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Maintenance Optimization for Two-Component Series Systems With Degradation Dependence

WEI-NING MA[1], HUA LI[2], ZHI-YUAN YANG[2], AND QI-WEI HU[1]

[1]Department of Equipment Command and Management, Shijiazhuang Campus, Army Engineering University, Shijiazhuang 050003, China
[2]Center of Teaching and Researching Support, Shijiazhuang Campus, Army Engineering University, Shijiazhuang 050003, China

Corresponding author: Qi-Wei Hu (huqiweiaeu@163.com)

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ABSTRACT This paper proposes a model of maintenance optimization for a system consisting of two dependent components in long-term operation, where both components are subject to dependent degradation. Gamma process is used to model the degradation, and Frank Copula is applied to describe the degradation dependence between the two components. We then consider degradation dependence to optimize maintenance strategy for the system to maximize its availability. The improved Artificial Bee Colony (ABC) algorithm is used to jointly determine inspection interval, opportunistic and preventive maintenance thresholds of the system. Finally, an example is provided to validate the proposed model.

INDEX TERMS Two-component system, maintenance optimization, degradation dependence, availability.

I. INTRODUCTION

With the rapid progress of science and technology, modern system has become increasingly sophisticated, and consists of more and more dependent components as well. Traditional maintenance optimization approaches are usually orienting single-component system, and cannot be applied to multi-component system. In this situation, it is of great significance to consider the degradation dependence in the maintenance optimization for multi-component system.

The dependence among components of a multi-component system can be economic, structural or stochastic [1], [2]. Economic dependence can be positive or negative [3]. Positive economic dependence refers to the case in which the maintenance cost of several components is less than that of an individual one; otherwise, it is seemed as negative economic dependence. Structural dependence refers to the case that one has to replace or at least dismantle some working components in order to replace or repair failed ones. Stochastic dependence refers to the case that the state of one component can affect the state of other components or their failure rate. There are many contributions concerning with the maintenance optimization problem for multi-component systems. Gustavsson *et al.* [4] developed a preventive maintenance optimization model for multi-component systems with the cost of each interval considered by applying the integer programming method. Tian and Liao [5] and Zhu *et al.* [6] identified the optimal maintenance strategy by establishing an expense ratio model. Duan *et al.* [7] considered the dependence of time as well as preparatory cost of maintenance, and established an opportunistic maintenance optimization model for a multi-component system, and then calculated the thresholds of opportunistic and preventive maintenance of different components. Olde Keizer, *et al.* [8] established a condition-based maintenance (CBM) optimization model in order to reduce the maintenance cost by combining various maintenance processes together for systems with redundancy and economic dependencies. Chalabi *et al.* [9] focused on minimizing maintenance cost and maximizing system availability, and established a multi-objective maintenance optimization model with incomplete maintenance considered for multi-component series repairable systems. Besides, the optimal maintenance plan for those systems was developed by applying the Particle Swarm Optimization (PSO) algorithm. Shafiee and Finkelstein [10] established a maintenance optimization model based on the service life of components in multi-component series system, and demonstrated various degradation patterns. Bouvard *et al.* [11] described the degradation process of components with Gamma process, and established a model of component replacement by group for heavy trucks based on service life. Also, they continuously updated the maintenance decisions using Sliding Time Window. Vu *et al.* [3] applied Birnbaum importance to establish a dynamic maintenance model considering complex

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system with economic dependence and structural dependence. On the basis of their research, Nguyen *et al.* [12] proposed a decision-making process considering two levels: system level and component level. Azadeh *et al.* [13] established a dynamic optimization model of replacing components considering the impact of person.

Stochastic dependence includes failure dependence and degradation dependence. Regarding failure dependence, Do van [14] considered the constraint of limited maintenance time in terms of failure dependence, and then developed a dynamic maintenance optimization model based on the distribution of failure rate. Zequeira and Berenguer [15] studied the reliability of dual-component parallel system under periodic inspection, and found that the failure probability of one component had an impact on that of another one. Niu and Jiang [16] presented a maintenance optimization strategy with health-oriented prognostic control and global optimization considered together. Rezaei [17] assumed that the failure of hard-fault components would accelerate that of soft-fault ones, and then established a periodic inspection optimization model considering stochastic dependence. Bouvard *et al.* [11] and Van Horenbeek and Pintelon [18] considered the change of working condition of a multi-component system in its operation, and updated the distribution of component failures based on the system state degradation, and thus established a dynamic maintenance model for multiple components in a long-time operation environment. Yu and Zhou [19] developed a maintenance decision model based on hierarchical interaction concept and interactive mode that the degradation state had an impact on the ratio of degradation aiming at minimizing maintenance cost. Rezaei [17] established a periodic inspection optimization model considering stochastic dependence, and applied the proposed model to optimize maintenance decision of a dual-component system of rotor and filter in a turbine engine. Rasmekomen and Parlikad [20] identified the interactive impact relation between two components with the method of regression, and got optimization result for the pipe in a low temperature box by applying simulated annealing algorithm, which demonstrated that the interaction among components had a significant impact on maintenance decision. Golmakani and Moakedi [21] assumed that failure dependence in a dual-component reparable system is unidirectional and established a periodic inspection optimization model based on that. With respect to degradation dependence, Hong *et al.* [22] investigated the influence of dependent stochastic degradation and used copula to model the dependent stochastic degradation of components, and formulated the optimal decision problem based on the minimum expected cost rule and stochastic dominance rules. Fan *et al.* [23] developed a reliability model for dependent competing failure processes with degradation-shock dependence considered, and Monte Carlo simulation was used to calculate the system reliability. Gao *et al.* [24] developed reliability models subject to dependent competing soft and hard failure processes with degradation-shock dependences. Those proposed models extended previous researches by considering shock effect patterns resulting from multiple species of external shocks. Do *et al.* [25] established a CBM optimization model for a two-component system with economic and stochastic dependencies considered together, and adaptive preventive and opportunistic maintenance rules were proposed. Zhang *et al.* [26] proposed a fractional Brownian motion (FBM) based degradation model with long-range dependence and multiple modes considering the prediction of remaining useful life, and proposed a two-step method, including change-points detection and linear segments clustering, to identify the multiple modes in the degradation process. Liu [27] and Liu *et al.* [28] proposed a method to model and evaluate system reliability for multi-state systems/components with state transition dependency, and the dependency among state transitions is characterized by copula functions. Yang *et al.* [29] studied the influence of degradation dependence on the reliability of dual-component degradation system, and established a model to predict system reliability and its residual life. Roy *et al.* [30] proposed a method to extract health indicators of a multi-component system by conducting a time-frequency domain analysis and degradation analysis with the experimental data generated by a gearbox-accelerated life testing platform.

