Optimisation of maintenance policies for a deteriorating multi-component system under external shocks

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Abstract: Many engineering systems are affected by shocks from their operating environments. When the state of a component degrades to a certain threshold level, preventive maintenance is needed for the purpose of reliability improvement. However, existing studies usually ignore the impact of shocks on different components of a system and therefore on the maintenance policies. This paper proposes to model the degradation processes of components with a k-dimensional Wiener process. Under both deterministic and stochastic environmental conditions, the Eyring model is used to measure the environmental importance of the multi-dimensional degradation process. Then, according to different failure scenarios, different maintenance strategies are proposed. A periodic inspection policy is considered for each component that may fail due to shock environments. As for multiple components, the maintenance priority is determined based on the joint importance, and optimal preventive maintenance is obtained under the condition of limited resources. Finally, a robot system is taken as an example to verify the correctness and effectiveness of the proposed methods.

Keywords: System Reliability; Preventive maintenance; Importance measure; Degradation

1. Introduction

The impact of external shocks, which are from the operating environment of an engineering system, on the reliability of the systems has been considered in the literature of reliability and maintenance [1, 2, 3]. Wang et al. [4] investigate the impact of shocks from multiple external sources. Zhao et al. [5] propose a new shock model for the scenarios that the damage process of a component accelerates with the increased damage from external shocks. Wu et al. [6] study a performance-sharing system under external shocks. Zhao et al. [7] jointly optimize inspection policies and condition-based mission abortion policies for systems subject to continuous degradation. Zhao et al. [8] investigate systems' executing missions in a random environment with a cumulative shock model and a run shock model. Song et al. [9] use both probabilistic and physical degradation modeling concepts to develop a new system reliability model by considering the effects of shock damages.

In reliability and safety engineering, many importance measures have been proposed. These importance measures have been widely used in maintenance policy optimisation to provide guidance during the stages for reliability improvement and maintenance policy optimization. Considering the maintenance cost, Bai et al. [10] propose an importance measure based on fuzzy cost and analyze weak links of the industrial robot system from the perspective of the maintenance economy. Dui et al. [11] propose an improved uncertainty significance analysis method to effectively characterize the reliability of polymorphic systems. Chen et al. [12] use the Wiener process to describe the continuous-time degradation process and develop a Copula Hierarchical Bayesian Network for system reliability estimation. In terms of system performance, Dui et al. [13,14] extend the materiality measurement standard to evaluate how the transfer of component state affects the change in system performance. Considering component maintenance cost and time, Dui et al. [15] propose a cost-based comprehensive importance measure to identify components or component groups that can be selected for preventive maintenance. Liu et al. [16] introduce an importance measure based on cost by comprehensively considering the objective function and constraint conditions. Levitin et al. [17] consider some commonly used importance measures in a generalized version for the application to multi-state systems. Si et al. [18] extend the integrated importance measure to estimate the effect of a component residing at certain states on the performance of the entire multi-state systems.

Preventive maintenance plays a critical role in ensuring reliable performance at the lowest cost. Levitin et al. [19] consider the problem of optimal maintenance strategies for networks affected by multiple performance degradation levels and performing real-time tasks, which enriches evaluation methodologies for software aging and rejuvenation systems. Zhao et al. [5] propose an opportunistic maintenance policy based on a new shock model and an optimization model is constructed to obtain the optimal maintenance solutions. Zhao et al. [20] investigated the component reassignment problem for a balanced system with multi-state components working in a shock environment. Zhu et al. [21] present the importance of considering various maintenance behaviors such as incomplete maintenance and replacement and propose preventive maintenance strategies based on residual life and residual profit. For the systems that fail due to degradation or external impact, Hashemi et al. [22] propose an optimal preventive maintenance model based on service age by considering preventive maintenance cost, corrective maintenance cost, and minimum maintenance cost. Shi et al. [23] establish an optimization model for the preventive maintenance policy of the system through an in-depth discussion of the impact of maintenance on structural performance function and use this model to estimate the reliability of the system. Levitin et al. [24] make contributions by modeling and optimizing the replacement and maintenance schedule (RMS) to minimize the total expected mission cost, covering operation, standby, and maintenance costs as well as mission failure penalty cost. Levitin et al. [25] formulate and solve a constrained optimization problem that determines the joint RMS and mission abort policy.

Existing literature, however, has paid little attention to the impact of external environments on reliability, and the impact of shock environments on maintenance policy is rarely considered. For example, extreme conditions including wet or muddy terrain, dust, moisture, vibration, corrosion, and toxic conditions (such as radiation) may have a great impact on the service life of industrial robots.

This paper focuses on the deterioration phase in shock environments when exploring an optimal preventive maintenance policy for the system. The major challenges and contributions of this paper are summarized in the following. First, a degradation process model in shock environments is developed to study the reliability of a system under the working state from deterministic and stochastic perspectives. Second, an environmental importance measure is used to assess the preventive maintenance priority of each component with external shocks. The importance takes the impact of the multi-dimensional deterioration period into account. Third, optimal preventive maintenance is developed to maximize reliable performances and minimize failure losses.

The remainder of this paper is organized as follows. Section 2 proposes a degradation model, which considers the characteristics of external shocks. Section 3 proposes a preventive maintenance policy on environmental importance. Section 4 presents a case study and illustrates the proposed metho on a robot system. Section 5 concludes the paper.

2. Degradation modeling in shock environments

System failures can usually be due to the failures of their components. In general, many components do not fail catastrophically but degrade over time, that is, the critical state of components usually changes over time and is affected by a series of factors, such as component reliability, degradation process, system structure, and environmental conditions. The criticality of components in the system can be obtained by using importance measures. The criticality of components usually depends on the degree of degradation, the level of fault threshold caused by degradation, dynamic environmental conditions, and system configuration.

Assuming that a system has n components, which are statistically independent of each other. The degradation process j of component i is expressed as $\left(X_j^{(i)}\right)_{j=1,2,\cdots,k}$. When any degradation process k_i relates to this component reaches the threshold level $n_j^{(i)}$, component i fails. That is, component i has multiple competing failure modes due to multi-dimensional degradation. For example, there are six failure modes of a six-axis robot's servo-driver components: IGBT overvoltage, IGBT overheating, IGBT overcurrent, resistance short circuit, resistance open circuit, and integrated circuit fault. The component will fail when any of the six degradation processes associated with the component reaches a certain threshold level.

