minimum optimal average cost rates of all components $\sum_{i\in I} Z_i^*(\tau)$, but also the average setup cost rate $\frac{S}{\tau}$. Hence, the optimization model is

$$\begin{aligned} \min_{\tau} \qquad & Z_{syst}(\tau) = \frac{S}{\tau} + \sum_{i\in I} Z_i^*(\tau) \\ \text{s.t.} \qquad & 0 < \tau < M_\tau \end{aligned}$$

where M_τ is the upper bound of the maintenance interval τ. In practice, there can be a limit on τ suggested by manufacturers or industry regulations [15]. The detailed explanation of the algorithm is summarized in Appendix C.

4. Numerical Study

To demonstrate the use of our model, we provide an example of a wind power farm with 20 wind turbines in this section. In each wind turbine, there are three main components: main bearing, gearbox and generator (see Figure 4). Hence, the total number of components in the wind power farm is 60, $i \in I = \{1, ..., 60\}$. For each component, micro-sensors can be installed to continuously monitor the rotational loads [31]. The wind power is generated from the rotational torque converted from aerodynamic force on wind blades. Hence, the three components experience the mechanic load from the torque (see Figure 4) and their degradations can be described by the Lundberg-Palmgren model [19, 52]. Taking the main bearing as an example, the maximum load capacity P can be calculated by the Lundberg-Palmgren formula [29], which is a monotonic degradation:

$$P = F * N^{\frac{1}{a}} \tag{14}$$

where the bearing load F depending on wind force is a random variable, which can be monitored continuously over time t by micro-sensors. Moreover, the bearing life in number of revolutions N can be recorded and a is a given constant depending on the types of bearing [29]. When the bearing load is above the maximum load capacity, a soft failure occurs. Suppose this mechanical degradation process is the failure mechanism of the three components [19, 52], the degradation $X_i(t; \phi_{i,1}, \phi_{i,2}, \theta_{i,1})$ can be described by the Random Coefficient Model [27] based on the Lundberg Palmgren formula:

$$X_i(t; \phi_{i,1}, \phi_{i,2}, \theta_{i,1}) = \phi_{i,1} + \theta_{i,1} * t^{\phi_{i,2}}, \qquad \forall i \in I$$

where the life time t represents N by converting the number of revolutions into operation days. The positive random parameter $\theta_{i,1}$ represents the load F in the Lundberg-Palmgren formula. The constant parameter $\phi_{i,2}$ is equal to $1/a$ and the constant parameter $\phi_{i,1}$ is the initial degradation level. Notice that the soft failure threshold H is equivalent to the maximum load capacity P and the passage time T_H is equivalent to N in the Lundberg Palmgren formula. The distribution of $\theta_{i,1}$ is assumed to be a Weibull distribution with two parameters: α_i and β_i, which can be obtained by condition data fitting [27, 28]. Therefore, we can use the mathematical expressions of Example 1 in Subsection 3.1 (Equations (7), (8), (9) and (13)) to formulate the degradation path of the Lundberg-Palmgren formula.

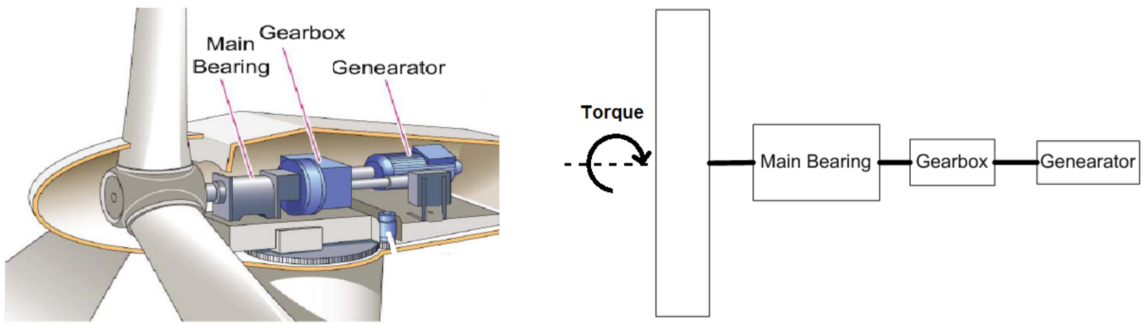

Figure 4: Major components in a wind turbine [2]

The parameter setting in Table 1 is obtained from the existing literature of wind turbine research and based on general cases [3, 6, 20]. The optimal maintenance policy can be obtained by solving the model in Subsection 3.2 with Example 1..