Two main observations from the above are in order. Firstly, to the best of our knowledge, most of the existing researches are focused on the economic dependence. There is more need to take into account stochastic and/or structural dependence [31] in maintenance optimization, compared to economic dependence. Secondly, many existing researches related to degradation dependence, proposed maintenance optimization models to maximize system reliability. Nevertheless, when a component of multi-component system occurs failure, if its function can be restored within limited time, it then can be deemed as accomplishing the task successfully. In this case, we should choose system availability as the objective of maintenance optimization rather than system reliability. So, there exists a demand to choose system availability to model maintenance optimization.

This paper proposes a model of maintenance optimization for a system consisting of two dependent components in long-term operation, where both components are subject to dependent degradation. Gamma process is used to model the degradation. Considering the practical impact of working condition, stochastic dependence resulted from failure propagation and load distribution [31] is analyzed. Degradation dependence between components is analyzed using copula function, and steady-state probability distribution of the system is calculated. Based on that, in order to maximize system availability, a maintenance optimization model is established, and the improved Artificial Bee Colony (ABC) algorithm is applied to obtain the optimal maintenance strategy.

The remainder of this paper proceeds as follows. Section II describes the system under research in this paper, and explains why the Frank Copula is chosen. A maintenance optimization model for two-component system under complete maintenance is developed in Section III. In Section IV, an example analysis, which chooses a two-component system in our Prognostics and Health Management (PHM) laboratory as the research object, is given to verify the feasibility and effectiveness of the proposed model. Section V summarized conclusions and future research.

II. SYSTEM DESCRIPTION AND DEGRADATION PROCESS MODEL SELECTION

A. SYSTEM DESCRIPTION AND ASSUMPTIONS

The system in this study consists of two different components in series. The performance of each component will degrade continuously. $\{X_i(t) : t \in R^+\}(i = 1, 2)$ represents the degradation process of component i at time t. When the cumulative degradation level exceeds the threshold, the component fails.

The assumptions pertaining to the system maintenance optimization problem are summarized as follows:

(1) Component failure is regarded as soft failure. It means that the component will continue to run even if it fails, although its performance can no longer meet the requirements for use. A component is brand new at the initial time, i.e., $X_i(0) = 0$;

(2) The degradation state of each component can only be identified through inspection which is conducted at the same time for both components. There is no error in the inspection result;

(3) Maintenance strategy for both components includes opportunistic, preventive and corrective maintenance.

B. THE SELECTION OF COPULAS

Copulas were first initiated to represent a function combining the one-dimensional marginal distribution to construct a joint distribution function. When the variance of variables is infinite or hard to obtain, copula functions can still characterize the correlation, and copulas can capture the non-linear and asymmetric correlation among variables, thus in recent years many researchers applied copulas to describe the interactive relations among components. There exist three common-used copulas: Gumbel Copula, Clayton Copula and Frank Copula, which all belong to the class of Archimedean copula functions. Since Gumbel Copula leads to a more significant correlation in the upper tail region, it is commonly used to analyze components' dependence for the system, which has a long service life or a low degradation rate. While Clayton Copula results in a more significant correlation in the lower tail region, it is commonly used to analyze early failure distribution and components' dependence for the system, which has a high degradation rate. In order to generalize the proposed optimization model, we use Frank Copula to describe the degradation dependence in this study. The n-variate Frank Copula function [32] can be expressed as follows:

$$C(u_1, u_2, \ldots, u_n) = -\frac{1}{\theta} \ln \left[1 + \frac{\prod_{i=1}^{n} (e^{-\theta u_i} - 1)}{(e^{-\theta} - 1)^{n-1}} \right] \tag{1}$$

where θ is the dependence parameter, and $\theta \in (0, +\infty)$. When $n \geq 3$, the bigger the value of θ is, the stronger the correlation among variables is. When $\theta \to 0$, the correlation among variables tends to be independent; and when $\theta \to +\infty$, the correlation among variables tends to be completely positive.

III. MAINTENANCE OPTIMIZATION MODELING FOR TWO-COMPONENT SYSTEMS UNDER COMPLETE MAINTENANCE

A. MAINTENANCE STRATEGY

The degradation state of each component is inspected when the system is operating. The time for the p-th inspection is represented as t_p, and the degradation level of component i at time t_p is represented as $X_i(t_p)$. For each component, a control limit strategy, which integrates opportunistic, preventive and corrective maintenance, is applied when the maintenance is carried out. The thresholds of opportunistic, preventive and corrective maintenance are represented as $O = \{O_1, O_2\}$, $M = \{M_1, M_2\}$ and $L = \{L_1, L_2\}$ respectively, and then $O_i \leq M_i \leq L_i$.

The system maintenance decision-making process can be stated as follows:

Step 1 (Determine Maintenance Strategy for Each Component): If $X_i(t_p) < M_i$, no maintenance is conducted. If $M_i \leq X_i(t_p) < L_i$, preventive maintenance should be carried out. If $X_i(t_p) \geq L_i$, corrective maintenance should be conducted. When preventive/corrective maintenance occurs on a component, namely $X_i(t_p) \geq M_i$, opportunistic maintenance should be conducted if the degradation level of another component meets the condition $O_j \leq X_j(t_p) < M_j$; otherwise, opportunistic maintenance should not be conducted.

Step 2 (Determine Inspection Interval): The inspection activity should be determined according to the present performance degradation state. Generally, when degradation level is higher than expected, the inspection interval should be decreased in order to prevent failure occur. Assume that the current degradation level is denoted as (x_1, x_2), the inspection interval can be expressed as follows [33]:

$$T(x_1, x_2) = \max\left\{T_{min}, \xi_1 - \frac{\xi_1 - T_{min}}{\xi_2} \times \max\left\{\frac{x_1}{L_1}, \frac{x_2}{L_2}\right\}\right\} \tag{2}$$

where T_{min} is the minimum inspection interval; ξ_1 represents the first inspection interval for the new system, and should be $\geq T_{min}$; ξ_2 is used to control the inspection frequency, and should be > 0.

It can be concluded from equation (2) that with the increase of ξ_2, inspection interval increases, and therefore inspection frequency decreases; conversely, inspection frequency increases. When $\xi_1 = T_{min}$, it is periodic inspection and the inspection interval is T_{min}. x_i/L_i represents the relative degradation level of component i, which is used to eliminate the influence of different degradation index dimensions.

The two-component system degradation and renewal process can be expressed in Fig. 1.