The degradation process of components is modeled as a K-dimensional Wiener process. Then the relationship between the degradation process and shock environments is established, and the expression of environmental importance is obtained.

2.1 Deterministic environmental condition

Let $e_t: [0, \infty) \rightarrow R$ be a time-dependent real-valued function that specifies the shock environment at time t. Under certain external shocks, $e_t = e_0, t \geq 0$, the degradation process j of component i is modeled as:

$$dX_j^{(i)}(t; e_0) = \mu_{j,0}^{(i)} dt + \sigma_{j,0}^{(i)} dB_t \quad (1)$$

where $(B_t)_{t \geq 0}$ is the standard Brownian motion, and $\mu_{j,0}^{(i)}$ and $\sigma_{j,0}^{(i)}$ are respectively the degradation rate and diffusion coefficient under a constant shock environment, e_0. In practice, the degradation rate under a constant environmental condition is often determined by the physics-of-failure and can be modeled by degradation testing. The diffusion coefficient refers to the expected value of degradation change per unit of time. The generalized Wiener process has a constant expected diffusion coefficient.

The function $k_j^{(i)}(e_t)$ models the influence of the shock environments on both the degradation rate and diffusion coefficient:

$$\frac{\mu_j^{(i)}(t,e_t)}{\mu_{j,0}^{(i)}} = \left(\frac{\sigma_j^{(i)}(t,e_t)}{\sigma_{j,0}^{(i)}}\right)^2 = k_j^{(i)}(e_t) \tag{2}$$

with $\mu_j^{(i)}(t,e_t)$ and $\sigma_j^{(i)}(t,e_t)$, respectively, being the degradation rate and diffusion coefficient of the degradation process j of component i at time t and under the shock environment e_t. The choice of $k_j^{(i)}(e_t)$ is always case dependent in practice. For example, the degradation of electronic devices can often be attributed to the free energy difference between the initial state and the degraded state, and the function $k_j^{(i)}(e_t)$ becomes the Arrhenius equation. However, in the Arrhenius model, only the influence of a single temperature stress on the change of physical and chemical properties of the system is considered. In engineering practice, multiple stresses are acting on the system at the same time. While the Eyring model belongs to the multi-stress model, it is more general to use the Eyring model to represent shock environments $k_j^{(i)}(e_t)$:

$$k_j^{(i)}(e_t) = K(T,S) = \frac{dM}{dt} = A\frac{kT}{h}e^{-k/ET}e^{S(C+D/kT)} = K_0 f_1 f_2 \tag{3}$$

where, T is the temperature stress (thermodynamic temperature), S is the non-temperature stress, $\frac{dM}{dt}$ is the chemical reaction rate, $K_0 = A\frac{kT}{h}e^{-k/ET}$ is the Eyring reaction rate with only temperature stress, h is Planck constant, E is the activation energy (obeying Boltzmann distribution), k is the Boltzmann constant, $f_1 = e^{SC}$ is the correction factor for the energy distribution in the presence of non-temperature stresses, while $f_2 = e^{DS/kT}$ is the correction factor for the activation energy in the presence of non-temperature stresses.

Let $x_j^{(i)}(0)$ be the initial degradation level of the degradation process j of component i. Thus, the degradation process under a time-varying shock environment e_t is:

$$
\begin{aligned}
X_j^{(i)}(t;e_0) &= x_j^{(i)}(0) + \int_0^t dX_j^{(i)}(x;e_0) \\
&= x_j^{(i)}(0) + \int_0^t \mu_{j,0}^{(i)} k_j^{(i)}(e_x)dx + \int_0^t \sigma_{j,0}^{(i)} \left(k_j^{(i)}(e_x)\right)^{\frac{1}{2}} dB_x
\end{aligned} \tag{4}
$$

According to Liu et al. [26], this process is a Wiener process with a time-dependent mean value function and diffusion.

The components suffer from the process of degradation, so each component has multi-performance states. Due to the dependence among phases, the state of a component at the beginning of the current phase depends on its state at the end of the previous phase, and the component's behavior in a future instant only depends on its current state. Thus, we assume that the state of each component follows a continuous-time discrete-state Markov stochastic process. In this paper, we only consider the stationary performance when the system operates for a rather long time, and focus on the stationary distributions of the Markov stochastic processes.

Component i has M_i different performance levels, represented by the set $w_i = \{w_{i,1}, w_{i,2}, \cdots, w_{i,M_i}\}$, where 1 indicates the faulty state, M_i indicates the intact state, and other states increase in the order from faulty to intact. The sets of stationary state probability associated with w_i is $\alpha_i = \{\alpha_{i,1}, \alpha_{i,2}, \cdots, \alpha_{i,M_i}\}$. The $\lambda_{m,l}$ describes the transition rate from state m to state l of component i in a period T, as shown in Figure 1 and equation (5).

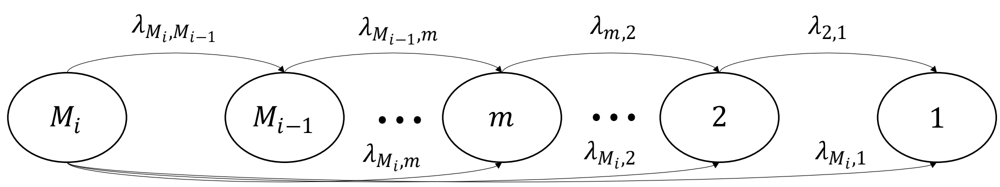


Fig. 1. State transition of component i

$$\Psi_i = \begin{bmatrix} \lambda_{M_i,M_{i-1}} & \cdots & \lambda_{M_i,1} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_{2,1} \end{bmatrix} \tag{5}$$

