Optimizing the Updating Stopping Condition for a Predictive Maintenance Policy

Ming-Yi You*

No. 36 Research Institute of CETC, No. 387 Hong Xing Rd., Jia Xing, Zhe Jiang Province, 314033, China

Abstract: The updating stopping condition (USC) has great impact on the effectiveness of a predictive maintenance (PdM) policy, but did not receive enough attention. This paper reviews the common USCs, proposes a residual life based USC, and evaluates the influence of the USCs on the effectiveness of a PdM policy. The commonly used USCs are concretely defined in a PdM policy based on the stochastic linear degradation model. An extensive numerical investigation compares the performances of the PdM policy using different USCs. The investigation results verify the importance of optimizing the USC for a PdM policy.

Keywords: Updating stopping condition, predictive maintenance, maintenance optimization, reliability.

1. INTRODUCTION

The economic relevance of maintenance in all sectors of industrial sectors is continuously promoting the advance of maintenance technology and management [1]. Nowadays, maintenance policies such as condition-based maintenance (CBM) and predictive maintenance (PdM) are important research subjects in reliability engineering. Due to the systematic collection of system condition information, reasonable prediction of future development of system condition, and a wise balance between maintenance cost and risk of system failure, PdM can effectively improve asset reliability, reduce maintenance cost, extend useful lifetimes and reduce safety risks [2-4]. Different from the population-oriented preventive maintenance (PM) policies and CBM policies, a PdM policy optimizes the maintenance schedule based on the system's condition information monitored in real time. Consequently, the optimized maintenance schedule in a PdM policy is only applicable to the specific system being monitored. In addition, the PdM policy updates the maintenance schedule with the arrival of the system's most recent condition monitoring information. Consequently, a PdM policy needs an updating stopping condition (USC) to stop the update of the maintenance schedule and decides the final maintenance time.

An updating step length based USC is proposed for a component-level sequential PdM policy in [5]. Based on the proposed USC, the update of the maintenance schedule is stopped once the distance between the maintenance schedule and the current moment is less than the updating step length. Kaiser and Cebraeel used a reliability based USC in a component-level PdM policy based on an updating system degradation model [6]. Curcuru, Galante and Lombardo decided the updating stopping moment through comparing the expected maintenance cost in the considered time interval with and without a PM action in each decision moment [7]. Zio and Compare proposed to perform a PM act when the current moment is the optimized maintenance schedule or the system's condition reaches the safety threshold with a given probability [1].

Although many researchers have used the USCs in different PdM policies, most of the studies focus on the development of PdM models and the optimization of maintenance schedule. Actually, a USC is a key factor which decides the final maintenance time and essentially influences the effectiveness of a PdM policy. Stopping the update of maintenance schedule when the system is still normally operating is ineffective, as the condition monitoring information closer to system failure is simply ignored when deciding the maintenance schedule. On the other hand, an overaggressive USC could lead to system failure before maintenance acts due to the rapid change of system condition. An ideal USC should make a wise balance between scheduling maintenance acts using more recent system conditions and the risk of unexpected system breakdowns. By the above motivations, this paper focuses on the effect of USCs on the effectiveness of PdM policies and their optimization. In addition, an extended updating step length based USC and a novel residual life based USC is proposed to be valuable alternates in the USC library.

The rest of the paper is organized as follows: Section II reviews the commonly used USCs, extends the updating step length based USC and proposes a

*Address correspondence to this author at the No. 36 Research institute of CETC, No.387 Hong Xing Rd., Jia Xing, Zhe Jiang Province, 314033, China; Tel: 86-0573-83678032; Fax: 86-0573-83683600; E-mail: youmingyi@126.com

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residual life based USC. Section III gives an example PdM policy, concretizes the USCs in the given PdM policy. Section IV evaluates the USCs based on an extensive simulation study. Finally, sectionV concludes the paper.

2. USCS FOR PDM POLICIES

This section reviews the commonly used USCs in PdM policies with some extensions. It is noted that the mentioned USCs are primarily proposed for single-unit systems, the relationship between units in multi-unit systems are not strictly considered, which may suggest group maintenance.