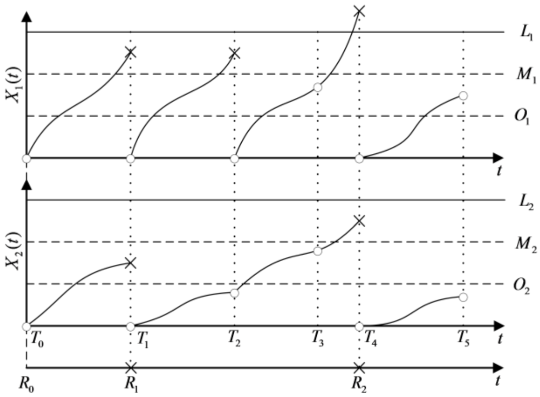


FIGURE 1. System degradation and renewal process in complete maintenance.

In Fig. 1, $T_m (m = 1, 2, \ldots)$ represents the inspection time. The degradation level of each component can be obtained through inspection. We then can see that when the two components are maintained simultaneously, the entire system will be renewed, that is, the system will be repaired to the status as new one. Therefore, under above maintenance strategy, the system state variation can be treated as renewal process, and the renewal time is $R_{m,}$, where $R_0 = T_0 = 0$.

B. MAINTENANCE OPTIMIZATION MODELING

Availability, which refers to the probability that a system is available when it is required at any time, is an important index of assessing equipment system performance. In this paper, we optimize maintenance strategy for two-component system by use of the steady availability when the system is long-term running. As prementioned maintenance strategy in Section II, system maintenance is determined by (M, O, ξ_1, ξ_2). System availability in long-term operation can be expressed as:

$$A(T) = \frac{E_R(TL) - E_R(TW)}{E_R(TL)} \tag{3}$$

where $E_R(TW)$ represents the expected maintenance downtime in a system lifecycle; $E_R(TL)$ represents the expected length of the system life.

Maintenance decision is made according to the system state at time T_m instead of its history states, which accords with Markov characteristics. Therefore, maintenance times can be regarded as semi-renewal points of the system degradation state [34], and the operation time between two consecutive maintenance decision points is regarded as a semi-renewal process. Based on that, the system degradation process between two consecutive maintenance decision points can be considered as the semi-renewal process of the system. Through analyzing the characteristics of the system degradation process in a semi-renewal process, we can then get the expected system availability expressed as follows:

$$TA_\infty(M, O, \xi_1, \xi_2) = \frac{E_T(TL) - E_T(TW)}{E_T(TL)} \tag{4}$$

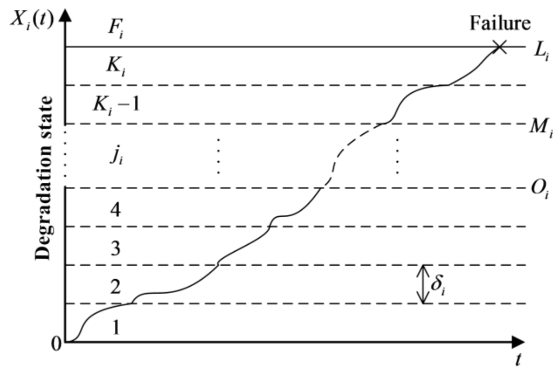


FIGURE 2. Discretization of degradation states.

where $E_T(TW)$ refers to the maintenance downtime within a semi-renewal process; $E_T(TL)$ refers to the expected length of the semi- renewal process.

C. DEGRADATION STATE SPACE PARTITIONING

In this study, continuous state stochastic process is used to model the performance degradation for the two-component system. In order to establish the analytical model, the continuous state degradation process is simplified through discretizing the degradation process to finite state spaces. Consequently, the component degradation process can be described with the degradation state space transition [35], [36]. The state space for component i is represented as $S_i = \{0, 1, \ldots, j_i, \ldots, K_i, F_i\}$, where 0 refers the component is new, while F_i refers it occurs failure. Obviously, $F_i = K_i + 1$. Based on that, the degradation process of each component can be described with $K_i + 2$ discrete states shown in Fig. 2.

The degradation state of component i at time t is denoted as $S_i(t)$, and then the relationship between $S_i(t)$ and $X_i(t)$ can be expressed as:

$$S_i(t) = \begin{cases} 0, & X_i(t) = 0 \\ j_i, & X_i(t) \in ((j_i - 1)\delta_i, j_i\delta_i], \ 0 < j_i \leq K_i - 1 \\ K_i, & X_i(t) \in ((K_i - 1)\delta_i, K_i\delta_i) \\ F_i, & X_i(t) \in [K_i\delta_i, +\infty) \end{cases} \tag{5}$$

where δ_i refers to the degradation level between two consecutive degradation states. When the component state is j_i and $1 \leq j_i \leq K_i$, the median value, $x(j_i) = j_i\delta_i - \delta_i/2$, is used to express the component degradation level. If $j_i = 0$, then $x(j_i) = 0$, and if $j_i = F_i$, then $x(j_i) \geq L_{f,i}$. As mentioned above, the failure threshold of component i is denoted as L_i. When the degradation level exceeds the threshold, the component occurs failure. Consequently, $L_i = K_i\delta_i$, then $\delta_i = L_i/K_i$.

Based on the partition of the degradation state space of a single component, the degradation state space of the system can be defined as $S = \{(j_1, j_2) \lfloor j_i \in S_i\}(i = 1, 2)$, and then the system state amounts $N = \prod_{i=1}^{2} (K_i + 2)$.

In order to facilitate the analysis, it is assumed that $S = \{(j_1, j_2)\, |\forall i, 0 \le x(j_i) < M_i\}(i = 1, 2)$, and S_1 refers to the system state set when no maintenance activity needs to be conducted after inspection, while S_2 refers to the system state set when preventive/ corrective maintenance activity needs to be conducted after inspection. Therefore, the set of system state space can be expressed as $S = S_1 \cup S_2$.

D. STEADY-STATE PROBABILITY DISTRIBUTION FOR SYSTEM DEGRADATION

In order to obtain the steady-state probability distribution of the system degradation, the transition probability between different degradation states needs to be calculated at first. According to the abovementioned state space partition method, the system degradation state is determined by the states of both components. Therefore, analyze the state transition probability of single component at first, and then calculate the state transition probability of the system, and get the steady-state probability distribution of the system at last.

