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A Condition-Based Maintenance Strategy for a Multi-Component System With Both Continuous and Discrete State Monitoring

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State monitoring is the foundation for condition-based maintenance of systems, and advancements in sensor technology have enabled real-time monitoring of the degradation processes in many systems. However, many complex multi-component systems, such as aircraft engine systems and various mechanical systems, cannot rely on sensors for real-time monitoring of all components' degradation states and must instead rely on inspections for determination. To address this, we modeled a multi-component system with both real-time monitored components and components requiring inspections, and proposed a condition-based inspection-opportunistic maintenance strategy. Real-time monitored components are replaced as needed based on their condition, while components requiring inspection are replaced when specific maintenance opportunities arise. A genetic algorithm is used to optimize the parameters of the proposed maintenance strategy, and comparisons were made with purely real-time monitored systems and inspection-based systems.

Keywords: Condition-Based Maintenance, Condition Monitoring, Periodic Inspection.

1. Introduction

Industrial and service systems suffer from degradation due to internal or external factors. The accumulation of such degradation may lead to system failures, causing a decline of system performance, reliability and availability. Thus, maintenance is needed to rejuvenate the system to guarantee a sustainable high-performance operation. According to Thomas (2018), maintenance cost makes up 15% to 60% of the overall operation cost of manufacturing systems. Properly scheduling maintenance activities has a huge impact on reducing the operating costs of the system.

Maintenance policies can be categorized into two major types: time-based maintenance policies (TBM) and condition-based maintenance policies (CBM). Availability of component state data is a critical factor in developing CBM policies. Technologies such as sensors help us keep track of real-time component conditions. However, the condition information is not always real-time available for structural or operational reasons. Under these circumstances, an inspection action is needed to reveal the condition of components and such action will incur costs and potentially cause system unavailability. One example of inspection in maintenance optimization is aircraft maintenance. The condition monitoring of aircraft involves disassembling and reassembling aircraft engines and special equipment is needed to perform fault diagnosis, which increases cost and occupies the aircraft (Levi, Magnanti, and Shaposhnik 2019). Components with real-time monitoring and that need inspection actions coexist in many complex systems, so it is significant to build a maintenance optimization model considering both real-time monitoring and monitoring by inspections.

A major difference in the modeling of multi-component and single-component lies in the interaction between components. Currently, three types of dependency between components are considered, namely economic dependency, structural dependency, and stochastic dependency. Economic dependency stands for the overall cost of maintaining multiple components is more profitable than maintaining them separately (De Jonge and Scarf 2020). Structural dependency exists when maintenance of a component needs other components to be disassembled (Keizer, Flapper, and Teunter 2017). Stochastic dependency exists when the failure time or degradation processes of components are stochastically dependent (De Jonge and Scarf 2020). In this paper, economic dependency and structural dependency will be considered.

TBM and CBM policies are applicable for both single-component systems and multi-component systems. However, if designing separate strategies for every component, the policy space suffers "curse of dimensionality" and the policy is unable to optimize effectively. To decrease the policy space and apply dependencies effectively, system-level maintenance strategies are proposed in the literature, mainly group maintenance and opportunity maintenance. Group maintenance aims to reduce the cost by combining maintenance actions that share a setup cost or system downtime (Liang and Parlikad 2020). Two types of group maintenance strategies are considered currently: components grouping and maintenance activities grouping. Opportunistic maintenance focuses on repairing those degraded (yet not failed) components in advance during a system outage (Hu and Zhang 2014). A notable study in the field of OM comes from Di Nardo et al., which combined proactive maintenance with OM and optimized maintenance grouping and inspection intervals.(Di Nardo et al. 2024). The system shutdown may have different reasons, including internal reasons such as component failure and external reasons such as material shortage, operation condition, etc. An opportunistic maintenance strategy is used in this paper, as both unplanned component failures and planned inspections can produce abundant repair opportunities.