The 1st commonly used USC is the updating step length based USC [5], and can be given as:

$$T^*\left(t\right)-t\le \Delta t \tag{1}$$

where t is the current moment, $T^*\left(t\right)$ is the PM schedule suggested by the PdM model closest to the current moment, Δt is the updating step length or the sampling interval of condition monitoring. The USC in Eq. (1) suggests updating stopping and PM acts at time t when the distance between the current moment and $T^*\left(t\right)$ is smaller than the updating step length. When the degradation process becomes noisy and the predictions of the system's future health become very uncertain, the USC in Eq. (1) may easily lead to abrupt system breakdown. To avoid the unexpected failure, the USC in Eq.(1) can be extended as

$$T^*\left(t\right)-t\le n\cdot\Delta t \tag{2}$$

where n is an positive integer.

The 2nd commonly used USC is the reliability based USC. Kaiser and Gebraeel proposed a reliability based USC as follows [6]:

$$\min_{0<t_k<\infty}\left\{1-\left[F_T\left(t_{k+\delta}\right)-F_T\left(t_k\right)\right]\right\}\ge R \tag{3}$$

where t_k and $t_{k+\delta}$ are time variable, δ is a small time interval, and $t_{k+\delta}>t_k$, $F_T\left(t_k\right)$ is the cumulative distribution function of system failure at time T predicted at time t_k, R is the ideal probability threshold. The interpretation for the USC in Eq. (3) is to stop updating of maintenance schedule when the failure probability in a time interval $\left(t_k,t_{k+\delta}\right)$ exceed a certain value. In practice, people may be more concerned with the reliability level of the system, and the reliability based USC can be in the form as follows:

$$1-F_T\left(T^*\left(t\right)\right)\le R' \tag{4}$$

where R' is the reliability threshold. The interpretation for the USC in Eq. (2) is to stop updating of maintenance schedule when the expected system reliability at time $T^*\left(t\right)$ is smaller than the ideal reliability level R'.

The 3rd commonly used USC is the condition based USC. Zio and Compare suggested performing the PM acts when the probability of system condition to be worse than the safety level is larger than a certain threshold [1]. They estimated the system condition using particle filtering. In a PdM policy, the condition based USC can be

$$p\left(s\left(t\right)\le s_r\right)\ge r_s \tag{5}$$

where $s\left(t\right)$ the system condition at current time t, s_r is the condition level, r_s is the probability threshold for the system's condition. The USC in Eq. (5) means to stop updating and perform a PM act at time $T^*\left(t\right)$ when the probability of the system's condition to be worse than s_r is larger than r_s. To use the USC in Eq. (5), the mapping function between the system's monitored performance variables and its health state should be defined. If the system's performance variables can directly reflect its health state, then the USC in Eq. (5) can be reduced as

$$v_i\left(t\right)\le s_{ir} \tag{6}$$

where $v_i\left(t\right)$ is the system's ith performance variable, and s_{ir} is the corresponding condition level. It is noted that Eq. (6) is applicable to the case of the greater $v_i\left(t\right)$ the better. In the case of the smaller $v_i\left(t\right)$ the better, Eq. (6) should be revised as

$$v_i\left(t\right)\ge s_{ir} \tag{7}$$

In some cases, the residual lifetime of a system may be a more understandable variable to maintenance engineers or manufacturing managers, as it directly tells the time interval the system can continue to survive. In such cases, a residual life based USC is proposed as

$$RL\left(t\right)\le r_l \tag{8}$$

where $RL\left(t\right)$ is the residual life of the system predicted at time t, r_L is the lifetime threshold.

3. PDM POLICY

This section gives a PdM policy widely used in manufacturing/production industry and concretizes the USCs. The established PdM policy constitutes the base for further numerical analysis.

This paper establishes a component-level PdM policy based on a stochastic linear degradation model. The key factors for the PdM policies are: 1) Objectives: minimizing the maintenance cost rate within a replacement cycle; 2) Maintenance policy: sequential maintenance; 3) maintenance effect: perfect PM and corrective maintenance (CM); 4) Degradation characteristics: stochastic liner degradation model; 5) maintenance constraints: none. The timing of the PdM policy is illustrated in Figure **1**.