The probability of component i with a transfer rate between any two states at instant time t can be expressed as:

$$\begin{cases} \dfrac{d\alpha_{i,1}(t)}{dt} = \sum_{l=2}^{M_i} \alpha_{i,l}(t)\lambda_{l,1} \\ \dfrac{d\alpha_{i,m}(t)}{dt} = \sum_{l=m+1}^{M_i} \alpha_{i,l}(t)\lambda_{l,m} - \alpha_{i,m}(t)\sum_{l=1}^{m-1} \lambda_{m,l} \\ \dfrac{d\alpha_{i,M_i}(t)}{dt} = -\alpha_{i,M_i}(t)\sum_{l=1}^{M_{i-1}} \lambda_{M_i,l} \end{cases} \tag{6}$$

The stationary state probability $\alpha_{i,l}$ can be obtained by letting the left side of Eq. (6) equal to 0 and solving the equation $\sum_{l=1}^{M_i} \alpha_{i,l}(t) = 1$. Since we just consider the stationary state of each unit, the state distribution of a unit keeps unchanged across all the phases.

2.2 Stochastic environmental condition

When e_t is stochastic, the degradation rates and diffusion coefficients of the k_i degradation processes associated with component i are also stochastic. Additionally, as the degradation rates and diffusion coefficients of the k_i degradation processes share the same environmental condition e_t, the k_i degradation processes are no longer statistically independent.

Suppose that the shock environment can be written as $e_t = \widehat{e_t} + b_t$, where b_t is a stochastic process and $\widehat{e_t}$ is the predicted shock environment at time t. The choice of b_t is always case-dependent. For example, if b_t is a Brownian motion with drift zero and diffusion σ_e—i.e., $b_t = (\sigma_e B_t)_{t\geq 0}$ and $\varepsilon_{tn} = 0$—then e_t is a Brownian motion with a mean value function $\widehat{e_t}$ and a fluctuation b_t, or b_t can be a normal random representing the white noise.

3. Preventive maintenance based on environmental importance

In this section, we study environmental importance and preventive maintenance. Under external shocks, a component may fail due to its degradation, or multiple components may fail together due to common fatal shocks arriving from external sources. For different scenarios, different preventive maintenance strategies are discussed as follows.

3.1 Scenario 1: Single-component failure caused by external shocks

A periodic inspection policy is considered for the system. It is assumed that the system is inspected at every interval T. The inspection time is assumed to be negligible and the inspection cost is c_i. The state of the component can be known only through inspection, but component failures can be detected immediately.

Assume that state n^i is the threshold state of component i. Once the state of component i degenerates below n^i, the component fails and is replaced, where the cost of replacement is c_f. Suppose the observed state is $(n_0)^i$, and the state of component i is below n^i, $(n_0)^i < n^i$. When the component state is $(n_0)^i > n^i$ at the epoch of inspection, preventive maintenance is executed immediately at the cost of c_p. The replacement and preventive maintenance of components are all instantaneous and perfect. The relationship among the costs involved in maintenance actions is $c_p < c_f$.

As for a component, the objective is to minimize the long-run expected average cost per unit of time by choosing the best combination of n^* and T^*. $w_i(t), i = 1,2,\cdots,M$ represent states of the component at time t and α_i represent the sets of steady-state probability associated with w_i.

In a word, the period length of the system is

$$L = T_L I_{\{X \leq T\}} + T I_{\{X > T\}} \tag{7}$$

where T_L represents the lifetime of the component, $I_{\{\}}$ denotes the indicator function which equals 1 if the argument is true and 0 otherwise.

Therefore, the average period length is:

$$E(L) = \left[\int_0^T td\,F_z(t) + \int_T^\infty Td\,F_z(t)\right]\sum_{i=1}^{n}\alpha_i = \int_0^T (1 - F_z(t))dt\sum_{i=1}^{n}\alpha_i$$
$$= \int_0^T R(t)dt\sum_{i=1}^{n}\alpha_i \tag{8}$$

where $F_z(t)$ represents the lifetime function of the system.

The expected cost of a period is:

$$E(C) = c_i\alpha_i w_M + \sum_{n<i<M}(c_i + c_p)\alpha_i w_i + \sum_{1\le i\le n}(c_i + c_f)\alpha_i w_i \tag{9}$$

For preventive maintenance thresholds, the objective function C_{min} can be obtained by solving the following linear equation.

$$minC = \frac{E(C)}{E(L)} = \frac{c_i\alpha_i w_M + \sum_{n<i<M}(c_i + c_p)\alpha_i w_i + \sum_{1\le i\le n}(c_i + c_f)\alpha_i w_i}{\sum_{i=1}^{n}\alpha_i\int_0^T R(t)dt} \tag{10}$$

3.2 Scenario 2: Multiple components' common cause failure

Let $n_j^{(i)}$ be the failure threshold of the degradation process j of component i. The time when $X_j^{(i)}(t;e_0)$ first attains the threshold $n_j^{(i)}$ —i.e., the first passage time—is given by $T_j^{(i)} = \inf(t; X_j^{(i)}(t;e_0) \ge n_j^{(i)})$. In a special case when the occurrence of external shocks is independent of time, it is well known that $T_j^{(i)}$ follows an inverse Gaussian distribution. Because component i is subject to k_i competing failure modes due to multi-dimensional degradation, the lifetime of component i is defined as $T^{(i)} = \min_{j=1,2,\cdots,k_i} T_j^{(i)}$.