In summary, the main contributions of the paper are listed as follows:

1) A series-parallel system model with both real-time condition monitoring and inspections is developed and the economic dependency and structural dependency are jointly considered.
2) A hybrid opportunistic maintenance strategy combining TBM and CBM is proposed and optimized with cost as objectives, considering opportunities caused by both component faults and inspections.
3) A genetic algorithm is proposed to optimize the maintenance optimization problem.

2. Model Development

2.1. *Degradation Model of Single Component*

It is assumed that all components of the system have measurable degradation levels, whether monitored continuously or by inspections and the degradation processes are continuous. We further assume that the degradation processes of components follow Gamma processes due to the independent increment and monotonicity property. Gamma process is suitable to model gradual damage such as wear, fatigue, corrosion etc. (Gorjian et al. 2010) Let $X_i(t)$ be the degradation level of component i at time t and $\Delta X_i(\Delta t)$ be the increment of degradation level during Δt, it follows that for all $0 \le s < t$,

$$X_i(t) = X_i(s) + \Delta X_i(t-s), \qquad (1)$$

in which $\Delta X_i(t-s)$ follows a Gamma distribution with rate parameter u and shape parameter shape parameter $v_i(t) - v_i(s)$ (Chatenet et al. 2021). The PDF of $\Delta X_i(t-s)$ is

$$f_{\Delta X_i(t-s)} = \frac{u^{v_i(t)-v_i(s)}}{\Gamma\big(v_i(t)-v_i(s)\big)} x^{v_i(t)-v_i(s)-1} e^{-ux}, x \ge 0.$$

The degradation stage space of component i is divided into two zones: operation zone and failure zone, with a predetermined fault threshold U_i. If the degradation stage $X_i(t)$ exceeds U_i, component i is regarded as failed.

2.2. *Multi-component System Structure and Structural Dependency*

Consider a series-parallel system consisting N components (a system with a complex structure can be converted into a series-parallel system), which has M parallel subsystems. Let the set of component index of subsystem $m, m \in \{1, \dots, M\}$ be S_m. An example is shown in Figure 1.

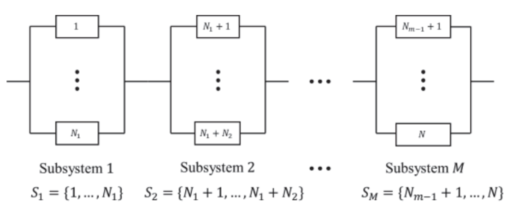

Fig. 1. Diagram of a Series-Parallel System

As stated in the Introduction, directed graph model is commonly used to represent the disassembly path of the components. For brevity, we only use a disassembly matrix D to model the structural dependence of the system instead of the directed graph model. It is defined as

$$D_{ij} = \begin{cases} 1, & \text{if } j \text{ should be disassembled to reach the component } i \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

which means that the indexes of components should be disassembled when maintaining component i is the ith row of matrix D. The disassembly cost is c_i^{dis} for all $i \in \{1, \dots, N\}$.

2.3. *Maintenance Actions and Economic Dependency*

In this paper, two types of maintenance actions are considered, including replacement and imperfect repair. Replacement makes a component back to the "as-good-as-new" state while imperfect repair causes a stochastic decrement of the component's degradation level. The cost of imperfect repair is less than replacement accordingly. Let T_j be the time of jth maintenance opportunity, A_j and B_j be the set of component indexes for which will be performed replacement and imperfect repair at the time T_j, $A_j, B_j \subset \{1, \dots, N\}, A_j \cap B_j = \emptyset$. The degradation level of component i after T_j, denoted as $X_i^+(T_j)$ can be expressed as

$$X_i^+(T_j) = \begin{cases} 0, & i \in A_j \\ \left[X_i^-(T_j) - \Delta X_i^b, 0\right]_+, & i \in B_j \\ X_i^-(T_j), & \text{otherwise} \end{cases} \quad (6)$$

where $X_i^-(T_j)$ represents the degradation level of component i before T_j, ΔX_i^b is a random variable indicating the degradation decrement of imperfect repair performed on component i and $[x]_+ = \max\{0, x\}$.