1) STATE TRANSITION PROBABILITY OF SINGLE COMPONENT

In the range $[T_m, T_{m+1}]$, the state transition probability of single component relates to its degradation state at time T_m and the maintenance strategy. It includes the following two cases:

1) If $x(j_i) < M_i$ at time T_m, then it is no need to maintain the component. According to the independent increment characteristics of Gamma process, the probability that the state of component i transfers from j_i to k_i $(j_i \le k_i \le K_i)$ in the range $[T_m, T_{m+1}]$ is expressed as:

$$\begin{aligned} P_{j_i,k_i}(T_m, T_{m+1}) &= P(S_i(T_{m+1}) \\ &= k_i\, |S_i(T_m) = j_i) = P(lb_i < \Delta x_i < ub_i) \\ &= \int_{lb_i}^{ub_i} \frac{1}{\Gamma(\alpha_i(T_{m+1} - T_m))\beta_i^{\alpha_i(T_{m+1}-T_m)}} \\ &\quad \times x^{\alpha_i(T_{m+1}-T_m)-1} e^{-\frac{x}{\beta_i}} dx \end{aligned} \tag{6}$$

where $\Delta x_i = X_i(T_{m+1}) - X_i(T_m)$, $ub_i = (k_i - j_i + 0.5)\delta_i$, and $lb_i = max\,\{0, (k_i - j_i - 0.5)\delta_i\}$.

If $k_i = F_i$, that is, the component occurs failure in the range $[T_m, T_{m+1}]$, the state transition probability can be calculated by letting $ub_i = +\infty$ in equation (6).

If $k_i < j_i$, then $P_{j_i,k_i}(T_m, T_{m+1}) = 0$. Because the component degradation process is incremental, we then have $P(X_i(T_{m+1}) - X_i(T_m) < 0) = 0$.

2) If $x(j_i) \ge M_i$ or $j_i = F_i$ at time T_m, then maintenance needs to be done on the component. Under complete maintenance, the component can be restored to the original state as a new one. The probability that the state of component i transfers from j_i to k_i in the range $[T_m, T_{m+1}]$ is expressed as:

$$\begin{aligned} P_{j_i,k_i}(T_m, T_{m+1}) &= P\left(S_i(T_{m+1}^+) = 0\, |S_i(T_m) = j_i\right) \\ &\quad \times P\left(S_i(T_{m+1}) = k_i\, \middle|S_i(T_m^+) = 0\right) \\ &= P_{0,k_i}(T_m, T_{m+1}) \end{aligned} \tag{7}$$

where $T_{\mathrm{m}}^+ = T_m + T_{mm}.T_m^+$ refers to the time of finishing maintenance activity at time T_m ; T_{mm} refers to the maintenance downtime at time. $T_m.P_{0,k_i}(T_m, T_{m+1})$ can be calculated by equation (6).

2) STATE TRANSITION PROBABILITY OF THE SYSTEM

Based on analyzing state transition probability of single component, we then calculate the state transition probability of the system. Also, the state transition of the system has two situations in the range $[T_m, T_{m+1}]$:

1) If the system state $(j_1, j_2) \in S_1$ at time T_m, then there is no maintenance on the system. In this case, the probability that the system state transfers from (j_1, j_2) to (k_1, k_2) for $\forall i, k_i \ge j_i$ is expressed as:

$$\begin{aligned} P_{(j_1,j_2,),(k_1,k_2)}(T_m, T_{m+1}) &= P\,(S_i(T_{m+1}) = k_i\, |S_i(T_m) \\ &= j_i;\, i = 1, 2) = \Delta_{F^{(1)}_{T_m,m+1}(lb_2)}^{F^{(1)}_{T_m,m+1}(ub_1)} \\ &\quad \times \Delta_{F^{(2)}_{T_m,m+1}(lb_2)}^{F^{(2)}_{T_m,m+1}(ub_2)} C(u_1, u_2) \end{aligned} \tag{8}$$

where Δ refers to difference operation; lb_i and ub_i are the same as those in equation (6); $\Delta_{lb}^{ub} f(x)(ub) - f(lb)$. For system state (k_1, k_2), if $\exists i, k_i < j_i$, then $P_{(j_1,j_2),(k_1,k_2)}(T_m, T_{m+1}) = 0$.

2) If $(j_1, j_2) \in S_2$ at time T_m, then at least one component needs to be maintained. Define Ω_p as the set of components under preventive or opportunistic maintenance, and Ω_f as the set of components under corrective maintenance at time T_m. In this case, the probability that the system state transfers from (j_1, j_2) to (k_1, k_2) for $\forall i, k_i \ge j_i$ under complete maintenance is expressed as:

$$\begin{aligned} &P_{(j_1,j_2),(k_1,k_2)}\,(T_m, T_{m+1}) \\ &\quad = \prod_{i \in \{\Omega_p \cup \Omega_f\}} P\left(S_i(T_m^+) = 0\, |S_i(T_m) = j_i\right) \\ &\quad \times P_{(j_1^+,j_2^+),(k_1,k_2)}\left(T_m^+, T_{m+1}\right) \\ &\quad = P_{(j_1^+,j_2^+),(k_1,k_2)}\,(T_m, T_{m+1}) \end{aligned} \tag{9}$$

where $j_i^+ = \begin{cases} 0, i \in \Omega_p \cup \Omega_f \\ j_i, otherwise \end{cases}$ and $P_{(j_1^+,j_2^+),(k_1,k_2)}(T_m, T_{m+1})$ can be obtained from equation (8).

3) SYSTEM STEADY-STATE PROBABILITY DISTRIBUTION

From the above analysis of system state transition probability, the system steady-state probability distribution can be derived as equation (10) according to the Markov steady-state distribution characteristics:

$$\begin{cases} \pi(j_1, j_2) = \sum_{(k_1,k_2)\in S} [P_{(k_1,k_2),(j_1,j_2)}\,(T_m, T_{m+1}) \\ \qquad \times \pi(k_1, k_2)] \\ \sum_{(j_1,j_2)\in S} \pi(j_1, j_2) = 1 \end{cases} \tag{10}$$

where $\pi(j_1, j_2)$ is the steady-state probability of the system in state (j_1, j_2).

E. SYSTEM AVAILABILITY MODELING

According to the above analysis on system steady-state probability distribution, the expected system availability in long-term operation can be calculated. T_c represents the duration of inspection, $T_{o,i}$ represents the duration of opportunistic maintenance, $T_{\mathrm{p},i}$ represents the duration of preventive maintenance, $T_{f,i}$ represents the duration of corrective maintenance, and $T_{r,i}$ represents the duration of maintenance preparation. Generally, $T_{f,i} > T_{\mathrm{p},i}$. Since opportunistic maintenance belongs to preventive maintenance in nature, it is assumed that the duration of opportunistic maintenance is equal to the duration of preventive maintenance, i.e., $T_{o,i} = T_{p,i}$. According to equation (4), in order to calculate the expected system availability, the system maintenance downtime and the length of system semi-renewal process should be calculated at first.