If e_t is deterministic, the degradation rates and diffusion coefficients of the k_i degradation processes associated with component i are also deterministic and are statistically independent. Hence, the reliability of the component i is given by:

$$R^{(i)}(t;e_t) = Pr\left(T^{(i)} > t; e_t\right) = \prod_{i=1}^{k_i}(1 - F_{T_j^{(i)}}(t;e_t)) \tag{11}$$

Let $Z^{(i)}(t) = 1$ when component i functions at time t, and $Z^{(i)}(t) = 0$ when component i is in a failed state at time t, and $Z(t) = \left(Z^{(1)}(t), Z^{(2)}(t), \cdots, Z^{(n)}(t)\right)$. Then the system structure function, φ$\left(Z(t)\right)$, is defined as:

$$\varphi\left(Z(t)\right) = \begin{cases} 1, if\ system\ functions\ at\ time\ t \\ 0, if\ system\ fails\ at\ time\ t \end{cases} \tag{12}$$

Thus, the environmental importance of component i with a multidimensional degradation process under deterministic environmental conditions can be obtained by:

$$BIM^{(i)}(t;e_t) = Pr\left(\varphi\left(Z(t)\right) = 1 \middle| Z^{(i)} = 1; e_t\right) - Pr\left(\varphi\left(Z(t)\right) = 1 \middle| Z^{(i)} = 0; e_t\right) = \frac{\partial R(t;e_t)}{\partial R^{(i)}(t;e_t)} \tag{13}$$

The environmental importance of component i under random shock environments can be calculated using the following Monte Carlo method.

$$BIM^{(i)}(t;e_t) \approx \widehat{BIM}^{(i)}(t;e_t) = \frac{1}{N}\sum_{p=1}^{N} BIM^{(i)}\left(t;\widetilde{e_t}^{(p)}\right) \tag{14}$$

Assuming that the states of each component corresponding to the positioning accuracy can be observed, to propose preventive maintenance strategies to achieve more accurate preventive maintenance and maximize the expected performance of the system, this section is based on the environmental importance proposed in the previous section. Combined with the concept of joint importance proposed by Dui et al. [27, 28], the influence of component j on system reliability when component i is repaired is expressed as:

$$BIM_{i|j}(t;e_t) = \frac{\partial^2 R(t;e_t)}{\partial R^{(i)}(t;e_t)\partial R^{(j)}(t;e_t)} \tag{15}$$

Let $Y_i(t)$ represent the state of component i at time t, $Y_i(t) = 0,1,2,\ldots,M_i$, $Y(t) = (Y_1(t), Y_2(t), \ldots, Y_n(t))$ represents the state vector of the component; $\Phi(Y(t))$ is the system structure function.

Once the state of a component degrades below its threshold state, the corresponding component may need to be located and must be repaired. In this case, the components being repaired may be critical or non-critical. Assuming that the component being served is important, the system must stop working. Preventive maintenance can be performed on all other components. If the maintenance component is not critical, the system does not need to stop working. Preventive maintenance can be performed on non-critical components.

Assuming that the state of component i is less than its threshold state n^i, namely $(< n)^i$, then under the above maintenance policy, let the component maintenance priority (CMP) of component $j (j \neq i)$ be:

$$CMP_{i|j}(t; e_t) = H_{j|i} \frac{\partial^2 R(t; e_t)}{\partial R^{(i)}(t; e_t) \partial R^{(j)}(t; e_t)} \tag{16}$$

$$H_{j|i} = \begin{cases} 1, \Phi\left((< n)^i, Y(t)\right) < N \\ 1, \Phi\left((< n)^i, Y(t)\right) \geq N \; and \; j \in \left\{j | \Phi\left((< n)^i, (< n)^j, X(t)\right) \geq N\right\} \\ 0, \text{other} \end{cases} \tag{17}$$

where $(< n)^i$ indicates that the state of component i degenerates below its threshold state n^i. The symbol $(< n)^j$ indicates that the state of component j degenerates below its threshold state n^j. If the state degradation of component i falls below n^i, causing the value of the system structure function $\Phi(\cdot)$ to fall below its threshold state N, i.e. $\Phi\left((< n)^i, Y(t)\right) < N$, component i becomes critical and the system stops functioning. Therefore, all other components $j \in \{1, \ldots, i-1, i+1, \ldots, n\}$ perform preventive maintenance. Component i is non-critical if $\Phi\left((< n)^i, Y(t)\right) \geq N$. So can non-critical components $j \in \left\{j | \Phi\left((< n)^i, (< n)^j, X(t)\right) \geq N\right\}$ perform preventive maintenance.

While servicing component i, which has the largest $CMP_{i|j}(t; e_t)$, should be chosen and preventive maintenance should be performed on component j so that system positioning accuracy can be optimally improved. Should be in accordance with the components $CMP_{i|j}(t; e_t)$ to establish the preventive maintenance order.

Given limited maintenance costs, the set of components to perform preventive maintenance should be determined to maximize the expected system positioning accuracy, given a fixed total maintenance cost of C. When the preventive maintenance costs of components are different, the more important components may lead to higher maintenance costs. When component *i* is serviced, the following integer programming issues need to be addressed：

$$\max_{z_j} \sum_{j \neq i} CMP_{i|j}(t; e_t) \cdot z_j \tag{18}$$

$$s.t.\ c^i + \sum_{j \neq i} c^j z_j \leq C \ \& \ z_j \in \{0,1\}$$

where, c^i is the maintenance cost of component i, c^j is the maintenance cost of component j, z_j is the preventive maintenance variable of component j and represents the decision variable of whether to maintain component j. z_j can only adopt the value between 0 and 1. When $z_j = 1$, preventive maintenance is carried out for the component j; otherwise, no maintenance is carried out.

4. Case study

An industrial robot system is a complex system composed of a mechanical body, electrical system, and control system. The robot system is composed of software and hardware subsystems. Its core components include a decelerator, servo-motor, servo-driver, demonstrator, control cabinet, and robot body. The failure mode of each component is different, which will affect the operation of the whole system differently.

The industrial robot RV reducer usually has low reliability as it fails frequently. Therefore, the failure of the RV reducer is used to demonstrate the proposed model.

It is assumed that the states of the RV reducer can be divided into different stages according to the degree of damage. In this model, $M = 6$, which means that state 6 represents a totally new state and the RV reducer is considered to be failed when it is in state 1. The system is inspected at every interval T and the inspection time can be ignored. Replacement and preventive maintenance of the RV reducer are all instantaneous and perfect. Suppose $c_i = 100$, 10, $c_p = 300$ and $c_f = 600$. n represents the thresholds of preventive maintenance and $1 < n < 6$.

The optimal inspection interval T^* under different n is calculated based on Eq. (10) and Eq. (11) to minimize the average cost per unit time. Fig. 2 shows cost curves under different n. The minimum cost in each curve and the corresponding inspection interval are recorded in Table 1.