A setup cost is considered to model the economic dependency. Let the setup cost be c_s, the replacement cost of component i be c_i^a, the imperfect repair cost of component i be c_i^b, the overall maintenance cost C_j at time T_j comes with

$$C_j(A_j, B_j) = \begin{cases} 0, & A_j = \emptyset, B_j = \emptyset \\ c_s + \sum_{i \in A_j} c_i^a + \sum_{i \in B_j} c_i^b, & \text{otherwise} \end{cases} . \quad (7)$$

2.4. *Condition Monitoring and Inspections*

The system is composed of both components with real-time monitoring and components need inspections. Let $G, \bar{G}$ be the sets of component indexes with and without real-time monitoring, $G \cup \bar{G} = \{1, \dots, N\}$. All faults of component $i \in \bar{G}$ are assumed to be not self-announcing, which means that inspections are needed to recognize them. However, as the availability of the whole system is self-announcing, which means that when the system fails and all components in G are operating, it can be inferred that there is at least one component in $\bar{G}$ fails. A periodic inspection policy is applied for components in $\bar{G}$ in this paper, with the inspection period T^{ins} and inspection cost c_i^{ins} for component $i \in \bar{G}$. The time consumption of maintenance and inspection is neglected in the model.

3. Opportunistic Maintenance Policies

3.1. *Condition Monitoring and Inspections*

Only maintenance opportunities generated by inspections and system failures are considered in this paper. From the model developed in Section 3, three types of maintenance opportunities can be identified:

- **Type-1 Opportunity**: Opportunity generated by periodic inspections
- **Type-2 Opportunity**: Opportunity generated by faults by components in G, and such faults cause system failures
- **Type-3 Opportunity**: Opportunity generated by faults by components in $\bar{G}$, and such faults cause system failures

The difference between type-2 and type-3 opportunities is that the fault components are known under type-2 opportunities, while when components in $\bar{G}$ fail, inspection actions are needed to recognize what components have failed. Thus, the cost of maintenance incurred by type-3 opportunity is more than that incurred by type-2 opportunity. Additionally, the inspections to identify failed components also provide an opportunity to maintain other components in $\bar{G}$. This difference makes it appropriate to imply different maintenance strategies for the two types of opportunities.

3.2. *Opportunistic Maintenance Policies*

To compare different types of maintenance policies, three types of Maintenance policies are considered, including TBM policy, CBM policy and hybrid policy. The decision variables and the details of implying maintenance measures are as follows:

TBM policy: Decision variables of the TBM policy are (T^{ins}, T^t). T^{ins} is the inspection period. When a type-1 opportunity comes, replace all components. When a type-2 opportunity comes, if the time between last inspection and the opportunity is less than T^t, the failed component i is replaced; otherwise, it is imperfectly repaired. When a type-3 opportunity comes, inspect all components that belong to $\bar{G}$. If the time between last inspection and the opportunity is less than T^t, the failed component in $\bar{G}$ is replaced; otherwise, it is imperfectly repaired.

CBM policy: Decision variables of the CBM policy are $(T^{\text{ins}}, X^{C1}, X^{C2})$. T^{ins} is the inspection period. When a type-1 opportunity comes, for all components $i \in \{1, \dots, N\}$, if $X_i(t) \geq X^{C1}$, component i is replaced; otherwise, do nothing. When a type-2 opportunity comes, for all components $i \in G$, i is imperfectly repaired if $X_i(t) \geq X^{C2}$; otherwise, no nothing. When a type-3 opportunity comes, inspect all components that belong to $\bar{G}$. For all components $i \in \bar{G}$, if $X_i(t) \geq X^{C2}$, component i is imperfectly repaired; otherwise, do nothing.

