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Selective Maintenance Policy for a Series-Parallel System Considering Maintenance Priority of Components

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ABSTRACT Many systems are required to execute a series of missions with a finite break between any two adjacent missions. In order to improve the reliability of the system completing the next mission successfully, it is necessary to perform maintenance actions on the components considering limited maintenance resources. A novel idea to solve the problem of selective maintenance for a series-parallel system is proposed in this paper. This problem consists in finding the best choice of maintenance actions on a multi-component system by maximizing the system reliability under limited resources. With the increased number of components in the system, the possible combinations of selective maintenance increase exponentially, which raises the difficulty of the problem. For better solution of the problem, from the perspective of maintenance benefit, we develop a selective maintenance policy under maintenance priority of components. Finally, numerical example of a series-parallel system is given to illustrate the proposed method and verify the correctness and accuracy of the method.

INDEX TERMS Selective maintenance, series-parallel system, limited resources, reliability, maintenance priority.

I. INTRODUCTION

In industrial environments, systems are intended to execute a sequence of missions with a finite break between two adjacent missions. These breaks between successive missions provide an opportunity to perform maintenance on the component of the system. However, restricted to the limited maintenance resources, such as budget, time, and manpower, etc., it may not be possible to perform all desirable maintenance activities for the component in the system [1]–[4]. In such circumstance, only an optimal subset of maintenance actions among all the options is chosen to ensure that the subsequent mission is successfully completed. This maintenance strategy is known in the literature as selective maintenance.

Selective maintenance problem was firstly introduced by Rice et al. in 1998 [5]. Since then, selective maintenance problems have been extensively investigated from various angles. Bris *et al.* [6] minimized the preventive maintenance cost under availability constraints of a series-parallel system. In their model, it was assumed that the components were replaced at the time of maintenance. They described the life of each component following the exponential distribution, that is, the hazard rate of the components was constant. Subsequently, Samrout *et al.* [7] and Wang and Lin [8] adopted the same model and the same assumptions as Bris et al. [6], and only the solution approach different from the genetic algorithm adopted by Bris *et al.* [6]. Barker and Newby [9] proposed a methodology to find an optimal maintenance and inspection strategy by minimizing cost under a limit probability that a performance measure of the system does not permanently exceed a predefined limiting threshold. All the above works consider that maintenance is instantaneous, which may not be practical. Therefore, maintenance duration should be considered in maintenance modeling.

Laggoune *et al.* [10] presented a preventive maintenance model is based on the partial periodic renewal policy in a multi-component system. Zhu *et al.* [11] proposed a cost-based selective maintenance decision in a limited maintenance period in order to reduce the total maintenance cost and fault loss of the system. Maaroufi *et al.* [12]

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presented the optimal selective maintenance strategy for systems subject to propagated fault with global effects and failure isolation phenomena. Maillart *et al.* [13] investigated the selective maintenance problem for a system which performs multiple continuous missions, and only the corrective replacement was considered in a break between two adjacent missions. Khatab and Aghezzaf [14] studied selective maintenance optimization problem for a multi-components system, carrying out several missions with scheduled break. Jiang *et al.* [15] proposed a methodology to maximize the reliability benefits from maintenance selection scheduled under the constraints of financial and labor resources and network security. Moghaddam and Usher [16] defined a plan of actions for each component in the system by minimizing the total cost and maximizing overall system reliability simultaneously over the planning horizon. Lai *et al.* [17] researched an optimization framework with an alternative evaluator and an investment selector to determine an optimal investment plan with a specific allocation for cost, system reliability and service reliability. They minimized the cost model by a mixed-integer programming. The above work considers the maintenance interval, but it is not comprehensive for the maintenance action.

Cassady *et al.* [18] extended the model presented by Rice *et al.* [5] to a more general case, the lifetimes of units were Weibull distributions and three optional maintenance actions, i.e., minimal repair on failed, replacement of failed components (corrective replacement) and replacement of functioning components (preventive replacement) were available to choose. Later, Schneider and Cassady [19] considered multiple systems simultaneously and called it as a fleet (consisting of multiple systems together), and solved the problem of selective maintenance for the fleet performance. Pandey *et al.* [20] considered effective age in the selective maintenance model and included imperfect repair as a maintenance option. Wang *et al.* [21] presented a novel selective maintenance model for multi-state deteriorating systems with multi-state components considering imperfect maintenance strategy to minimize the total maintenance costs. Yang *et al.* [22] investigated a novel two-phase preventive maintenance policy for a single-component system considering imperfect repair to maximizing the revenue. The above research work shows that the increased number of maintenance policies, which will lead to the complexity of the system.