Parameter	Explanation	Main Bearing: $i \in \{1, ..., 20\}$	Gearbox: $i \in \{21, ..., 40\}$	Generator: $i \in \{41, ..., 60\}$
$C_{PM,i}$	PM cost [K-Euro]	$C_{PM,i} = 7$	$C_{PM,i} = 15$	$C_{PM,i} = 10$
$C_{CM,i}$	CM cost [K-Euro]	$C_{CM,i} = 30$	$C_{CM,i} = 70$	$C_{CM,i} = 50$
$C_{p,i}$	Soft failure cost rate [K-Euro]	$C_{p,i} = 7.2$	$C_{p,i} = 7.2$	$C_{p,i} = 7.2$
S	Setup cost, S=50 [K-Euro]	-	-	-
α_i	Scale parameter of Weibull distribution	$\alpha_i = 2.12$	$\alpha_i = 2.52$	$\alpha_i = 1.02$
β_i	Shape parameter of Weibull distribution	$\beta_i = 7.9$	$\beta_i = 7.5$	$\beta_i = 6.9$
H_i	Soft failure threshold	$H_i = 10$	$H_i = 20$	$H_i = 15$
$\phi_{i,1}$	Initial degradation level	$\phi_{i,1} = 1$	$\phi_{i,1} = 2$	$\phi_{i,1} = 3$
$\phi_{i,2}$	Constant parameter for different rotational mechanisms	$\phi_{i,2} = 0.33$	$\phi_{i,2} = 0.41$	$\phi_{i,2} = 0.51$
G_i *	Estimated passage time of H_i [days]	$G_i = 96.07$	$G_i = 141.11$	$G_i = 143.43$

Table 1: The parameter setting (*: $G_i = (H_i - \alpha_i)/\mathbb{E}\{\theta_i\}$, where $\mathbb{E}\{\theta_i\}$ is the mean value of the Weibull distribution)

By the nested enumeration algorithm (see Appendix C), the optimal maintenance policy is found and shown in Table 2. The optimal policy is to set the maintenance interval at 36.1 days and the control limits on the physical condition of the three types of components (main bearing, gearbox and generator) are 8.11, 17.12 and 12.72 respectively. The resulting average maintenance cost rate of this wind power farm with 20 wind turbines (60 components) is 7424 Euros per day.

Optimal Policy	Values	Explanation
$Z_{syst}(\tau^*)$	7424	the minimum average cost rate of the overall system [Euro / day]
τ^*	36.1	the optimal maintenance interval of the overall system [day]
$\{C_a^*(\tau^*), C_b^*(\tau^*), C_c^*(\tau^*)\}$	$\{8.11, 17.12, 12.72\}$	the optimal control limits of each component
$\{Z_a(\tau^*), Z_b(\tau^*), Z_c(\tau^*)\}$	$\{94.3, 126.2, 81.2\}$	the minimum average maintenance cost rate of each component [Euro / day].

Table 2: The optimal maintenance policy of the numerical example in Table 1 (index: a = Main Bearing, $i \in \{1, ..., 20\}$; b = Gearbox, $i \in \{21, ..., 40\}$; c = Generator, $i \in \{41, ..., 60\}$)

In Figure 5, the average cost rate of the overall system $Z_{syst}(\tau)$ is a function of the maintenance interval τ, in terms of the sum of two elements: the setup cost rate $\frac{S}{\tau}$ and the maintenance cost rate of all components $\sum_{i\in I} Z_i^*(\tau)$. When τ increases, $\frac{S}{\tau}$ decreases due to the less frequent setups of maintenance actions, on one hand; but on the other hand, $\sum_{i\in I} Z_i^*(\tau)$ increases due to the higher probability that CM occurs in a maintenance interval and higher s-expected soft failure costs.