1) SYSTEM MAINTENANCE DOWNTIME

If the system state is (j_1, j_2) when performing inspection, the expected maintenance downtime of the system in the semi-renewal process is denoted as $T_{(j_1,j_2)}$. Maintenance downtime $T_{(j_1,j_2)}$ can be calculated with equation (11).

$$T_{(j_1,j_2)} = \begin{cases} T_c, (j_1, j_2) \in S_1 \\ \\ T_c + \sum_{i=1}^{2} \left(I_{O_i \le x(j_i) < M_i} T_{o,i} + I_{M_i \le x(j_i) < L_i} T_{p,i} + \right. \\ \left. I_{M_i \le x(j_i) < L_i} T_{r,i} + I_{j_i = F_i} T_{f,i} \right), (j_1, j_2) \in S_2 \end{cases} \tag{11}$$

where $I_{(\cdot)}$ is the characteristic function.

According to the steady-state probability distribution function of the system, $\pi(j_1, j_2)$, the expected maintenance downtime in a semi-renewal cycle can be calculated by equation (12).

$$E_T(TW) = \sum\nolimits_{(j_1,j_2)\in S} T_{(j_1,j_2)} \pi(j_1, j_2) \tag{12}$$

2) LENGTH OF THE SEMI-RENEWAL CYCLE

As shown in Fig. 1, the length of a semi-renewal cycle is inspection interval. The inspection interval is determined by the degradation state at the time of inspection and the maintenance strategy. $\tau_{(j_1,j_2)}$ represents the length of the semi-renewal cycle when the current system state is (j_1, j_2).

1) When $(j_1, j_2) \in S_1$, the length of the semi-renewal cycle can be expressed as equation (13) according to equation (2) and the degradation state space partition.

$$\tau_{(j_1,j_2)} = T(x_1, x_2) = \max \left\{ T_{\min}, \xi_1 - \frac{\xi_1 - T_{\min}}{\xi_2} \times \max\left(\frac{j_1 - 0.5}{K_1}, \frac{j_2 - 0.5}{K_2}, 0 \right) \right\} \tag{13}$$

2) When $(j_1, j_2) \in S_2$, the length of semi-renewal cycle can be expressed as equation (14).

$$\tau_{(j_1,j_2)} = \prod_{i \in \{\Omega_p \cup \Omega_f\}} P\left(S_i(T_m^+) = 0 \,|S_i(T_m) = j_i \right) \times \tau_{(j_1^+, j_2^+)} = \tau_{(j_1^+, j_2^+)} \tag{14}$$

where j_i^+ represents the degradation state of component i after maintenance; $j_i^+ = \begin{cases} 0, i \in \Omega_p \cup \Omega_f \\ j_i, otherwise \end{cases}$ and $\tau_{(j_1^+, j_2^+)}$ can be calculated with equation (13).

According to $\pi(j_1, j_2)$, the expected length of the semi-renewal cycle can be expressed as:

$$E_T(TL) = \sum\nolimits_{(j_1,j_2)\in S} \tau_{(j_1,j_2)} \pi(j_1, j_2) \tag{15}$$

To sum up, the expected system availability under (M, O, ξ_1, ξ_2) can be expressed as equation (16).

$$TA_\infty(M, O, \xi_1, \xi_2) = \frac{E_T(TL) - E_T(TW)}{E_T(TL)} = 1 - \frac{\sum_{(j_1,j_2)\in S} T_{(j_1,j_2)} \pi(j_1, j_2)}{\sum_{(j_1,j_2)\in S} \tau_{(j_1,j_2)} \pi(j_1, j_2)} \tag{16}$$

3) OPTIMIZATION OBJECTIVE

In this study, the objective of optimizing (M, O, ξ_1, ξ_2) is to maximize the expected availability of the system. Considering the constraints of decision variables, system maintenance optimization can be modelled as follows:

$$(M^*, O^*, \xi_1^*, \xi_2^*) = \arg Max TA_\infty(M, O, \xi_1, \xi_2) \quad s.t. \begin{cases} 0 < O_{\mathrm{i}} \le M_{\mathrm{i}} \le L_i \\ \xi_1 \ge T_{\min}, \xi_2 > 0 \end{cases} \tag{17}$$

F. MODEL SOLUTION BASED ON IMPROVED ABC ALGORITHM

There are several decision variables in the optimization model, and the relation between decision variables and objective function is nonlinear and non-differentiable. Therefore, it is difficult to calculate the analytical results. Then, we use the improved Artificial Bee Colony (ABC) algorithm [37] to optimize maintenance strategy. For the decision variables, M_i and O_i, the expected availability TA_∞ in the ranges $j_{p,i}\delta_i - \delta_i/2 < M_i \le j_{p,i}\delta_i + \delta_i/2$ and $j_{o,i}\delta_i - \delta_i/2 < O_i \le j_{o,i}\delta_i + \delta_i/2$ are the same with TA_∞ under $M_i = j_{p,i}\delta_i$ and $O_i = j_{o,i}\delta_i$. Thus, the searching space of decision variables M_i and O_i can be converted to $j_{p,i}, j_{o,i} \in \{0, 1, 2, \ldots, K_i\}, j_{o,i} < j_{p,i}$. Consequently, the searching space of the algorithm is reduced and the searching efficiency is improved greatly.

Based on the above analysis, for the decision variables, M_i and O_i, the searching equations for honey-harvesting and observation stages as follows:

$$\begin{cases} y_{new} = y_{old} + rand[\mathrm{int}(-|y_{old} - y_{rnd}|, |y_{old} - y_{rnd}|)] \\ y_{new} = y_{best} + rand[\mathrm{int}(-|y_{rnd1} - y_{rnd2}|, |y_{rnd1} - y_{rnd2}|)] \end{cases} \tag{18}$$

where y_{new} and y_{old} represent the new and initial location of the honey source respectively; y_{best} denotes the optimal location of current population; y_{rnd}, y_{rnd1} and y_{rnd2} represent the locations of other randomly-selected honey sources; and $rand[\mathrm{int}(x, y)]$ represents a random integer in the range $[x, y]$. For decision variables ξ_1 and ξ_2, original searching equations are used to generate candidate solutions.

IV. EXAMPLE ANALYSIS

In order to demonstrate the effectiveness and feasibility of the proposed method, this paper takes a two-component system, consisting of bearing and gear in the gear transmission system in our Prognostics and Health Management (PHM) laboratory, as an example. Bearing and gear are the important parts in the gear transmission system. The states of bearing and gear have gradually degraded in long-term operation, and finally they occur failure because of wear, crack, gear breakdown, etc. And there exists degradation dependence between the two components.