Hybrid Policy: Decision variables of the Hybrid policy are $(T^{\text{ins}}, T^H, X^{H1}, X^{H2})$. T^{ins} is the inspection period. When a type-1 opportunity comes, for all components $i \in \{1, \dots, N\}$, if $X_i(t) \geq X^{H1}$, component i is replaced; otherwise, do nothing. When a type-2 opportunity comes, for all components $i \in G$, i is replaced if $X_i(t) \geq X^{H2}$ and the time between last inspection and the opportunity is less than T^H; i is imperfectly repaired if $X_i(t) \geq X^{H2}$ and the time between last inspection and the opportunity is more than T^H; otherwise, do nothing. When a type-3 opportunity comes, inspect all components that belong to $\bar{G}$. For all components $i \in \bar{G}$, i is replaced if $X_i(t) \geq X^{H2}$ and the time between last inspection and the opportunity is less than T^H; i is imperfectly repaired if $X_i(t) \geq X^{H2}$ and the time between last inspection and the opportunity is more than T^H; otherwise, do nothing.

4. Objective Function

The optimization objective of the maintenance optimization problem is to minimize the total cost, including maintenance cost, disassembly cost and inspection cost within a fixed overall time horizon T^{end}. With the development of system degradation and the definition of maintenance cost, we can give the objective function of the maintenance optimization problem with the three maintenance policies as follows.

Let K be the number of maintenance opportunities until reaching the time horizon T^{end}, T_k be the time of kth maintenance opportunity, $C_k(A_k, B_k)$ be the maintenance cost at T_k, g_{ki} denote whether component i is inspected at T_k, h_{ki} denote whether component i is disassembled at T_k. Consequently, the maintenance optimization problem can be defined as follows.

$$\min_{T^{\text{ins}}, T^T} C_{all}^{TBM} = \sum_{k=1}^{K} \left(C_k(A_k, B_k) + \sum_{i \in \bar{G}} c_i^{ins} g_{ki} + \sum_{i=1}^{N} c_i^{dis} h_{ki} \right)$$

$$\min_{T^{\text{ins}}, X^{C1}, X^{C2}} C_{all}^{CBM} = \sum_{k=1}^{K} \left(C_k(A_k, B_k) + \sum_{i \in \bar{G}} c_i^{ins} g_{ki} + \sum_{i=1}^{N} c_i^{dis} h_{ki} \right)$$

$$\min_{T^{\text{ins}}, T^H, X^{H1}, X^{H2}} C_{all}^{H} = \sum_{k=1}^{K} \left(C_k(A_k, B_k) + \sum_{i \in \bar{G}} c_i^{ins} g_{ki} + \sum_{i=1}^{N} c_i^{dis} h_{ki} \right)$$

5. Simulation and Maintenance Optimization

A discrete event simulation framework is proposed in this section. The core of the simulation procedure is alternately generating the next maintenance opportunity and the system degradation at the opportunity time point as shown in Algorithm 1.

Algorithm 1.

Input System Structure Parameters SS (Including Structural Dependence Information), Component Degradation Parameters CD, Maintenance, Inspection and Disassembly Cost Parameters MC, Maintenance Policy Parameters PP, Inspection Period T^{ins}, Overall Time Horizon T^{end}
Output Overall Cost C^{all}
$T \leftarrow 0, C \leftarrow 0$
While
If $T \geq T^{\text{end}}$, **return** C
$T \leftarrow \text{Next\_Opportunity}(SS, CD, T, T^{\text{ins}})$
$C \leftarrow C + \text{Policy\_Cost}(MC, PP)$

Since the model involves different types of maintenance opportunities and structural dependency, deriving the analytical solution faces difficulties. A genetic algorithm is developed to give a heuristic solution to the maintenance optimization problem. The procedure of the genetic algorithm includes selection generation and mutation (Lambora, Gupta, and Chopra 2019). Due to the intrinsic constraints on the parameters of the three strategies, which is shown in Table 1. We need to correct the newly generated incumbent solutions if they do not belong to the feasible region. The procedure of the genetic algorithm is shown in Algorithm 2.