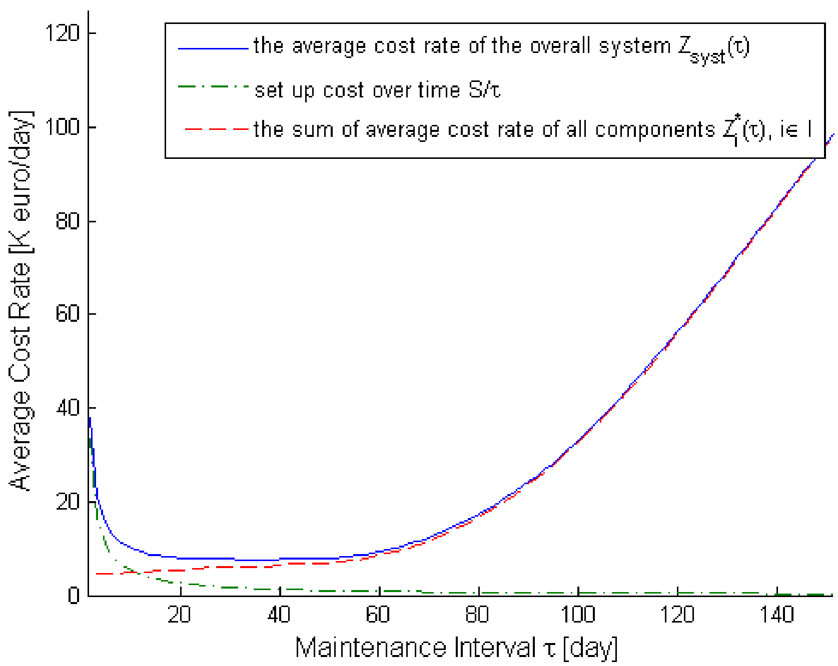

Figure 5: Average cost rate [K-Euros per day] at the system level over τ [days]

To obtain further insight, the optimal solution of a single component is analyzed. Taking component 1 as an example, we investigate the changes of the average maintenance cost rate $Z_1(\tau, C_1)$ under given τ values over the control limit C_1 as shown in Figure 6. For $\tau = 15, 20$ and 25, the optimal control limit $C_1^*(\tau)$ is $9.28, 8.92$, and 8.83 respectively and the minimum average cost rate $Z_1(\tau, C_1^*)$ is $75.0, 82.2$ and 91.9 Euros per day. We can observe that the larger τ value is, the higher $Z_1(\tau, C_1^*)$ and the lower C_1^* becomes. This is because the probability that CM occurs in a maintenance interval increases and the s-expected soft failure cost becomes higher. Consequently, the average cost rate of maintenance for each component increases, even though lower control limits are set on the degradation levels. (The plot of Z_1 under a larger τ value is included in Appendix A)

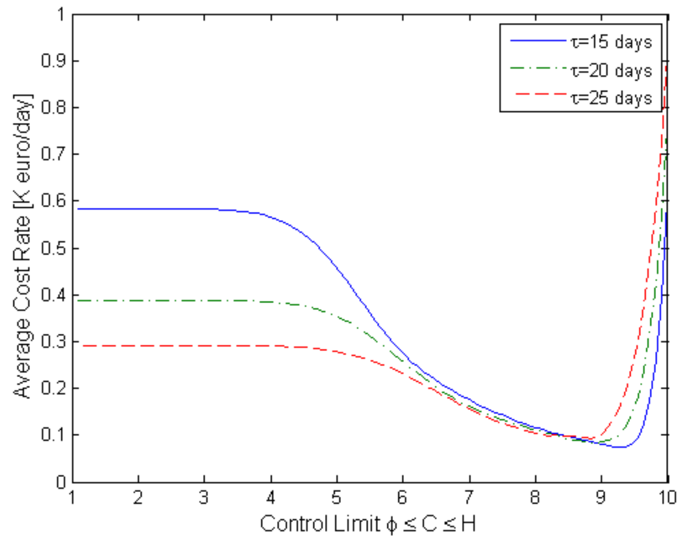

Figure 6: Average cost rate [K-Euros per day] on component 1 over C_1 for various τ value