The degradation processes of both components start from state 0, and accord with Gamma distribution. α_1 and α_2 denote the shape parameters, which are equal to 1 and 2 respectively; β_1 and β_2 represent the scale parameters, which are equal to 2/3 and 1/2 respectively. For the two components, assume their corrective maintenance thresholds, L_1 and L_2, are $4mm$ and $5mm$ respectively; the duration of preventive maintenance, $T_{p,1}$ and $T_{p,2}$, are $0.1h$ and $0.15h$ respectively; the duration of corrective maintenance, $T_{f,1}$ and $T_{f,2}$, are $0.5h$ and $0.6h$ respectively; the duration of inspection (T_c) for both components is 0.01h; the duration of maintenance preparation, $T_{r,1}$ and $T_{r,2}$, are 0.1h; and the amount of degradation state partition (K) for both components is 10. Based on that, the degradation level between two consecutive degradation states of the components, δ_1 and δ_2, are $0.4mm$ and $0.5mm$ respectively.

According to the n-variate Frank Copula function, the bivariate Frank Copula function can be expressed as following:

$$C(u, v; \theta) = -\frac{1}{\theta} \ln \left[1 + \frac{(e^{-\theta u} - 1)(e^{-\theta v} - 1)}{(e^{-\theta} - 1)} \right] \tag{19}$$

In this example, the parameter of degradation dependence θ is set to be 5.

A. CALCULATING SYSTEM STEADY-STATE PROBABILITY DISTRIBUTION

According to the maintenance optimization model, the steady-state distribution of the system closely relates to the decision variables (M, O, ξ_1, ξ_2). Namely, the system steady-state distribution varies with the decision variables (M, O, ξ_1, ξ_2), and so does the expected system availability. Fig. 3 (a) shows the steady-state probability distribution of the system with degradation dependence considered when $(M, O, \xi_1, \xi_2) = (2.4, 2, 1.2, 1, 2.5, 1)$. In the same manner, in order to illustrate the influence of components dependence on the steady-state distribution, Fig. 3 (b) shows the steady-state distribution of the system without degradation dependence considered.

Because the two components are different and dependent, the steady-state distribution surface is asymmetric. Through analyzing (a) and (b) in Fig. 3, the distribution of system degradation state with dependence considered, is more intensive, compared to the situation without dependence considered under long-term operation. It means that system state

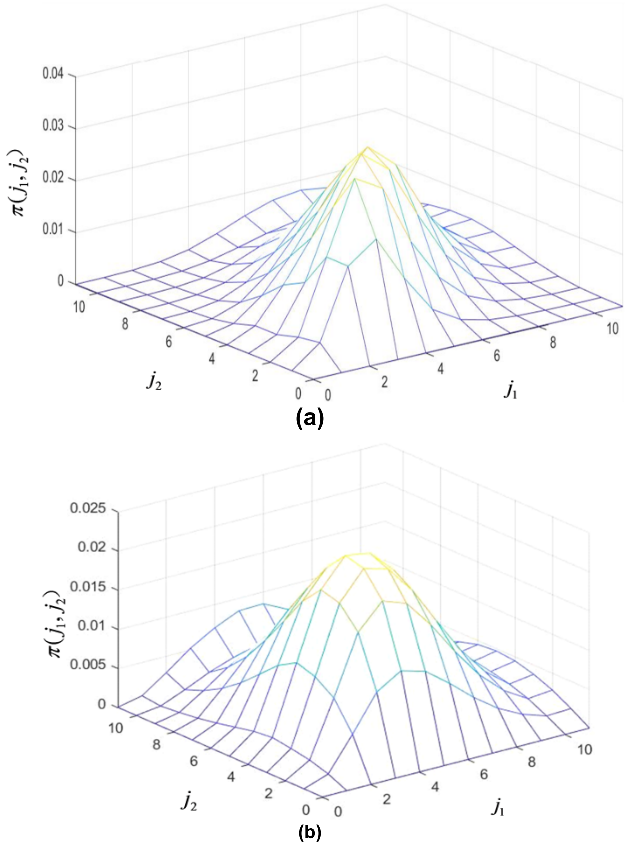


FIGURE 3. (a) Steady-state probability distribution of the system with degradation dependence considered. (b) Steady-state probability distribution of the system without degradation dependence considered.

transition is more probable in the situation shown in Fig. 3 (a) than Fig. 3 (b). We then can conclude that the degradation dependence has obvious effects on the characteristics of the steady-state distribution.

B. OPTIMIZING MAINTENANCE STRATEGY

1) INFLUENCE OF THE PARAMETER OF INSPECTION INTERVAL ON SYSTEM AVAILABILITY

Further, we analyze the influence on expected system availability TA_∞ when the parameter of inspection interval (ξ_1, ξ_2) varies. Assume that preventive & opportunistic maintenance thresholds are fixed, then we analyze the variation trend of system availability depending on the variation of inspection interval. Given $(M_1, M_2) = (2.8, 2.6)$ and $(O_1, O_2) = (1.6, 3.5)$, the variation trend of system availability (ξ_1 and ξ_2 range in [1, 5] and [0.2, 2] respectively) is shown in Fig. 4.

We can see from Fig. 4 that, the value of TA_∞ increases first and then decreases depending on the increase of (ξ_1, ξ_2). It is because when inspection interval is short enough, frequent inspection can cause maintenance downtime increasing, system operation duration decreasing, and thus availability lowing. With the increase of (ξ_1, ξ_2), inspection interval will prolong, and system operation duration will increase correspondingly. When inspection interval is long enough, it will lead to increasing probability of system occurring failure.

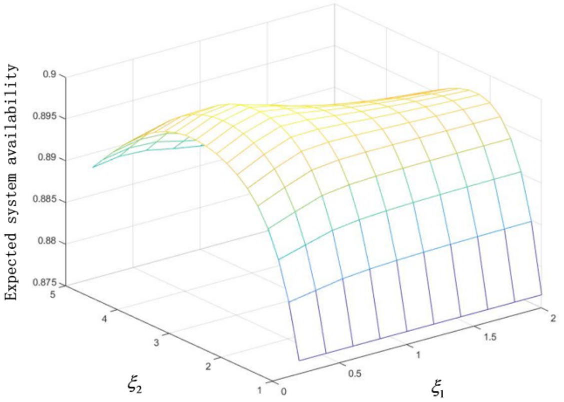


FIGURE 4. Influence of the parameter of inspection interval on system availability.

Usually, corrective maintenance duration is fairly long, and then it will result in system availability decreasing. Therefore, there exists an optimal (ξ_1, ξ_2) to maximize system availability.