With the increased complexity of selective maintenance models, the maintenance policy optimization problem cannot be converted into a simple mathematical programming as that in [18]. In order to deal with the reliability problem of large sized systems, Rajagopalan and Cassady [23] proposed four improved enumeration procedures to reduce the CPU time for optimizing the selective maintenance. They assumed that all components in a subsystem were similar, and only the failed components were replaced. However, when the components are different, the number of maintenance options increases, the heuristic algorithm becomes inefficient. Lust *et al.* [24] proposed an exact method based on the branch-and-bound procedure combined with a Tabu search based algorithm. In their work, an evolutionary approach was firstly introduced to solve the selective maintenance problem. In addition, some advanced computational intelligence technologies also have been widely adopted to find global optimal maintenance strategies in a computationally efficient manner. For example, the modified great deluge algorithm, a local search meta-heuristic method which combines the worse solution acceptance with well-known hill climbing rule [25]. Liu *et al.* [26] solved the constrained combinatorial optimization problem through customized ant colony optimization algorithm. Zhang *et al.* [27] proposed a two-phase method integrating fuzzy Choquet integral based on λ-fuzzy measure and dynamic multi-objective artificial bee colony (DMABC) to optimize the SMP models. Bae *et al.* [28] used a neuro-genetic methodology to optimize the maintenance reliability allocation of urban transit break system. Diallo *et al.* [29] developed a new two-phase approach which transforms the problem into a multidimensional multiple-choice knapsack problem (MMKP) to optimally solve the selective maintenance problem of large serial k-out-of-n and complex reliability systems. The practicality and diversity of these intelligent algorithms are showed in above work. However, the shortcomings of these advanced intelligent algorithms have to be considered, for instance, Chalabi *et al.* [30] implemented particle swarm optimization to determine the best planning of maintenance grouping, but the particle swarm algorithm is easy to converge to the local optimum. Doostparast *et al.* [31] utilized the simulated annealing algorithm to maintain a certain level of reliability for a system with minimal total maintenance related cost, but the parameters of the simulated annealing algorithm are difficult to control, and it cannot guarantee to converge to the optimal value at one time. Liu and Huang [32] used genetic algorithm (GA) instead of enumeration method to solve complex optimization problems. Zhao *et al.* [33] used genetic algorithm to solve a selective maintenance optimization model for an MSS. However, genetic algorithm programming is more complicated, and the choice of three operator parameters seriously affects the quality of the solution. Furthermore, most of these parameters are based on experience. When the system is complex, it is not practical to use the enumeration method to verify the correctness of the calculation results of the intelligent algorithms.

In order to ensure the accuracy of selective maintenance results for a series-parallel system under resource constraints, we established a selective maintenance decision model under maintenance priority of components to maximize mission reliability under resource constraint. From the perspective of maintenance benefit, by evaluating the benefit of the corresponding maintenance actions for the system reliability, the bad maintenance actions were eliminated, and the best maintenance alternative on this basis is selected. By this way, the reliability of the system mission is ensured and the solution methodology has a good computational efficiency.

The remainder of this article is described below. A system is presented in Section 2 to describe the component state

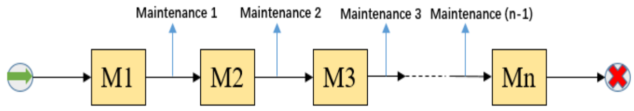

FIGURE 1. Schematic diagram of sequential mission with maintenance.

change model, system state model, and system reliability model for continuous mission intervals. The maintenance modeling is described in Section 3. The maintenance priority of components will be explained in the Section 4. The decision objective function and its solution methodology of decision-making are provided in Section 5. An illustrative example and detailed numerical analysis and discussion are given in section 6, and then the conclusions and future work are summarized in Section7.

II. SYSTEM DESCRIPTION

In industrial field, the manufacture systems are always performed with a series of missions under limited interval between two adjacent missions. For ensuring the reliability of each mission, it is necessary to perform maintenance activities on the components of the system with limited intervals. The sequence mission process under maintenance conditions is shown in Fig.1.

As seen in the above picture, the selective maintenance within a limited time is performed to improve the reliability of the system during various missions. The purpose of this paper is to provide decision makers with a selective maintenance solution approach that possess accurate result.

A. BASIC ASSUMPTIONS OF THIS PAPER ARE AS FOLLOWS:

For clearly describing the following, here are the basic assumptions given in this paper:

1. It is assumed that each component inside the system has a unique failure mode, i.e., the state of the components is either failed or functioning
2. Two possible maintenance actions are considered during the break. The replacement actions are to replace a failed or a functioning component (the component is as' good as new'); the minimal repair is to restart the functioning state for a failed component (the component age after the action is unchanged).
3. The amount of resources required for maintenance actions is known and we are only interested by optimizing the reliability at the end of a given mission.