To evaluate the performance of our model, we also calculate the optimal maintenance policy of the model without the control limits C_i for PM actions, i.e., there are only CM actions for components. In this *CM-only policy*, a CM actions is performed when the degradation of a component $X_i(t)$ in the overall system reaches H_i. The formulas for evaluating the CM-only policy are given in Appendix B. Using the same parameter setting in Table 1, the optimal solution of the CM-only policy suggests to have a joint maintenance interval of $\tilde{\tau} = 5.98$ days and the corresponding average cost rate $\tilde{Z}_{syst}(\tau^*)$ is 36817 Euros per day (see Table 3). Notice that the maintenance interval of this policy is much smaller than the policy with control limits, because a shorter maintenance interval helps to decrease the CM probability and soft failures costs when no PM actions are taken.

Optimal Policy	Values	Explanation
$\tilde{Z}_{syst}(\tau^*)$	36817	the minimum average cost rate of the overall system [Euro / day]
$\tilde{\tau}^*$	5.98	the optimal maintenance interval of the overall system [day]
$\{\tilde{Z}_a(\tau^*), \tilde{Z}_b(\tau^*), \tilde{Z}_c(\tau^*)\}$	$\{432.1, 553.8, 438.3\}$	the minimum average maintenance cost rate of each component [Euro / day].

Table 3: The optimal maintenance policy under corrective-maintenance-only scenario (index: a = Main Bearing, $i \in \{1, ..., 20\}$; b = Gearbox, $i \in \{21, ..., 40\}$; c = Generator, $i \in \{41, ..., 60\}$)

The comparison of the optimal policies in Table 2 and Table 3 demonstrates that the model with control limit ($Z_{syst}(\tau^*, C_i^*) = 7424$) outperforms the CM-only policy ($\tilde{Z}_{syst}(\tau^*) = 36817$). In this wind power farm case, about 80% cost reduction can be achieved by implementing the optimal maintenance policy of our model.

5. Sensitivity Analysis

A sensitivity analysis is performed based on varying one parameter from Table 1 by 50 % from the original setting and the rest of parameter setting remains unchanged. Four cost parameters ($C_{PM,i}$, $C_{CM,i}$, S and $C_{p,i}$) and the degradation rate α_i are chosen from Table 1 to perform the analysis. Based on the fluctuation of 50% on the parameter setting, the sensitivity of the optimal maintenance policy can be observed in Table 4.

	$Z_{syst}(\tau^*)$	τ^*	$C_a^*(\tau)$	$C_b^*(\tau)$	$C_c^*(\tau)$
Original optimal solution	7424	36.1	8.11	17.12	12.72
New parameter setting:					
$C_{PM,i} * 50\%$	86%	94%	99%	97%	98%
$C_{PM,i} * 150\%$	108%	105%	101%	102%	102%
$C_{CM,i} * 50\%$	98%	106%	101%	101%	102%
$C_{CM,i} * 150\%$	101%	97%	98%	99%	99%
$S * 50\%$	90%	56%	109%	106%	108%
$S * 150\%$	112%	113%	96%	97%	97%
$C_{p,i} * 50\%$	96%	103%	102%	103%	102%
$C_{p,i} * 150\%$	103%	97%	98%	99%	99%
$\alpha_i * 50\%$	22%	411%	97%	98%	98%
$\alpha_i * 150\%$	276%	33%	102%	102%	104%

Table 4: Sensitivity analysis: the percentages of the new optimal solutions divided by the original optimal solution. Notice that only one of the parameters in the original parameter setting changes by ±50% and the rest remains the same. (index a = main bearing, b = gearbox, c= generator)