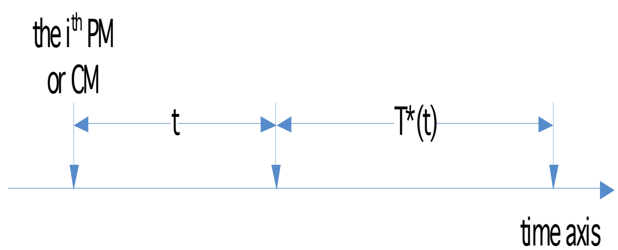

Figure 1: Timing of the PdM policy.

Based on the above factors, the maintenance cost rate within a replacement cycle estimated at time t in the PdM policy is

$$r(t) = \frac{C_{CR}(t) + C_{PR}(t)}{T_O(t)} \tag{9}$$

where $r(t)$ is the maintenance cost rate within the replacement cycle estimated at time t, $C_{CR}(t)$ is the CM cost within the replacement cycle estimated at time t, $C_{PR}(t)$ is the PM cost within the replacement cycle estimated at time t, $T_O(t)$ is the operation time within the replacement cycle estimated at time t.

In Eq. (9), $C_{CR}(t)$ could be estimated as

$$C_{CR}(t) = CCR \cdot \left[1 - R\left(T(t)\middle|t\right)\right] \tag{10}$$

where CCR is the maintenance cost per CM, $T(t)$ is the PM schedule estimated at time t, $R\left(T(t)\middle|t\right)$ is the system reliability at time $T(t)$ predicted based on its condition monitoring information up to time t. On the other hand, $C_{PR}(t)$ in Eq.(9) can be concretized as

$$C_{PR}(t) = CPR \cdot R\left(T(t)\middle|t\right) \tag{11}$$

where CPR is the maintenance cost per PM. In Eq.(9), $T_O(t)$ could be estimated as

$$T_O(t) = t + \int_t^{T(t)} R(\upsilon|t)d\upsilon \tag{12}$$

where $R(\upsilon|t)$ is the system reliability at time υ predicted based on its condition monitoring information up to time t and $\upsilon \geq t$. At time t, to find the optimal $T(t)$ (denoted as $T^*(t)$) that minimizes $r(t)$, the estimation method for $R(\upsilon|t)$ must be clearly defined. This paper considers a single-unit system with one performance variable, characterizes the performance variable using the stochastic linear degradation model, and further calculates $R(\upsilon|t)$. Examples for the single-unit system with one performance variable modeled by the stochastic linear degradation model include rolling bearings [8], laser systems [9], thrust drillers [10], etc. The stochastic linear degradation model is [11]:

$$L(t) = \theta + \beta t + \varepsilon(t) \tag{13}$$

where $L(t)$ is the monitored performance variable at time t, θ is a constant and $\theta \sim N(\mu_0, \sigma_0^2)$, where $N(\mu_0, \sigma_0^2)$ means normal distribution with mean μ_0 and variance σ_0^2, β reflects the changing rate of the system condition and $\beta \sim N(\mu_1, \sigma_1^2)$, $\varepsilon(t)$ is an error term which follows centralized Brownian motion and $\varepsilon(t) \sim N(0, \sigma^2 t)$. In the operation process of the system, the most recent condition monitoring information arrives at each condition sampling point. Gebraeel etc. proposed a Bayes based method for updating the model parameters in Eq. (13) [11]. Based on the updated model parameters, $R(\upsilon|t)$ can be predicted as

$$R(\upsilon|t) = P\left(L(\upsilon|t) \leq CL\right) = \Phi\left(\frac{CL - \tilde{\mu}_1(\upsilon)}{\tilde{\sigma}_1(\upsilon)}\right) \tag{14}$$

where $P(A)$ means the probability of event A, $L(\upsilon|t)$ is the system's performance variable at time υ predicted based on its condition monitoring information up to time t, CL is the critical level for the performance variable and the system is considered failed once its performance variable exceeds CL. $\Phi(\cdot)$ is the cumulative distribution function of standard normal distribution. $\tilde{\mu}_1(\upsilon)$、$\tilde{\sigma}_1(\upsilon)$ is the predicted values of μ_1 and σ_1 and are given as:

$$\begin{aligned}\tilde{\mu}(\upsilon) &= L(t)+\mu_\beta(\upsilon-t)\\ \tilde{\sigma}(\upsilon) &= \sqrt{\sigma^2(\upsilon-t)+\sigma_\beta^2(\upsilon-t)^2}\end{aligned} \tag{15}$$

where μ_β and σ_β are respectively the updated values of μ_1,σ_1 at time t. The details of the updating method of model parameters can be referred to [11]. Substituting Eqs. (10) ~ (12) and Eq. (14) into Eq.(9) gives:

$$r(t)=\frac{CCR\cdot\left[1-\Phi\left(\frac{CL-L(t)-\mu_\beta(T(t)-t)}{\sqrt{\sigma^2(\upsilon-t)+\sigma_\beta^2(\upsilon-t)^2}}\right)\right]+CPR\cdot\Phi\left(\frac{CL-L(t)-\mu_\beta(T(t)-t)}{\sqrt{\sigma^2(\upsilon-t)+\sigma_\beta^2(\upsilon-t)^2}}\right)}{t+\int_t^{T(t)}\Phi\left(\frac{CL-L(t)-\mu_\beta(\upsilon-t)}{\sqrt{\sigma^2(\upsilon-t)+\sigma_\beta^2(\upsilon-t)^2}}\right)d\upsilon} \tag{16}$$

Based on Eq. (16), $T^*(t)$ is given as:

$$T^*(t)=\arg\min_{T(t)}\left[r(t)\right] \tag{17}$$

By Eq. (17), there is a temporary $T^*(t)$ at each condition monitoring moment, and consequently a USC is needed to stop updating and determine the final PM time. The updating step length based USC is clearly defined in Eq. (2). For reliability based USC defined in Eq. (4), the USC for the PdM policy can be more concretely written as:

$$\Phi\left(\frac{CL-L(t)-\mu_\beta\left(T^*(t)-t\right)}{\sqrt{\sigma^2\left(T^*(t)-t\right)+\sigma_\beta^2\left(T^*(t)-t\right)^2}}\right)\le R' \tag{18}$$

The PdM policy is established based on the fact that the performance variable can directly reflect the system's health state, and hence the condition based USC is

$$L(t)\ge s_r \tag{19}$$

In addition, the residual life based USC can be concretized as

$$\int_t^\infty \Phi\left(\frac{CL-L(t)-\mu_\beta(\upsilon-t)}{\sqrt{\sigma^2(\upsilon-t)+\sigma_\beta^2(\upsilon-t)^2}}\right)d\upsilon\le r_l \tag{20}$$

4. NUMERICAL INVESTIGATION

This section conducts an extensive numerical investigation on the effect of the USCs on the effectiveness of the typical PdM policy given in Section III, and discusses the problem of USC optimization.

Table 1: Model Parameters

parameter	μ_0	σ_0	μ_1	σ_1	σ	CL
value	1	1	4	1	1/2/4	200

The 1st step of the numerical investigation is data generation, and failure definition. The stochastic linear

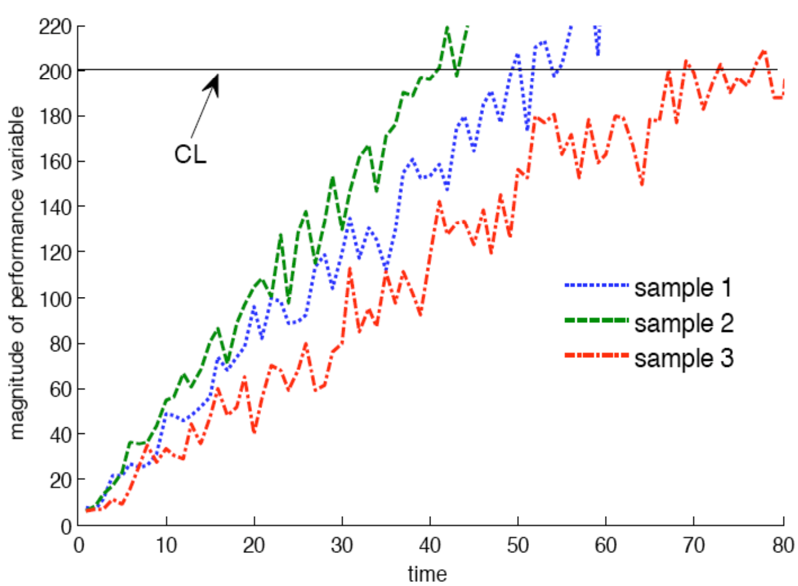

Figure 2: 3 Randomly selected degradation processes with $\sigma=2$.