B. FUNCTIONING PROBABILITY OF A COMPONENT, SUBSYSTEM AND SYSTEM

In this paper, a series-parallel system is considered where $i(i = 1, 2, \ldots, m)$ independent subsystems are connected in series, and each subsystem i has $n_i(j = 1, 2, \ldots, n_i)$ components connected in parallel. The state of each component, subsystem and system is functioning properly or failed [34], and each component in the system is denoted by C_{ij}, where i and j denotes the location of components in the system. Between mission intervals, maintenance of components will result in changes in the state of their respective components, which will affect the reliability of the system. Let $X_{ij,k}$ and $Y_{ij,k}$ denote the state of the component at the beginning of a mission $k(k = 1, 2, \ldots)$ and at the end of a mission $k(k = 1, 2, \ldots)$, respectively. At the beginning of a mission k, the state of a component can be given as:

$$X_{ij,k} = \begin{cases} 1, & \textit{if } C_{ij} \textit{ is functioning at the} \\ & \textit{beginning of mission } k \\ 0, & \textit{otherwise} \end{cases} \tag{1}$$

Similarly, the state of the subsystem and the entire system at the beginning of a mission k is also denoted by $\{0, 1\}$, where 0 denotes the failed state and 1 denotes the functioning state. Since each subsystem is composed of n_i parallel components, its state at the beginning of a mission k can be determined as:

$$X_{i,k} = \coprod_{j=1}^{n_i} X_{ij,k} = 1 - \prod_{j=1}^{n_i} (1 - X_{ij,k}) \tag{2}$$

The state of the entire system at the beginning of a mission k is defined as:

$$X_k = \prod_{i=1}^{m} X_{i,k} = \prod_{i=1}^{m} \coprod_{j=1}^{n_i} X_{ij,k} \tag{3}$$

Also, at the end of a mission k, the state of a component can be written as:

$$Y_{ij,k} = \begin{cases} 1, & \textit{if } C_{ij} \textit{ is functioning at} \\ & \textit{the end of mission } k \\ 0, & \textit{otherwise} \end{cases} \tag{4}$$

The state of the subsystem and the entire system at the end of a mission k is also denoted by $\{0, 1\}$, where 0 denotes the failed state and 1 denotes the functioning state. Since each subsystem is composed of n_i parallel components, its state at the end of a mission k is given as:

$$Y_{i,k} = \coprod_{j=1}^{n_i} Y_{ij,k} = 1 - \prod_{j=1}^{n_i} (1 - Y_{ij,k}) \tag{5}$$

The state of the entire system at the end of a mission k can be determined as:

$$Y_k = \prod_{i=1}^{m} Y_{i,k} = \prod_{i=1}^{m} \coprod_{j=1}^{n_i} Y_{ij,k} \tag{6}$$

It is assumed that the lifetime of component j in subsystem i follows the Weibull distribution of shape parameters β_i and scale parameters η_i. Let x_k denote effective age of the component C_{ij}, let $\lambda_{ij,k}$ denote the failure rate of the component, and let L_k denote the length of mission$k$, then the reliability of the component C_{ij} in the length of mission k can be given as:

$$R_{ij,k} = \exp\left(- \int_0^{L_k} \lambda_{ij,k}(x_k + x)dx \right) \cdot X_{ij,k} \tag{7}$$

Since each subsystem consists of n_i parallel components, the reliability of subsystem i during the length of mission k can be determined as:

$$R_{i,k} = 1 - \prod_{j=1}^{n_i} (1 - R_{ij,k}) \tag{8}$$

Similarly, the reliability of the system during the mission k can be written as:

$$R_k = \prod_{i=1}^{m} R_{i,k} = \prod_{i=1}^{m} \left(1 - \prod_{j=1}^{n_i} (1 - R_{ij,k})\right) \tag{9}$$

The probability of completing the next mission can be recursively determined for each component based on age at the beginning of the next mission, its initial state and the mission duration. The reliability of the whole system can be determined by using Eq. (9).

III. MAINTENANCE MODELING

For ensuring the smooth and reliable performance of each mission, it is essential to take full advantage of the time to adopt the optimal maintenance actions under the limited time by maximizing the reliability of the next system mission. After each mission, the components of the system may be in functioning properly or failed state, and the corresponding maintenance actions are selected according to the state of each component in the system. Let $H_{ij,k}$ denote the maintenance decision variable of component C_{ij} during maintenance period k and use a unique constants to denote it, and $B_{ij,k}$ denotes the age of component j of subsystem i at the beginning of a mission k. The effects of maintenance on component state and age, and corresponding value assignment of maintenance policy are presented in Table 1.

It can be seen from Table 1 that when the value of $H_{ij,k}$ is 0 and 1, the component age is unchanged, thus the reliability of the component does not change; when $H_{ij,k}$ is 2 or 3, replacement maintenance result in it was restarted to the state 'as good as new'.

Let $S_{ij,k}$ denote the age of the component C_{ij} at the end of a mission k, and assuming that the initial age of each component is 0, and then its calculation can be given as:

$$\begin{cases} S_{ij,k} = e_{ij,k-1} S_{ij,k-1} + L_k \\ \qquad \vdots \\ S_{ij,2} = e_{ij,1} S_{ij,1} + L_2 \\ S_{ij,1} = L_1 \end{cases} \tag{10}$$

It can be seen from Eq. (10) that after the k-1th maintenance action, the component age will be restarted from $S_{ij,k-1}$ to $e_{ij,k-1}S_{ij,k-1}$. Where e is the improvement factor in effective age, When $e = 1$ represents minimal repair; $e = 0$ represents the replacement action.