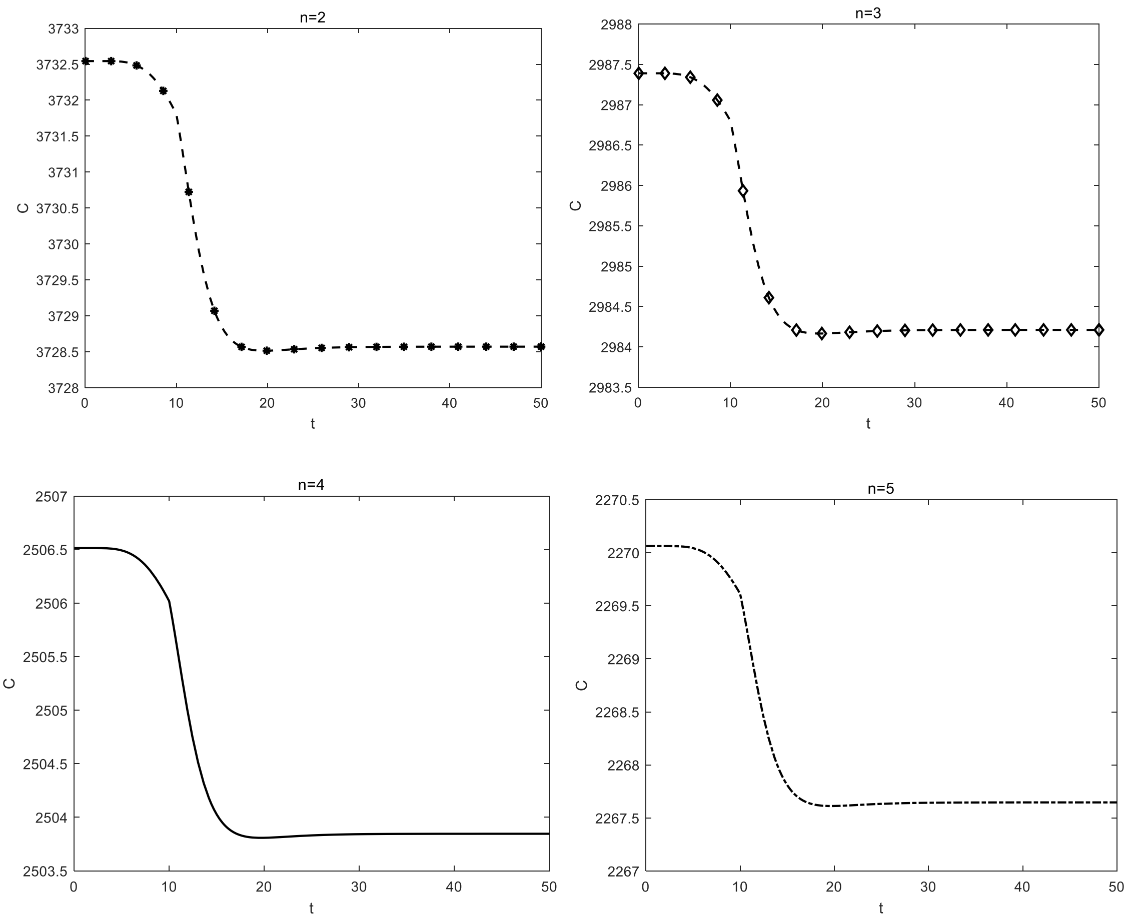


Fig. 2. Cost functions under different threshold

Table 1. Optimal inspection interval and the corresponding minimum cost under different thresholds

No.	n	T^*	$C(T^*)$
1	2	18.7	3729
2	3	18.9	2984
3	4	19.3	2504
4	5	18.8	2268

As shown in Table 1 and Fig. 2, when the preventive maintenance threshold and inspection interval are 5 and 18.8, respectively, the average cost per unit time can be minimized to 2268. The calculation methods and results of the optimal inspection interval, and the preventive maintenance threshold in this paper are valuably managerial suggestions for engineers to minimize average cost per unit time in reality.

Considering multiple components, the failure modes of each component of the robot are different, and each failure mode is related to the degradation process. The main failure modes of each component are presented in Table 2.

Table 2. The main failure modes of six-axis handling industrial robot components

Number	Name	Number	Name
A1	Needle tooth failure	D1	CPU failure
A2	Planetary gear failure	D2	LCD screen failure
A3	Crankshaft failure	D3	Software main control module failure
A4	Bearing failure	D4	Mainboard failure
A5	Cycloidal wheel failure	D5	Button failure
A6	Seal failure	D6	Instructor system failure
A7	Tooth belt transmission failure	E1	Converter failure
B1	Stator failure	E2	Heat exchanger failure
B2	Rotor failure	E3	Fan failure
B3	Bearing wear and tear	E4	Bus communication failure
B4	Bearing cracking	E5	I/O module failure
B5	Excessive deflection of rotating shaft	E6	Relay failure
C1	IGBT overvoltage	F1	Washer wear
C2	IGBT overheating	F2	Ring aging
C3	IGBT overflows	F3	Coupling failure
C4	Resistance short circuit	F4	Power failure

C5	Resistance open circuit	F5	Sensor failure
C6	Integrated circuit failure	F6	Insufficient strength of the member

Assuming that the environmental condition is determined and fully known before $t = 30$, the external shocks e_t is expressed by the piecewise function as:

$$e_t = \begin{cases} 6, 0 \leq t < 10 \\ 7, 10 \leq t < 30 \end{cases} \quad (19)$$

The specific parameter values of the robot used in this example are shown in Table 3, and the data comes from the service data of a domestic robot.