The results of the sensitivity analysis match our intuition. The optimal maintenance interval τ^* increases when the PM cost $C_{PM,i}$ or setup cost S increases, which implies that it is economically beneficial to have longer maintenance interval and less frequent maintenance setups when the preventive maintenance and the set-up are more expensive. The optimal control limits increase when $C_{PM,i}$ increases, which means at the individual component level the control policy becomes less strict to avoid high $C_{PM,i}$. However, when τ becomes larger due to a higher S, the optimal control limits decrease in order to avoid the high CM cost $C_{CM,i}$ and soft failure costs at the individual component level. In other words, the optimal maintenance interval and control limits decrease when $C_{p,i}$ or $C_{CM,i}$ increases, which suggests that it is economically beneficial to have more frequent maintenance setups and tighter control over the degradations of components. Compared with the changes in the cost parameters, the optimal solution is much more sensitive to the change in the degradation rate α_i. If α_i increases, namely, the degradation is faster and s-expected maintenance cycle length gets shorter; the probability of CM and soft failure cost will increase, which also results in a higher $Z_{syst}(\tau^*)$ and a shorter τ^*.

6. Conclusions

In this paper, we proposed a new condition-based maintenance model for multi-component systems with continuous stochastic deteriorations. In order to reduce the high setup cost of maintenance for multi-component systems, we used a joint maintenance interval τ to coordinate the maintenance tasks. In addition, we introduced the control limits C_i on the degradation levels of components to trigger the preventive maintenance actions. The optimal maintenance control limits of components and the optimal joint maintenance interval were determined by minimizing the average long-run cost rate related to maintenance and failures. A nested enumeration approach was proposed to solve this large-scale optimization problem. We first decomposed the optimization of the overall system into the optimization at the individual component level to obtain the optimal C_i for a given τ. Afterwards, we enumerated τ to find the minimum average maintenance cost rates of the overall system. The numerical example with a wind power farm demonstrated that our model and the nested enumeration approach can be applied on complex systems with a large number of non-identical components. Comparing with a corrective-maintenance-only policy, our optimal maintenance policy has a large cost-saving potential. Moreover, a sensitivity analysis was conducted to investigate the influence of different parameter settings on the optimal solutions.

Our model can be utilized to solve the maintenance scheduling problems of various engineering systems with a large number of non-identical components (e.g., offshore platforms, solar energy farms), because 1) it is convenient in practice to implement such a static maintenance interval for planning; 2) different physics of failures and degradations models can be described by the random coefficient model; 3) our model can be integrated with different maintenance policies (e.g., age-based maintenance, periodic inspection) due to the static maintenance interval.

For future research, the maintenance interval can be dynamic, rather than static, in order to further reduce the average long-run cost rate. Another possible extension of the model is to consider the system structures or the dependency of components in the systems. Moreover, the effect of hard failures on the maintenance policies of complex systems can also be investigated, since many components in a system are subject to multiple failure processes (e.g., random shocks, wear-out, and crack growth). Finally, it is also possible to include additional constraints in our model, such as the resource capacity or the service level target.

7. Appendices:

A. The average cost rate of component 1 over two decision variables C_1 and τ

We plot the the average cost rate of component 1 as a function of both C_1 and τ in Figure 7.

B. Description of CM-only policy

For each component $i \in I$, the CM-only policy implies that there is no PM action taken, so that no control limit C_i is set on the degradation before H_i is reached (see Figure 2). Or equivalently, $C_i = H_i$. The