The change in the failure rate function after different maintenance actions can be determined as:

$$\lambda_{ij,k}(x_k + x) = \begin{cases} \lambda_{ij,k-1}(S_{ij,k-1} + x), & H_{ij,k-1} \in \{0, 1\} \\ \lambda_{ij,k-1}(x), & H_{ij,k-1} \in \{2, 3\} \end{cases} \tag{11}$$

where $H_{ij,k-1} \in \{0, 1\}$ denotes do not perform maintenance or minimal repair action; $H_{ij,k-1} \in \{2, 3\}$ denotes that the replacement action is performed and the component age is cleared to 0.

Ideally, failed components with $\beta_i > 1$ would be replaced prior to the next mission, failed components with $\beta_i \le 1$ should be minimally repaired and functioning components having $\beta_i > 1$ should be replaced. However, all maintenance actions may not be performed due to the limited time.

By expressing these times as known constants, the time $T_{ij}(H_{ij,k})$ consumed by component C_{ij} can be given as:

$$T_{ij}(H_{ij,k}) = \begin{cases} 0, & H_{ij,k} = 0 \\ t_{ij,mr}, & H_{ij,k} = 1 \\ t_{ij,fr}, & H_{ij,k} = 2 \\ t_{ij,pr}, & H_{ij,k} = 3 \end{cases} \tag{12}$$

where $H_{ij,k} = 0$ denotes that no time is consumed; $H_{ij,k} = 1$ denotes that the minimal repair action is performed, where $t_{ij,mr}$ is the time to perform minimal repair; $H_{ij,k} = 2$ denotes replacement of failed components action, where $t_{ij,fr}$ is the time to perform corrective replacement; $H_{ij,k} = 3$ denotes that the preventive replacement action, where $t_{ij,pr}$ is the time to perform preventive replacement. Hence, for decision variable $H_{ij,k}$, related maintenance time of a component C_{ij} can be estimated and the total maintenance time for the whole system can be determined as:

$$T_k = \sum_{i=1}^{m} \sum_{j=1}^{n_i} T_{ij}(H_{ij,k}) \tag{13}$$

It is evident from Eq. (13) that for a particular decision variable for maintenance level $H_{ij,k}$, the corresponding time involved in system maintenance can be determined.

IV. MAINTENANCE PRIORITY OF COMPONENTS

Although advanced intelligent algorithms play an important role in the combinatorial problem of selective maintenance, these intelligent algorithms cannot always ensure the accuracy of each result for the problem in this paper. In order to ensure the accuracy of each policy and accelerate computational efficiency as much as possible, a selective maintenance policy under maintenance priority of components is proposed in this paper. The maintenance priority of components (MPOC) can be written as:

$$MPOC = \begin{cases} \dfrac{P'(C_{ij,k} = 0) - P(C_{ij,k} = 0)}{P(C_{ij} = 0)}, & H_{ij,k} \in \{1, 2\} \\ \dfrac{P'(C_{ij,k} = 1) - P(C_{ij,k} = 1)}{P(C_{ij,k} = 1)}, & otherwise \end{cases} \tag{14}$$

where $P'(C_{ij,k} = 0)$ denotes that the failed component is repaired at the end of a k mission, which improve the expected value of the system reliability for the k + 1 mission; $P(C_{ij,k} = 0)$ denotes the reliability value of the k + 1 mission when the failed component does not take any maintenance activities; $P'(C_{ij,k} = 1)$ denotes the functioning component

TABLE 1. Effects and value assignment of maintenance policy.

Type of maintenance policy	$Y_{ij,k}$	$X_{ij,k+1}$	$B_{ij,k+1}$	$H_{ij,k}$
Do nothing	1	1	$B_{ij,k}+L_k$	0
Minimally repair failed component	0	1	$B_{ij,k}+L_k$	1
Replace failed component	0	1	0	2
Replace functioning component	1	1	0	3

is replaced at the end of a k mission, which improve the expected value of the system reliability for the k + 1 mission; $P(C_{ij,k}=1)$ denotes the reliability value of the k + 1 mission when the functioning component does not take any maintenance activities.

Decision-makers can evaluate maintenance policy through MPOC-time ratio, MPOC-cost ratio, and MPOC-manpower ratio, etc. In this paper, maintenance interval as a constraint, the MPOC-time ratio will play a crucial role in the results of selective maintenance. Assume that the first step of maintenance action set is $\{a, b, c, d, e\}$ and c denotes reference maintenance (the maintenance action with the highest MPOC-time ratio is represented by r_m), then the maintenance actions of MPOC greater than or equal to c are retained. By this way, the first selection of maintenance actions are reduced, that is, the final solution set is reduced from $\{\{a,\ldots\},\{b,\ldots\},\{c,\cdots\},\{d,\ldots\},\{e,\ldots\}\}$ to $\{\{a,\ldots\},\{b,\ldots\},\{c,\ldots\}\}$. And the retained options proceed to the next selection individually until there is no remaining time to perform further maintenance actions. Finally, the maintained component set and the maintenance option set are obtained in excellent solution set.