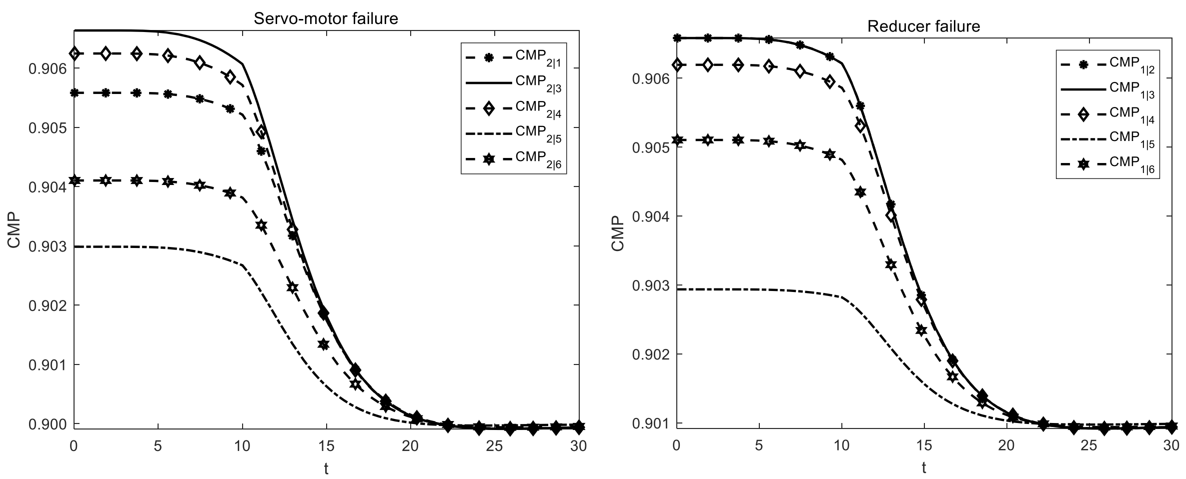
Table 3. Parameter values of simulation

Failure mode	$\mu_{j,0}^{(i)}$	$\sigma_{j,0}^{(i)}$	Initial degradation level $x_j^{(i)}(0)$	$n_j^{(i)}$
Reducer				
A1	1	0.5	0	11
A2	1	0.8	0	11
A3	0.8	1	0	11
A4	0.8	0.7	0	11
A5	1	1	0	11
A6	0.9	0.6	0	11
A7	0.7	1.5	0	11
Servo-motor				
B1	0.8	0.5	1	12
B2	0.7	1	1	12
B3	0.6	1	1	12
B4	1.1	0.5	1	12
B5	0.5	1	1	12
Servo-driver				
C1	0.7	1	4	15
C2	0.9	0.8	4	15
C3	1	0.5	4	15
C4	0.5	1	4	15
C5	0.8	1.1	4	15
C6	0.6	1	4	15
Demonstrator				
D1	1.1	0.7	2	13
D2	1.3	0.9	2	13

D3	0.6	1.3	2	13
D4	1.4	0.7	2	13
D5	1	1	2	13
D6	0.9	0.5	2	13
Control cabinet				
E1	0.8	1.2	0	11
E2	0.7	0.7	0	11
E3	0.5	1.4	0	11
E4	0.9	1.1	0	11
E5	1	1	0	11
E6	1.1	0.7	0	11
Robot body				
F1	1.5	0.5	3	14
F2	0.5	1.3	3	14
F3	1	1	3	14
F4	1.2	1.1	3	14
F5	1	1	3	14
F6	0.7	1	3	14

In component criticality analysis, the handling robot is a repairable system and its components are not new, so in this example, it is assumed that the initial degradation level of the servo-motor, servo-driver, demonstrator, and robot body is greater than zero.

The preventive maintenance policy model is simulated and analyzed, and the parameters of each component are analyzed to obtain the preventive maintenance priority of the other components in case of a component failure. The simulation results are shown in Figure 3.