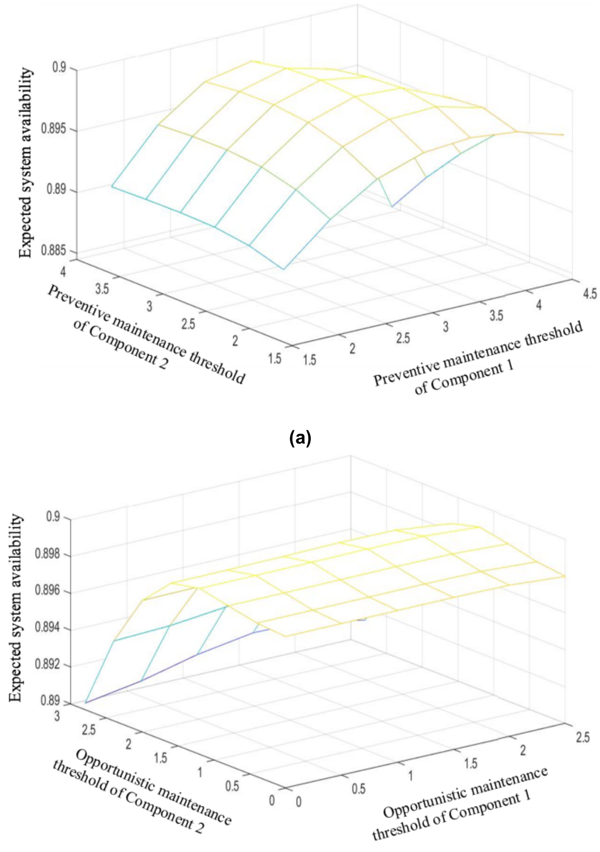
2) INFLUENCE OF MAINTENANCE THRESHOLD ON SYSTEM AVAILABILITY

Similarly, we further analyze influence of maintenance threshold on system availability. Firstly, assume that opportunistic maintenance thresholds are fixed, then we analyze the variation trend of system availability depending on the variation of preventive maintenance threshold. Given $(O_1, O_2) = (1.6, 3.5)$, the variation trend of system availability (M_1 and M_2 range in $[1.5, 4.5]$ and $[1.6, 3.6]$ respectively) is shown in Fig. 5 (a). Hereafter, assume that preventive maintenance thresholds are fixed, then we analyze the variation trend of system availability depending on the variation of opportunistic maintenance threshold. Given $(M_1, M_2) = (2.8, 2.6)$, the variation trend of system availability (O_1 and O_2 range in $[0, 2.5]$ and $[0, 2.8]$ respectively) is shown in Fig. 5 (b).

We can see from Fig. 5 that, the value of TA_∞ increases first and then decreases depending on the increase of M_i or O_i. When M_i or O_i are small enough, the frequency of preventive & opportunistic maintenance in a semi-renewal cycle will be high. Thus, the useful life of the component cannot be fully taken advantage of, whilst it will cause maintenance downtime increasing. With M_i or O_i increasing, the frequency of preventive & opportunistic maintenance will decrease, and system downtime will decrease as well, and thus system availability will increase correspondingly. When M_i or O_i is big enough, the probability of component occurring failure will be high. Usually, corrective maintenance duration is fairly long, and then it will result in system availability decreasing. Therefore, there exists an optimal M_i and O_i to maximize system availability.

3) MAINTENANCE OPTIMIZATION BASED ON ABC ALGORITHM

Given the parameters of ABC algorithm, i.e., $NP = 10$, $Limit = 20$, and $Maxcycle = 100$, the optimization process of an iteration of ABC algorithm is shown in Fig. 6.



(a)

(b)

FIGURE 5. (a) Influence of preventive maintenance threshold on system availability. (b) Influence of opportunistic maintenance threshold on system availability.

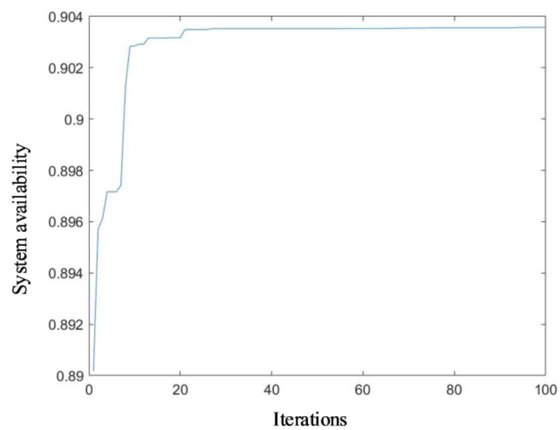


FIGURE 6. The optimization process of an iteration of ABC algorithm.

The approximate optimal solution of the optimization model is calculated with the algorithm, and then the maintenance strategy obtained is denoted as solution I. We then have the optimal result $(M^*, O^*, \xi_1^*, \xi_2^*) = (2.8, 3.5, 1.2, 1.5, 2.73, 0.45)$ and the optimal availability $TA_\infty^* = 0.9036$.

Meanwhile, in order to illustrate the necessity of considering degradation dependence when making maintenance

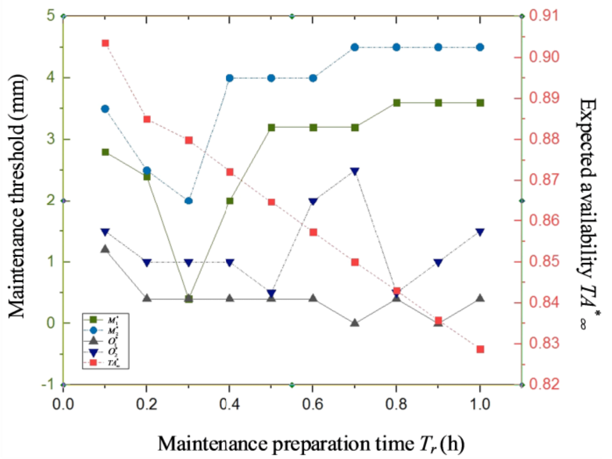


FIGURE 7. The influence of maintenance preparation time on maintenance optimization result.

decision, we also obtain the optimal maintenance strategy without degradation dependence considered, denoted as solution II: $(M^*, O^*, \xi_1^*, \xi_2^*) = (2.8, 3.5, 1.2, 2, 2.69, 0.50)$. The optimal availability is $TA^*_\infty = 0.9006$.

By contrast, system availability TA_∞ of solution I is higher than that of solution II. We can conclude that degradation dependence has effects on maintenance optimization results, thus degradation dependence should not be neglected when making maintenance decision. If degradation dependence is not considered, maintenance threshold, to some extent, will make change. It also indicates that, in order to ensure the effectiveness of maintenance, we should make decision based on the system-level instead of the component-level for multi-component system.

C. SENSITIVITY ANALYSIS

Maintenance preparation time T_r, degradation dependence parameter θ and state amount parameter K_i have major effects on system availability, then we analyze the influence of these three parameters on optimization results.

1) INFLUENCE OF T_r ON OPTIMIZATION RESULT

Under the fixed values of other parameters, the influence of maintenance preparation time on maintenance optimization result is shown in Fig. 7.