degradation model is used to simulate the performance variables in the system degradation processes. The model parameters are defined in Table **1** without loss of generality. In addition, the CL is also defined in Table **1**. Using the model parameters in Table **1**, 100 degradation processes are simulated. Figure **2** illustrates 3 degradation processes randomly selected out of the simulated samples.

The 2nd step of numerical investigation is to establish the PdM model in Eq.(17) and calculate $T^*(t)$ for each simulated sample and at each condition monitoring point. Without loss of generality, $\Delta t = 1$ is used in this paper. To establish the PdM model, the maintenance cost rate CCR/CPR needs to be defined at first. Herein, two typical cases for $CCR/CPR = 2$ and $CCR/CPR = 4$ are considered.

The 3rd step of numerical investigation is to determine the maintenance schedule for each sample based on different USCs and analyze the performance of each USC based on the performance of the PdM using the USC. The performance of the PdM can be defined as

$$r_A = \frac{PPR \cdot n_{PM} + CPR \cdot n_{CM}}{\sum_{i=1}^{100} T_{Oi}} \tag{21}$$

where r_A is the actual average maintenance cost rate for the simulated samples, n_{PM} is the actual number of samples receiving PM acts before failure, and n_{CM} is the actual number of samples which fail before receiving PM acts, T_{Oi} is the actual operation time for sample i. T_{Oi} equals the maintenance schedule if sample i receives a PM act, and equals its lifetime if sample i fails in the end.

Figure **3** ~ Figure **10** demonstrate the performance of the PdM policy using 4 USCs. Based on the results, the best performance of the PdM policy using 3 USCs for CCR/CPR=2 comes close to 0.02CPR, while the reliability based USC gives slightly worse results. Based on the results in Figure **3** ~ Figure **10**, the best performance of the PdM policy using a certain USC and a given noise level of degradation process may differ greatly from its suboptimal performance. For example, r_A=0.020 CPR for the time-based USC for CCR/CPR=2 and n=3, and r_A=0.033 CPR for the time-based USC for CCR/CPR=2 and n=20. This verifies the importance of optimizing the USC for a PdM policy.

In practice, the cross validation method can be adopted to obtain the optimal value for a given USC based on historical samples. Actually, these historical samples are not only a prerequisite for optimizing a USC, they are used to establish the model of degradation processes for a PdM policy as well.

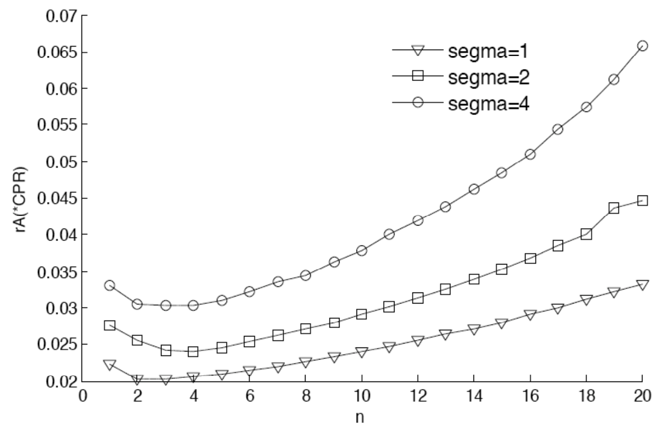

Figure 3: r_A with respect to different n for time-based updating stopping condition for CCR/CPR=2.