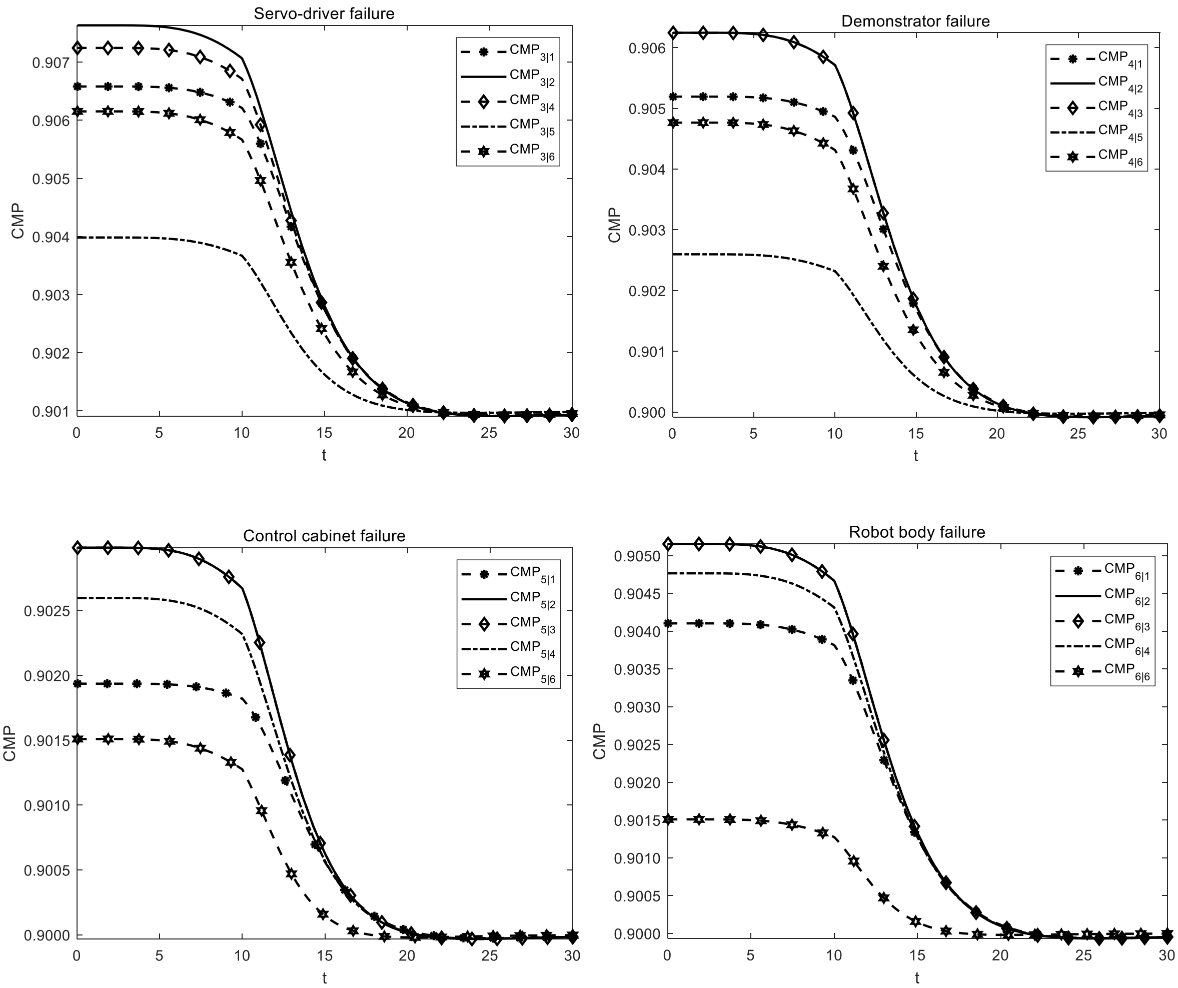


Fig. 3. CMP of each component under different failure modes

As shown in Fig. 1, when a certain component degrades below the threshold value, the priority of preventive maintenance of other components will first remain unchanged, then decline and become flat. In addition, the CMP values of the servo-motor and the servo-driver are almost the same in the period $0 \leq t < 30$, and the CMP ranking is higher than that of the other components when the decelerator, the demonstrator, the control cabinet and the robot body fail. The results of the analysis provide a comprehensive ranking of the preventive maintenance priorities of the remaining components in the event of a component failure, as shown in Table 4.

Table 4. Cropland node number table

	Reducer	Servo-motor	Servo-driver	Demonstrator	Control cabinet	Robot body

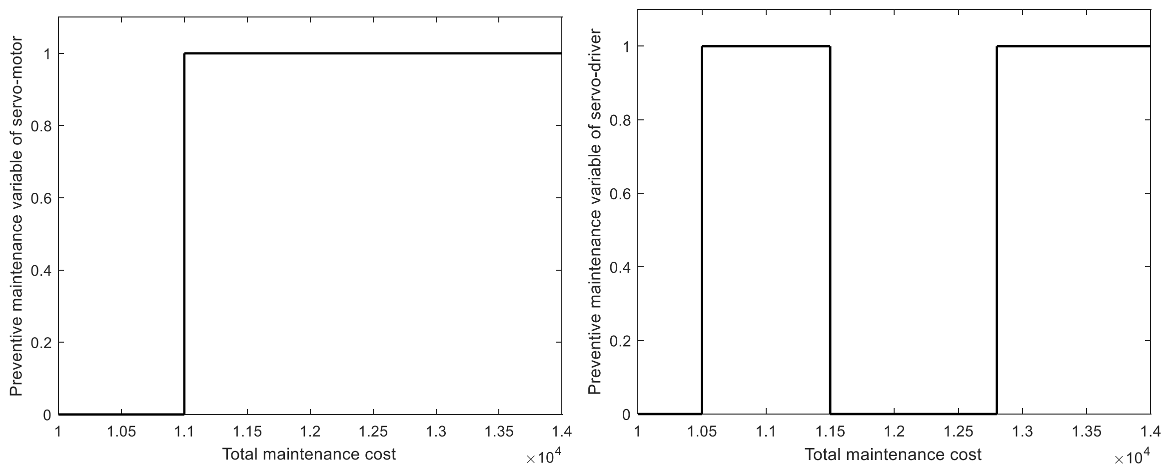
Reducer failure	--	1	2	3	5	4
Servo-motor failure	3	--	1	2	5	4
Servo-driver failure	3	1	--	2	5	4
Demonstrator failure	3	1	2	--	5	4
Control cabinet failure	4	1	2	3	--	5
Robot body failure	4	1	2	3	5	--

After determining the comprehensive ranking of the CMP of each component, considering that maintenance incurs certain cost, maintenance costs per component are shown in Table 5.

Table 5. Cost of component maintenance and preventive maintenance

No.	Component	Maintenance cost	Preventive maintenance cost
1	Reducer	7000	2200
2	Servo-motor	4000	1800
3	Servo-driver	3900	1700
4	Demonstrator	2600	1400
5	Control cabinet	3500	1500
6	Robot body	3000	1000

As shown in Table 4, when a component fails at different time t, the component set for preventive maintenance is selected under different cost constraints. Taking the failure of the decelerator for $t = 10$ and preventive maintenance as an example, the simulation results are shown in Figure 4.