As shown in Fig. 7, the distinction between the optimal thresholds of preventive and opportunistic maintenance increases generally depending on maintenance preparation time increasing. Especially when the maintenance preparation time is long enough, the opportunistic maintenance threshold will be 0. It indicates that the component should be replaced when carrying out inspection. So, it is of great significance to make full use of maintenance downtime to maintain components as many as possible.

2) INFLUENCE OF θ ON OPTIMIZATION RESULT

With the system degradation process and other parameters fixed, the influence of degradation dependence parameter on optimal maintenance strategies is shown in Tab. 1.

TABLE 1. Influence of degradation dependence parameter on optimal maintenance strategies.

θ	$(M^*, O^*, \xi_1^*, \xi_2^*)$	TA^*_∞
0.1	(2.8,3.5,1.2,2,2.7080,0.4916)	0.9007
0.5	(2.8,3.5,1.2,2,2.7205,0.4945)	0.9010
1	(2.8,3.5,1.2,1.5,2.7093,0.4778)	0.9013
3	(2.8,3.5,1.2,1.5,2.7381,0.4684)	0.9026
5	(2.8,3.5,1.2,1.5,2.7284,0.4684)	0.9036
7	(2.8,3.5,1.2,1.5,2.7136,0.4358)	0.9042

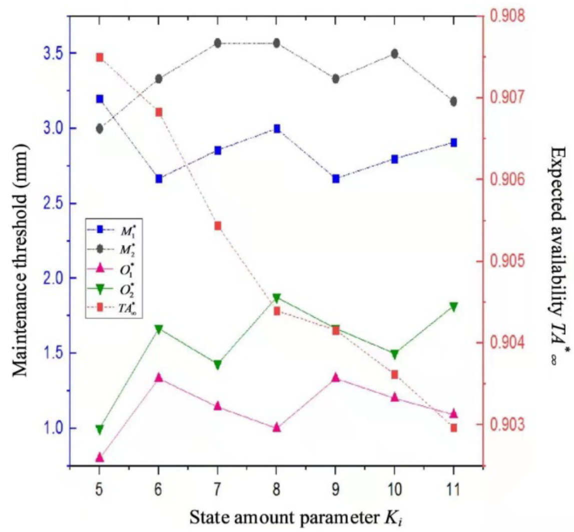


FIGURE 8. The influence of state amount parameter on optimization result.

We can see from Tab. 1 that, the optimal maintenance strategy will be different depending on the value of degradation dependence parameter θ increasing (i.e., the degradation dependence between components enhancing). When $\theta > 1$, the opportunistic maintenance threshold of component 2 decreases. The reason is the reduction of maintenance threshold can shorten preventive maintenance interval to ensure the system running stably and reliably, and then system availability is improved.

We can also conclude that, system availability increases depending on the value of degradation dependence parameter θ increasing. It is because that with degradation dependence between components enhanced, other components can be maintained simultaneously when a component under maintained. Consequently, extra maintenance downtime can be reduced, and system availability can be improved.

3) INFLUENCE OF K_i ON OPTIMIZATION RESULT

When deriving the steady-state probability distribution, we replace continuous state degradation process with discretized system states approximately. Consequently, the accuracy of system availability can be affected by state amount parameter K_i. The influence of state amount parameter K_i on optimization result is shown in Fig. 8.

As shown in Fig. 8, the optimal thresholds of preventive and opportunistic maintenance vary depending on state amount parameter. With the state amount parameter increasing, system availability will decrease gradually. The reason is that, variation of state amount leads to the variation of thresholds of preventive and opportunistic maintenance, and system maintenance downtime increases. Consequently, system availability decreases.

V. CONCLUSION AND FUTURE RESEARCH

In this study, maintenance optimization for a system consisting of two dependent components in long-term operation, where both components are subject to dependent degradation, is resolved. Gamma process is used to model the degradation, Frank Copula is applied to describe the degradation dependence between the two components, and improved Artificial Bee Colony (ABC) algorithm is used to maintenance optimization. Consequently, inspection interval, preventive and opportunistic maintenance thresholds of the system can be jointly obtained. Through an numerical example, it shows that it is of great significance to consider the degradation dependence in the maintenance optimization for multi-component system.

In future research, we will extend the model developed in this paper to a more complex model of multi-component system and the improvement of opportunistic maintenance. Firstly, this paper only studies two-component system. Compared with two-component system, multi-component system has more complex degradation dependence, e.g., a system is composed of four components, where component 1 and component 2 have degradation dependence, while component 3 or component 4 may also have a degradation dependence with component 1 or component 2. Study of this kind of more complex system is of great interest. Then, a more complex model needs to be established and analyzed. Secondly, opportunistic maintenance strategy in this paper only based on condition monitoring. Condition-based and age-based opportunistic maintenance policy [34] needs to be further investigated in maintenance optimization for multi-component system.

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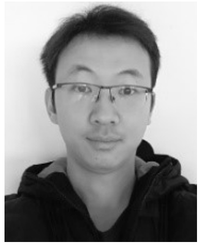
WEI-NING MA was born in Shandong, China, in 1982. He received the B.S. degree and the M.S. degree in management engineering from the Army Engineering University of PLA, Shijiazhuang, in 2006 and 2009, respectively, where he is currently pursuing the Ph.D. degree in maintenance engineering.

He is currently a Lecturer with the Shijiazhuang Campus, Army Engineering University of PLA. His research interests include equipment maintenance engineering, maintenance management of complex systems, residual life prediction of complex systems, PHM, optimization algorithm, and so on.

HUA LI was born in Hebei, China, in 1986. She received the B.S. degree from the Wuhan University of Technology, Wuhan, in 2009, and the M.S. degree in computer technology from the Army Engineering University of PLA, Shijiazhuang, China, in 2017.

She is currently a Lecturer with Army Engineering University. Her research interests include computer technology, data mining, cyber security, and so on.



ZHI-YUAN YANG was born in Hebei, China, in 1991. He received the B.S. degree in management engineering from Nankai University, Tianjin, in 2013, and the M.S. degree in management engineering and the Ph.D. degree in armament science and technology from the Army Engineering University of PLA, Shijiazhuang, in 2015 and 2020, respectively.

He is currently a Lecturer with the Joint Operations College, National Defense University, Shijiazhuang. His research interests include equipment maintenance engineering, maintenance management of complex systems, residual life prediction of complex systems, PHM, optimization algorithm, and so on.

QI-WEI HU was born in Hebei, China, in 1979. He received the M.S. degree and the Ph.D. degree in management engineering from the Army Engineering University of PLA, Shijiazhuang, in 2005 and 2016, respectively. He is currently an Associate Professor with the Shijiazhuang Campus, Army Engineering University of PLA. His research interests include maintenance optimization, spare parts management, and so on.