Table 1.

Policy	Feasible Region
TBM Policy	$(T^{\text{ins}}, T^t) \in \{(x_1, x_2): x_1 \in [0, T^{\text{end}}], x_2 \in [0, x_1]\}$
CBM Policy	$(T^{\text{ins}}, X^{C1}, X^{C2}) \in \{(x_1, x_2, x_3): x_1 \in [0, T^{\text{end}}], x_2, x_3 \in [0, U]\}$
Hybrid Policy	$(T^{\text{ins}}, T^H, X^{H1}, X^{H2}) \in \{(x_1, x_2, x_3, x_4): x_1 \in [0, T^{\text{end}}], x_2 \in [0, x_1], x_3, x_4 \in [0, U]\}$

Algorithm 2.

Input Population Size N, number of generations n_G, mutation rate ρ
Output Heuristic Solution X^*
$X \leftarrow \text{Initialize\_Population}(N)$
$n \leftarrow 0$
While $n < n_G$
$Y \leftarrow \text{Simulation}(X)$
$X' \leftarrow \text{Crossover\_and\_Mutation}(X, \rho)$
$X' \leftarrow \text{Correct}(X')$
$X' \leftarrow \text{Selective}(X')$
If $\text{Converge}(X, X')$
Break
Return $\text{Best\_of\_Solution}(X)$

In the maintenance optimization problem, we apply a single-point crossover operator, a Gaussian mutation operator and the roulette wheel selection method. The correction procedure is realized by projecting infeasible solutions to feasible sets.

6. Result Analysis of a Parallel System

We apply the model to the case of a synthetic parallel system with identical components as Figure 2 shows. The case of series-parallel systems can be derived from parallel systems, as any fault of the series-connected subsystems will cause a type-2 or type-3 opportunity. The model parameters are listed in Table 2.

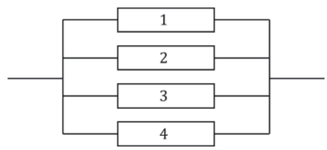

Fig. 2. Diagram of the Example Parallel System

Table 2.

Parameters	Values
u	$u_i = 1, i \in \{1,2,3,4\}$
$v(t)$	$v_i(t) = 2t, i \in \{1,2,3,4\}$
U	$U_i = 20, i \in \{1,2,3,4\}$
D	$D = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{pmatrix}$
ΔX_i^b	$\Delta X_i^b \sim Uni(10,20), i \in \{1,2,3,4\}$
c^a	$c_i^a = 3, i \in \{1,2,3,4\}$
c^b	$c_i^b = 1, i \in \{1,2,3,4\}$
c_s	$c_s = 2$
c^{ins}	$c_i^{\text{ins}} = 0.2, i \in \{1,2,3,4\}$
c^{dis}	$c_i^{\text{dis}} = 0.2, i \in \{1,2,3,4\}$
$G, \bar{G}$	$G = \{1,3\}, \bar{G} = \{2,4\}$
T^{end}	$T^{\text{end}} = 100$

6.1. *TBM Policies*

With population Size $N = 20$, number of generations $n_G = 100$, mutation rate $\rho = 0.1$, the optimal solution and optimal value are shown in Table 3. The trajectories of components' degradation level and applied maintenance actions from one simulation using the optimal TBM policy are shown in Figure 3 and Figure 4.

Table 3.