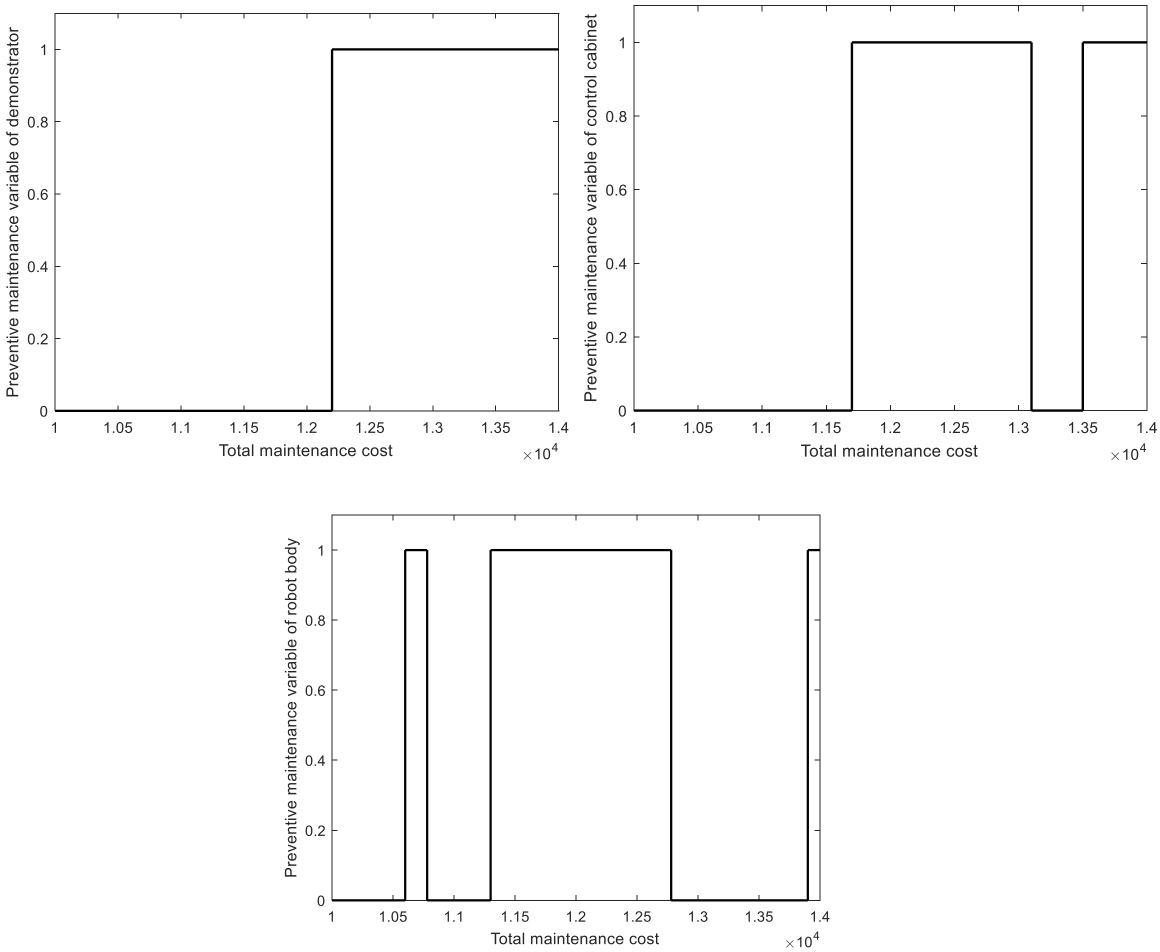


Fig. 4. Selection of preventive maintenance components under different total maintenance costs

According to Figure 4, considering the limitation of preventive maintenance cost and consideration of component maintenance priority, it can be seen that although the servo-motor and servo-driver have higher preventive maintenance costs, the higher component maintenance priority makes these two components have the top priority for preventive maintenance regardless of the changes of the total maintenance cost. In addition, although the component maintenance priority of the robot ontology ranks lower, the preventive maintenance cost is the lowest. As such, when the remaining maintenance cost is not enough to support the maintenance of other high-priority components, the robot ontology will be selected to enter the preventive maintenance component set.

Taking the failure of the decelerator at $t = 10$ and the total maintenance cost of 11200 RMB yuan as an example, the component set for preventive maintenance was determined to be servo-motor and servo-driver, and the influence of this preventive maintenance policy on system reliability was analyzed. The variation curves of the reliability of each component with running time before and after preventive maintenance are shown in Figure 5 and Figure 6.

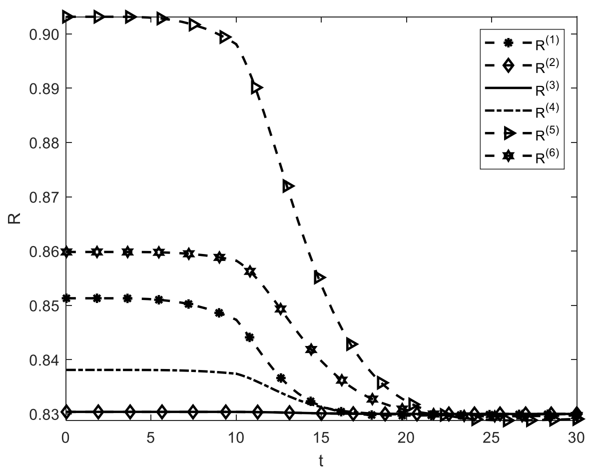


Fig. 5. Before preventive maintenance

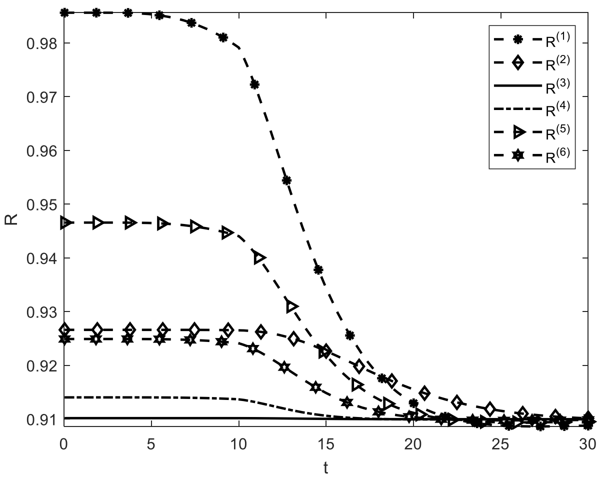


Fig. 6. After preventive maintenance

When $t = 10$, the reliability values of each component are shown in Table 6. The comparison shows that the preventive maintenance policy plays a significant role in improving system reliability.

Table 6. Reliability value of each component when $t = 10$

Component reliability	Before preventive maintenance	After preventive maintenance
Reducer$R^{(1)}$	0.847	0.978
Servo-motor $R^{(2)}$	0.831	0.927
Servo-driver$R^{(3)}$	0.830	0.910
Demonstrator $R^{(4)}$	0.838	0.914
Control cabinet$R^{(5)}$	0.898	0.945
Robot body$R^{(6)}$	0.860	0.926

5. Conclusions

This paper provided a technical guidance for improving the performance of an engineering system under the influence of external shocks and developed a preventive maintenance policy. The Wiener process was used to model the deterioration processes the components in the system, which is more suitable for practical engineering. An importance measure, the component maintenance priority, was proposed to prioritise weak components. In the case study, the service data of a robot were used to demonstrate the applicability of the proposed method and showed how the reliability of the whole industrial robot was affected by external shocks.

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