V. MAINTENANCE DECISION MODEL

For complex systems in many industrial environments, how to perform selective maintenance within a limited maintenance interval as much as possible to improve the reliability of the system over the mission period is a major problem.

A. DECISION OBJECTIVE FUNCTION

Under the constraint of limited mission interval, selective maintenance decision-making is made by maximizing mission reliability. The decision-making content includes the required maintenance components and their corresponding maintenance actions. Besides, the maintenance actions of components in the system must be a feasible solution corresponding to the real-time state. According to the above analysis, its decision objective function and related constraints can be given as:

Objective:

$$\max(R_{k+1}) = \max \prod_{i=1}^{m}\left(1-\prod_{j=1}^{n_i}\left(1-R_{ij,k+1}\right)\right) \tag{15}$$

$$\text{Subject to: } \sum_{i=1}^{m}\sum_{j=1}^{n_i} T_{ij}\left(H_{ij,k}\right) \le T_{\max} \tag{16}$$

$$V_{ij,k} = \begin{cases} 1, & \text{if } H_{ij,k} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{17}$$

$$X_{ij,k+1} == \begin{cases} Y_{ij,k}+V_{ij,k}, & \text{if } Y_{ij,k}=0 \\ Y_{ij,k}, & \text{otherwise} \end{cases} \tag{18}$$

In this formulation, constraint (16) denotes the system maintenance time cannot exceed the maximum interval, and constraints (17) and (18) denote that the state of components at the beginning of next mission depending on corresponding maintenance actions performed and the state at the end of previous mission.

B. SOLUTION METHODOLOGY

As shown in equations (15)-(18), the proposed selective maintenance model is a complex, non-linear, discrete problem, and the number of solutions will increase exponentially with the quantity of elements in a system. Due to their easiness in use and adaptability to the problem, evolutionary algorithms (like genetic algorithm (GA), differential evolution (DE), etc.) are widely used in the maintenance optimization ([20], [24], [35], [36] etc.). In order to ensure the accuracy of selective maintenance results, the MPOC-based method is used to solve the selective maintenance problem in this paper. Let T_r denote remaining maintenance time, and let $K_{\max}$ denote specified number of missions. The decision-making process of the selective maintenance is shown in Fig.2.

It can be seen from Fig.2, when each mission ends, the age of each component is updated and the state of each component is simulated by generating a random number. According to the corresponding state of the components in system, the corresponding value of the MPOC is calculated by Eq. (14), and selecting excellent solution set using r_m action. It should be noted that the above reserved maintenance actions meet the constraints. After all maintenance alternatives fail to perform the next maintenance action, then selecting the best solution from the excellent solution set. Finally, the calculation is finished until the system time reaches the specified $K_{\max}$, and the maintained component set C and corresponding maintenance option set H are obtained.

VI. NUMERICAL ANALYSIS AND DISCUSSION

A. CASE VERIFICATION

To demonstrate the correctness of the proposed decision method, an illustrative case is taken from Dao *et al.* [3]. In this example, a series parallel system is considered which consists

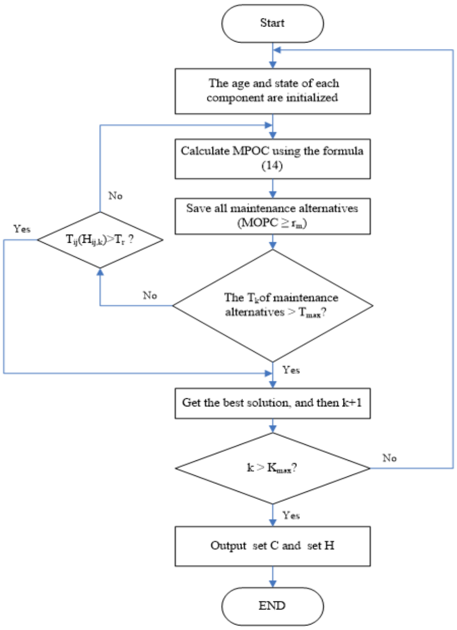

FIGURE 2. Decision-making process of the selective maintenance.

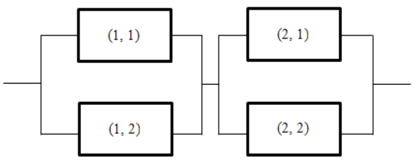

FIGURE 3. Series parallel system.

TABLE 2. System parameters and maintenance time.

(i, j)	$\beta_{i,j}$	$\eta_{i,j}$	$t_{ij,mr}$	$t_{ij,fr}$	$t_{ij,pr}$
1,1	1.5	15	3	5	1
1,2	1.5	15	3	5	1
2,1	3	20	2	4	2
2,2	3	20	2	4	2

of two subsystems connected in series. Each subsystem has two components connected in parallel. This system is shown in Fig. 3.

The system parameters, time required for various maintenance actions are given in Table 2.