Variables	Values
T^{ins}	26.5
T^{t}	13.8
C_{all}^{TBM}	86.6

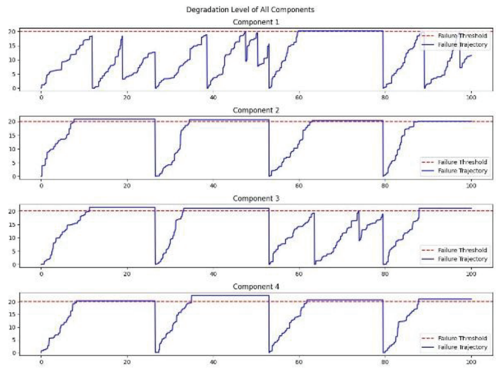

Fig. 3. The Degradation Level of Components from one Simulation under CBM Polices

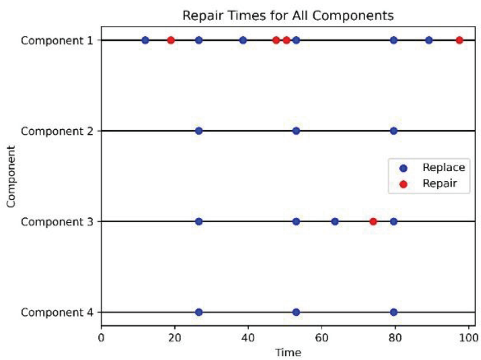

Fig. 4. The Times of Replacements and Repairs of Components from one Simulation under CBM Polices

It can be seen that when applying a group replacement policy on a parallel system with i.i.d. degrading components, the optimal inspection interval T^{ins} depends on the last component to fail and the optimal replacement time threshold T^{t} depends on the cost of imperfect maintenance compared to perfect maintenance. In this instance, there are four unplanned (corresponding to type 2 and type 3 opportunities) replacements and five unplanned imperfect repairs due to the existence of parameter T^{t}, which helps to reduce the total cost. We also find that the components in G (i.e. 1 and 3) tend to be repaired more than that in $\bar{G}$ (i.e. 2 and 4) while performing optimal TBM policy. This is due to maintaining components in $\bar{G}$ costs more than G as the inspection cost exists.

6.2. *CBM Policies*

With population Size $N = 20$, number of generations $n_G = 100$, mutation rate $\rho = 0.1$, the optimal solution and optimal value are shown in Table 44. The trajectories of components' degradation level and applied maintenance actions from one simulation using the optimal CBM policy are shown in Figure 5 and Figure 6.

Table 4.

Variables	Values
T^{ins}	34.5
X^{C1}	18.5
X^{C2}	12.1
C_{all}^{CBM}	66.8

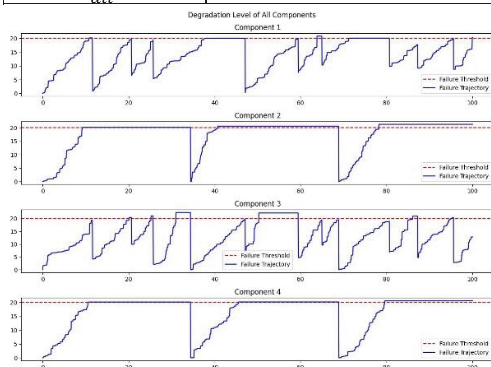

Fig. 5. The Degradation Level of Components from one Simulation under TBM Polices

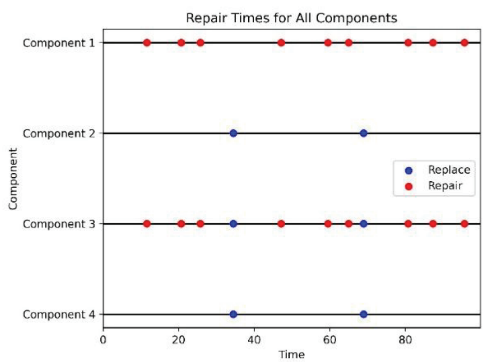

Fig. 6. The Times of Replacements and Repairs of Components from one Simulation under TBM Polices

With the failure threshold $U_i = 20, \forall i \in \{1,2,3,4\}$, X^{C1} is close to the failure threshold, which indicates that a pure CBM policy without periodic inspection may produce a better solution. However, as the components in $\bar{G}$ is not continuously monitored, such policy is not applicable. The group maintenance actions on $\bar{G}$ help to reduce potential future failure of the system. Lastly, the optimal cost C_{all}^{CBM} is less than C_{all}^{TBM}, demonstrating the advantages of state-detecting actions compared to pure TBM policy.