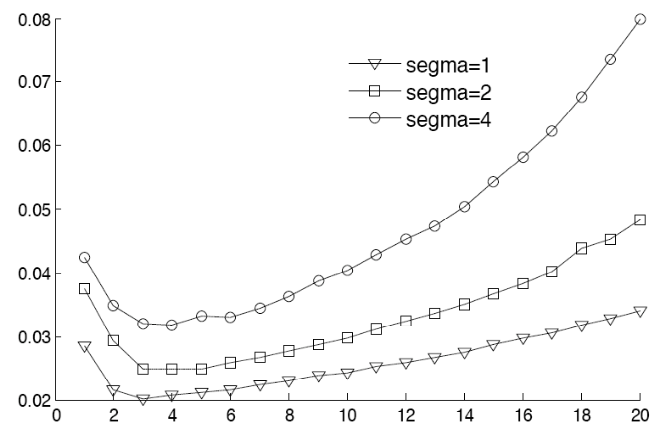

Figure 4: r_A with respect to different n for time-based updating stopping condition for CCR/CPR=4.

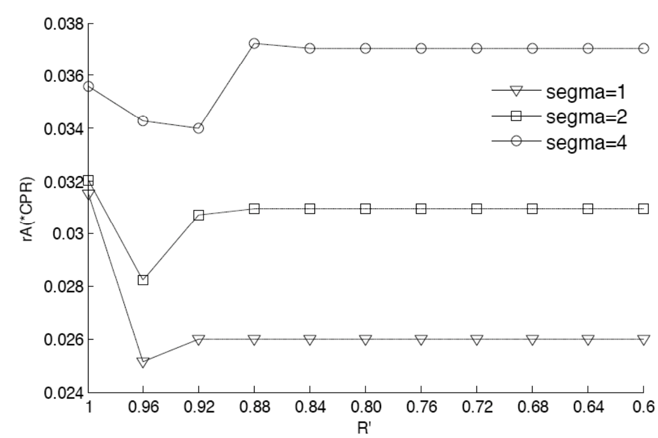

Figure 5: r_A with respect to different reliability threshold for reliability-based updating stopping condition for CCR/CPR=2.

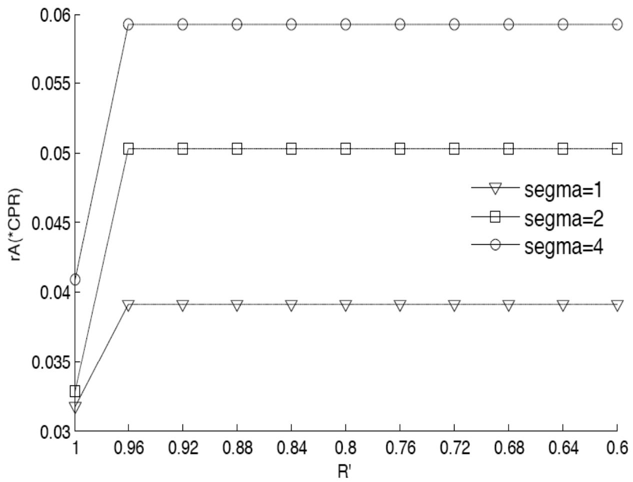

Figure 6: r_A with respect to different reliability threshold for reliability-based updating stopping condition for CCR/CPR=4.

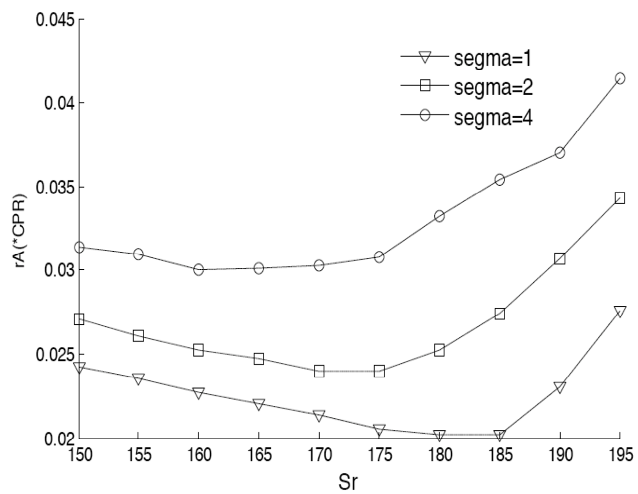

Figure 7: r_A with respect to different residual life threshold for condition-based updating stopping condition for CCR/CPR=2.