Assume that the next mission is of length $L_{k+1} = 8$ and the current time interval between missions is $T_{\max} = 8$. A decision must be made as to improve the reliability for next mission. According to the available data, the MPOC of the maintenance actions are calculated by Eq. (14) and the state and age of each component are shown in Table 3.

It can be seen from Table 3 that the failed component 3 is replaced has the highest priority (1.8767), but the MPOC-time ratio of the component 3 is small. Since the MPOC-time ratio of the preventive replacement component 4 is the largest, it is used as a reference operation and eliminates the maintenance actions in which the MPOC is smaller than

TABLE 3. State, age and MPOC of components in the system after a k mission.

(i, j)	$S_{ij,k}$	$Y_{ij,k}$	$H_{ij,k}=1$	$H_{ij,k}=2$	$H_{ij,k}=3$
1,1	15	1	-	-	0.3992
1,2	20	1	-	-	0.5175
2,1	8	0	1.2782	1.8767	-
2,2	15	1	-	-	1.8148

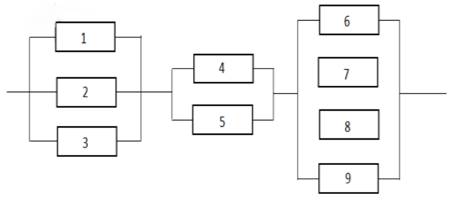

FIGURE 4. Block diagram of a system.

this action. By this way, the first selection of maintenance actions are reduced, that is, the final solution set is reduced. And the retained options proceed to the next selection individually until there is no remaining time to perform further maintenance actions. Finally, the maintained component set $C = \{1, 2, 3, 4\}$ and the maintenance option set $H = \{3, 3, 2, 3\}$ are obtained in excellent solution set. By the above maintenance policy, the system can get the maximum reliability (0.8925) for the next mission.

In order to verify the correctness of the method, an enumeration method is used to prove it. Since there are four components and two binary decision variables for each component, there are $2^8 = 256$ theoretical maintenance options of which only 24 are feasible. The details are shown in Table 4.

From the data in Table 4, it can be seen that the optimal solution of the feasible solution is obtained by the method proposed in this paper, and the maintenance time meets the constraint. The above case proves that the method of decision model proposed in this paper is feasible and correct.

B. COMPARATIVE ANALYSIS WITH DIFFERENT METHOD

A manufacturing system composes of subsystems 1, 2 and 3 in series, where subsystem 1 is composed of components 1, 2 and 3 in parallel, subsystem 2 is composed of components 4 and 5 in parallel, subsystem 3 is composed of components 6, 7, 8 and 9 are composed in parallel, and the system structure is shown in Fig.4.

The system parameters, time required for various maintenance actions, age and state of the components in the system are shown in Table 5.

It is assumed that the length of the next mission is $L_{k+1} = 100$, and the current time interval between missions is $T_{\max} = 8$. The main problem solved is to determine the best maintenance combination under limited mission time by maximizing the reliability of the system for the next mission. According to the available data, the MPOC of the maintenance actions are calculated by Eq. (14) are shown in Table 6.

TABLE 4. Feasible solutions for selective maintenance.

Solution	$H_{11,k}$	$H_{12,k}$	$H_{21,k}$	$H_{22,k}$	$B_{11,k+1}$	$B_{12,k+1}$	$B_{21,k+1}$	$B_{22,k+1}$	R_{k+1}	T_k
1	3	3	2	3	0	0	0	0	0.8925	8
2	3	3	1	3	0	0	8	0	0.8759	6
3	3	3	2	0	0	0	0	15	0.8580	6
4	3	3	0	3	0	0	8	0	0.8404	4
5	0	3	2	3	15	0	0	0	0.8056	7
6	3	0	2	3	0	20	0	0	0.7918	7
7	0	3	1	3	15	0	8	0	0.7906	5
8	3	0	1	3	0	20	8	0	0.7770	5
9	0	3	2	0	15	0	0	15	0.7753	5
10	3	0	2	0	0	20	0	15	0.7620	5
11	0	3	0	3	15	0	8	0	0.7586	3
12	3	0	0	3	0	20	8	0	0.7455	3
13	3	3	1	0	0	0	8	15	0.6802	4
14	0	0	2	3	15	20	0	0	0.6205	6
15	0	3	1	0	15	0	8	15	0.6140	3
16	0	0	1	3	15	20	8	0	0.6089	4
17	3	0	1	0	0	20	8	15	0.6034	3
18	0	0	2	0	15	20	0	15	0.5971	4
19	0	0	0	3	15	20	8	0	0.5843	2
20	0	0	1	0	15	0	8	15	0.4729	2
21	3	3	0	0	0	0	8	15	0.2985	2
22	0	3	0	0	15	0	8	15	0.2695	1
23	3	0	0	0	0	20	8	15	0.2648	1
24	0	0	0	0	15	20	8	15	0.2075	0

TABLE 5. Reliability parameter, maintenance time, state and age of components in system after a k mission.