6.3. *Hybrid Policies*

With population Size $N = 20$, number of generations $n_G = 100$, mutation rate $\rho = 0.1$, the optimal solution and optimal value are shown in Table 5. The trajectories of components' degradation level and applied maintenance actions from one simulation using the hybrid policy are shown in Figure 7 and Figure 8.

Table 5.

Variables	Values
T^{ins}	46.8
T^H	8.0
X^{H1}	18.8
X^{H2}	9.5
C_{all}^H	56.0

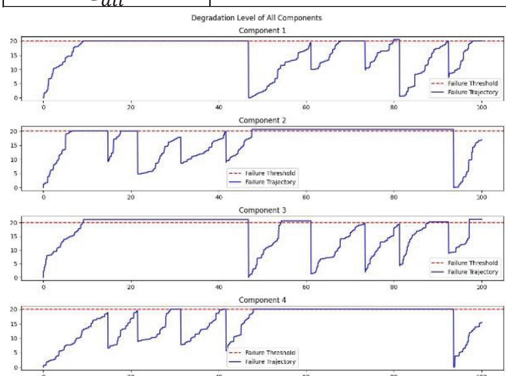

Fig. 7. The Degradation Level of Components from one Simulation under Hybrid Polices

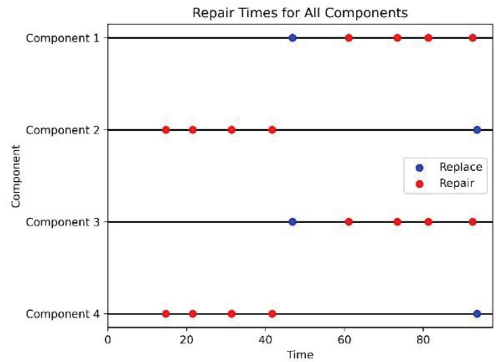

Fig. 8. The Times of Replacements and Repairs of Components from one Simulation under Hybrid Polices

In optimal hybrid policy, X^{H1} is still close to the failure threshold similar to the case of CBM policy, showing that inspection is economically less feasible. If the components in $\bar{G}$ are regarded as continuously monitored, it may cost less to repair them at type-2 opportunities, as the cost of inspections is overlooked. Grouping by G and $\bar{G}$ reduces the number of maintenance activities, as the unplanned maintenance actions can only take place in one group between two inspections (The repair activities take place in $\bar{G}$ during the first period and take place in G during the second). The optimal cost C_{all}^H is less than C_{all}^{TBM} and C_{all}^{CBM}, showing that the hybrid policy produces better solutions by enlarging the space of parameters.

7. Conclusion

In this study, we proposed a degradation and maintenance model suitable for multi-component systems with complex structures with real-time monitored components and inspected components. In this model, the economic and structural dependency are considered and opportunities caused by inspection and system failure are exploited. Simulation is performed to derive the overall cost and a genetic algorithm is proposed to optimize the TBM, CBM and hybrid policy. The result shows that:

1) Considering both components with real-time monitoring and components periodic inspection provides more maintenance opportunities and reduces the number of maintenance activities.

2) A hybrid policy jointly considers TBM and CBM policy is capable of outperforming the two policies, aiding to reduce the overall maintenance cost.

In this study, we only considered static maintenance strategies characterized by time and condition thresholds. From the independent increment property of the Gamma process, a predictive maintenance strategy defined by a function of the current system state may produce a better solution and bring some theoretical insights. Furthermore, the proposed model in this study can be extended to any continuous-state stochastic process with the Markov property. On one hand, it ensures that the probability of components in $\bar{G}$ failing at the next inspection can be estimated. On the other hand, it also guarantees the applicability of the stepwise simulation algorithm.

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