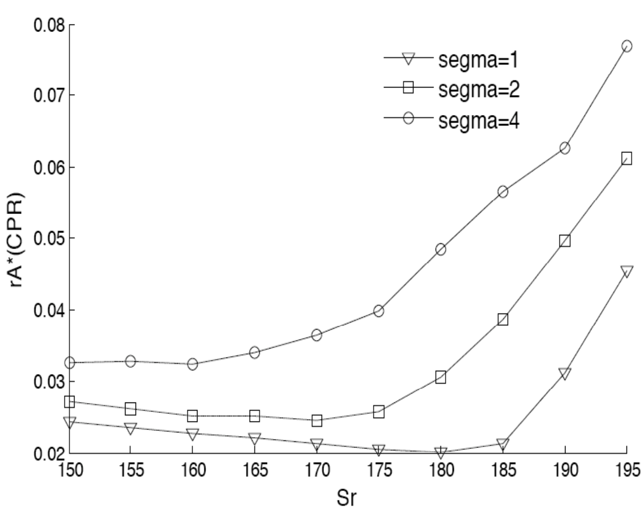

Figure 8: r_A with respect to different residual life threshold for condition-based updating stopping condition for CCR/CPR=4.

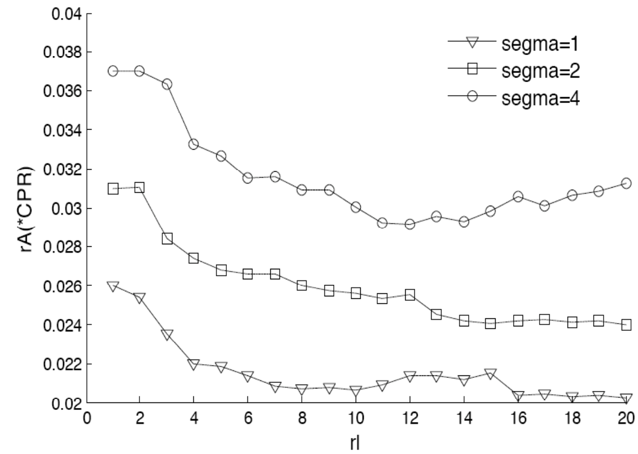

Figure 9: r_A with respect to different residual life threshold for residual life-based updating stopping condition for CCR/CPR=2.

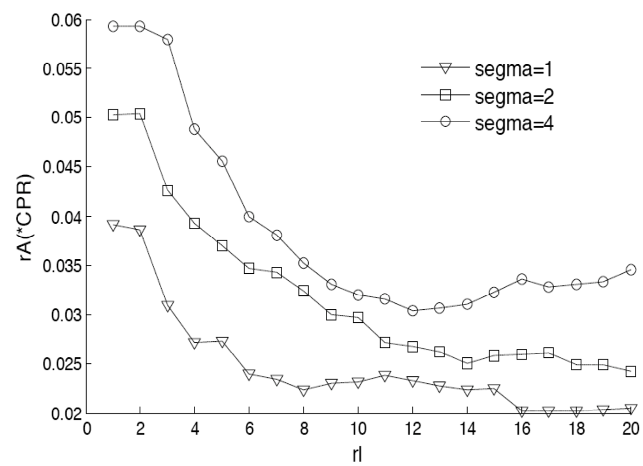

Figure 10: r_A with respect to different residual life threshold for residual life-based updating stopping condition for CCR/CPR=4.

5. CONCLUSION

This paper reviews the common USCs, proposes a residual life based USC, and evaluates the influence of the USCs on the effectiveness of a PdM policy. The commonly used USCs are concretely defined in a PdM policy based on the stochastic linear degradation model. An extensive numerical investigation compares the performances of the PdM policy using different USCs. The investigation results verify the importance of optimizing the USC for a PdM policy. Investigating the effect of a USC on the effectivenesss of a system-level PdM policy may be a valuable topic in the future.

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