No. of component	$\beta_{i,j}$	$\eta_{i,j}$	$t_{ij,pr}$	$t_{ij,mr}$	$t_{ij,fr}$	$S_{ij,k}$	$Y_{ij,k}$
1	1.6	250	1.9	1.6	2.1	200	0
2	2.4	300	1.8	1.5	2	107	1
3	1.5	300	1.6	1.4	1.8	105	1
4	2.5	200	1.8	1.6	2	111	0
5	2.4	175	1.7	1.5	1.8	106	1
6	2	375	1.8	1.6	2	103	1
7	1.2	400	1.7	1.5	1.9	200	1
8	1.4	400	1.5	1.4	1.8	200	1
9	1.3	400	1.6	1.5	1.7	108	0

It can be seen from Table 6 that the failed component 4 is replaced has the highest priority, and the MPOC-time ratio of the component 4 is also the largest. Therefore, the failed component 4 is replaced is the first action. The selection idea has been specifically described in the above section and case verification. We executed the program in MATLAB

TABLE 6. The maintenance priority of components after the first mission completed.

No. of component	$H_{ij,k}=1$	Priority	$H_{ij,k}=2$	Priority	$H_{ij,k}=3$	Priority
1	0.0481	6	0.0725	4	-	-
2	-	-	-	-	0.0686	5
3	-	-	-	-	0.0380	7
4	0.9024	3	1.8856	1	-	-
5	-	-	-	-	1.5036	2
6	-	-	-	-	0.0075	10
7	-	-	-	-	0.0032	12
8	-	-	-	-	0.0054	11
9	0.0093	9	0.0101	8	-	-

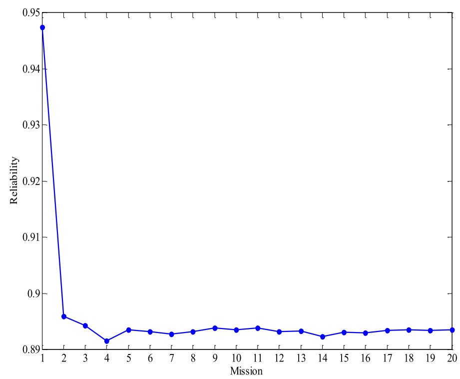

FIGURE 5. Estimates of mission reliability.

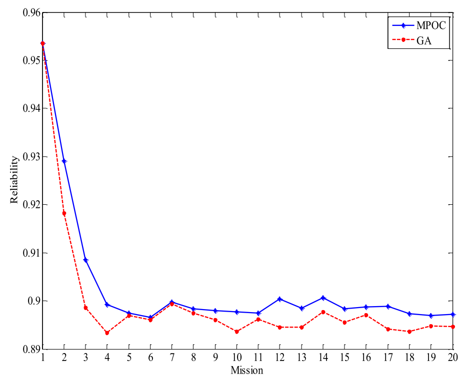

FIGURE 6. Estimates of mission reliability in case 1.

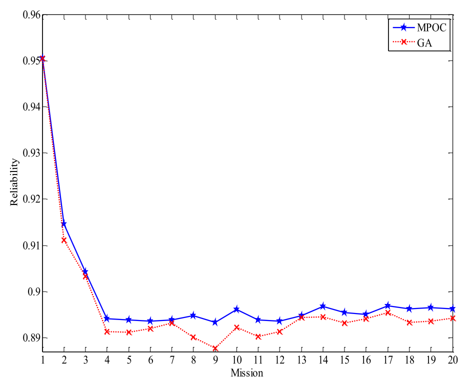

FIGURE 7. Estimates of mission reliability in case 2.

2014, the maintained component set $C = \{1,2,4,5\}$ and the corresponding option set $H = \{2,3,2,3\}$ can be obtained. By the above maintenance policy, the system can get the maximum reliability (0.9474) for the next mission.

Assume that the mission is executed 20 times, and the length of the mission and the mission interval remain unchanged. Through multiple simulations, the curve of mission reliability is shown in Fig.5.

It can be seen from Fig.5 that the selective maintenance decision model proposed in this paper can keep the system in a stable reliability range, which shows that the selective maintenance policy is feasible. The initial reliability of the system is 0.9251, after four missions, the reliability stabilizes at 0.8936 as shown in Fig.5.

Since the state and age of the components are randomly assigned, the single simulation results cannot fully reflect the correctness of the maintenance policy proposed in this paper. In order to eliminate the existence of contingency, the age of the components in Table 5 was changed and divided into four cases. Simultaneously, in order to prove the accuracy of the method proposed in this paper, we use the genetic algorithm toolbox GAOT to solve the non-linear problem and compare it with the method based on MPOC. The simulation conditions are the same as above, the system reliability curves and simulation comparison results for the four cases are shown in Fig.6-9.