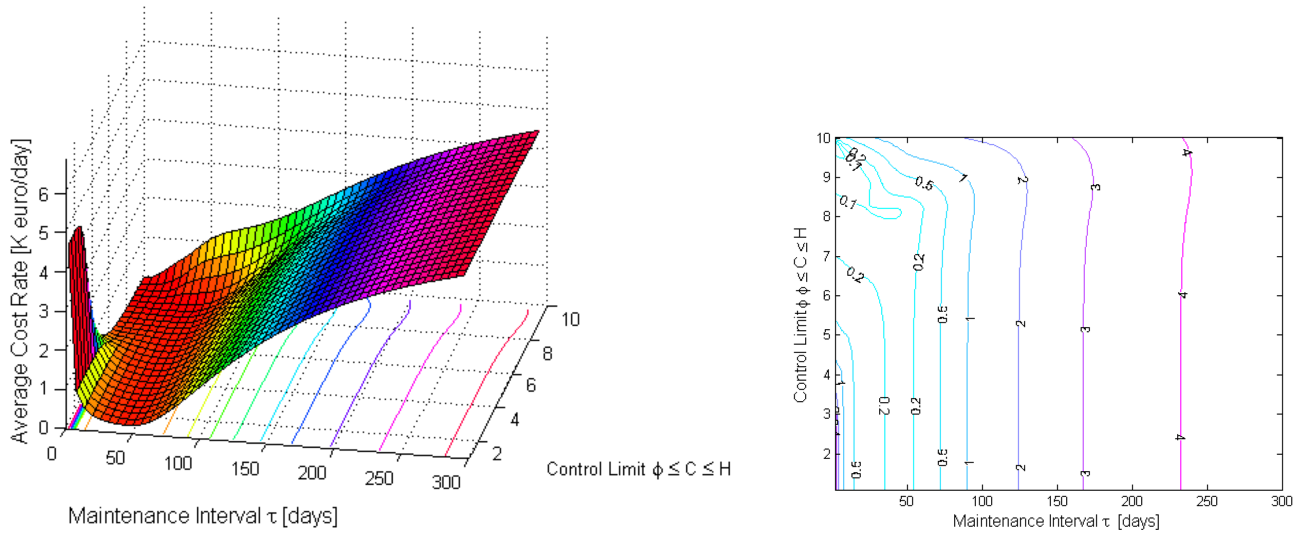

Figure 7: Average cost rate on component 1 over τ and C_1 (Left: 3D plot; Right: contour plot)

optimization algorithm of our model in Section 3.2 remains unchanged, and Equation (5), (6), (10), (12) and (11) are derived as follows:

$$\mathbb{E}\Big[K_i(\tau, H_i)\Big] = \sum_{n\in\mathbb{N}} \Bigg[Pr\{PM\ at\ n\tau\}C_{PM,i} + Pr\{CM\ at\ n\tau\}C_{CM,i} + \mathbb{E}\Big[D_i(\tau, H_i)\Big]C_{p,i}\Bigg]$$

and

$$\mathbb{E}\Big[L_i(\tau, H_i)\Big] = \sum_{n\in\mathbb{N}} n\tau Pr\{(n-1)\tau \le T_{H_i} < n\tau\}$$

where

$$Pr\{PM\ at\ n\tau\} = 0$$
$$Pr\{CM\ at\ n\tau\} = Pr\{(n-1)\tau \le T_{H_i} < n\tau\}$$

$$\mathbb{E}\Big[D_i(\tau, H_i)\Big] = \sum_{n\in\mathbb{N}} \int_{(n-1)\tau}^{n\tau} (n\tau - x)\ f_{T_{H_i}}(x)dx$$

C. Optimization Algorithm

The procedure of the nested enumeration algorithm can be summarized as follows:

Notice different grid sizes can be used for optimizing C_i and τ , which will also affect the computational duration. In this paper, we use the grid size $H_i/500$ and $M_\tau/500$ for C_i and τ respectively. The upper bound M_τ is a very large value (at least larger than $max_{i\in I}\{G_i\}$.). In this paper, we choose $M_\tau] = 300$ days [15].

Algorithm 1 Nested optimization algorithm.

Initialize
for all $\tau \in (0, M_\tau]$ **do**
  for all $i \in I$ **do**
    for all $C_i \in [\phi_{i,1}, H_i]$ **do**
      $Z_i(\tau, C_i) = \frac{\mathbb{E}\left[K_i(\tau,C_i)\right]}{\mathbb{E}\left[L_i(\tau,C_i)\right]}$
    end for
    $C_i^*(\tau) = argmin\{Z_i(\tau, C_i)\}, \quad i \in I$
  end for
  $Z_{syst}(\tau) = \frac{S}{\tau} + \sum_{i \in I} Z_i^*(\tau)$
end for
$\tau^* = argmin\{Z_{syst}(\tau)\}$
Results: optimal maintenance policy $\{\tau^*, C_i^*(\tau^*)\}, \forall i \in I$

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