It can be seen from Fig.6-9 that different component ages have the impact on system reliability, but as that in Fig.5 can keep the system in a stable reliability range, which shows that the selective maintenance policy is applicable. In addition, the comparison between the decision-making method proposed in this paper and the solution of genetic algorithm shows that the accuracy of the decision-making method based on MPOC is better than that of genetic algorithm. This is because the decision method proposed in this paper is to accurately

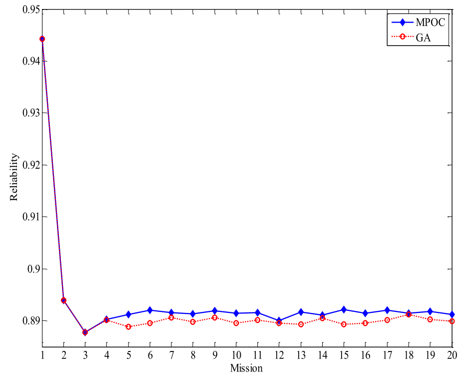

FIGURE 8. Estimates of mission reliability in case 3.

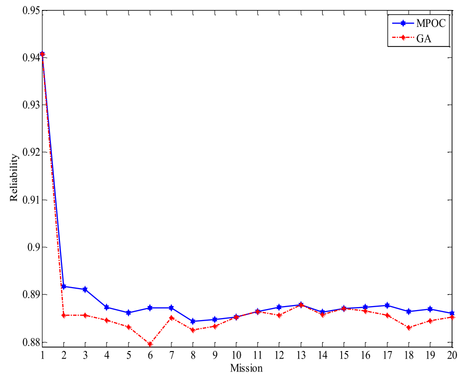

FIGURE 9. Estimates of mission reliability in case 4.

calculate each result, and the genetic algorithm may cause premature convergence due to the unreasonable selection of three operators. Moreover, the reliability value in the figure is the average value obtained by repeated simulation. If the result of the genetic algorithm has a local optimal solution, the final reliability will be affected. It can also be seen from Fig.6-9 that there is an overlap between the curves of the two methods. In fact, since the data in Fig.6-9 retains only four significant digits, the error between the two methods may be greater. Therefore, an accurate and unambiguous decision-making method is the key to achieving maximum benefit for decision makers.

C. SENSITIVITY OF MAINTENANCE TIME

After verifying the correctness and accuracy of the method above, this section discusses the impact of maintenance resources on system reliability. This paper considers the influence of time resource on system reliability, but the maintenance interval in the above case is known, which may not be practical especially in a finite horizon planning. Thus sensitivity of the selective maintenance decision with respect to the time limitation is required to be investigated. To find the effect of variation of time limit, the system maintenance time in decision-making model is changed, the ages of components at the end of the k mission in Table 5 are adopted, and the maintenance interval $T_{\max}$ is 4, 6, 8, 10 and 12, respectively. The number of missions is set to 20 and the average value of multiple simulations is calculated, and the simulation results are shown in Fig. 10.

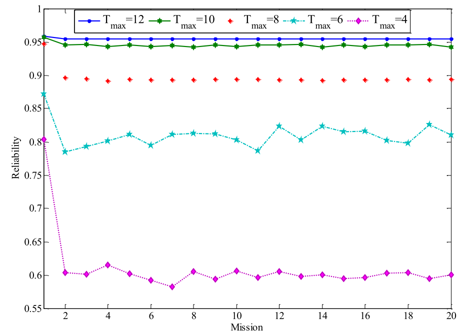

FIGURE 10. Mission reliability under different maintenance time.

It can be seen from Fig. 10 that under the given maintenance time, the reliability of the simulation system shows a downward trend, and the shorter the maintenance time, the more significant the trend of reliability degradation. Similarly, the reliability of system mission is gradually stabilized within a certain range with the progress of mission. When $T_{\max} \geq 8$, the reliability of system mission remains above 0.8916; when $T_{\max} \leq 4$, the reliability of system mission cannot be kept above 0.6, and the minimum reliability reaches 0.5821, which makes it difficult to ensure the completion of the mission. Therefore, a reasonable allocation of limited time is critical to the reliability of the next mission system. In addition, the simulation results can provide information for the optimization of the maintenance time, if the decision-maker's acceptable threshold for the performance of 20 sequential missions is 0.8, the minimum maintenance time should be kept above 6.

VII. CONCLUSION REMARK

A mission reliability model for complex series-parallel systems is established in this paper. Minimal repair, preventive replacement and corrective replacement are taken as maintenance options for components of the manufacture, and a selective maintenance decision-making model is constructed by maximizing reliability as the objective. The benefit of maintenance actions is considered, and a novel policy is presented in this paper to ensure the accuracy of the calculation results. The case shows that a selective maintenance model under maintenance priority of components is feasible and applicable. In addition, selective maintenance decisions are not limited to maintenance time, but also constraints other than costs, spare parts, and tools, which will make the problem has become more complicated and it is necessary to conduct further research on this issue in the next step.

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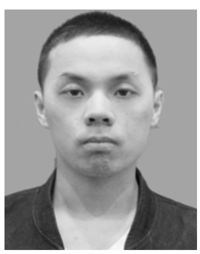

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