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Multi-component manufacturing system maintenance scheduling based on degradation information using genetic algorithm

Qinming Liu Wenyuan Lv

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Qinming Liu and Wenyuan Lv
Department of Industrial Engineering Business School, University of Shanghai for Science and Technology, Shanghai, China

Abstract

Purpose – The traditional maintenance scheduling strategies of multi-component systems may result in maintenance shortage or overage, while system degradation information is often ignored. The purpose of this paper is to propose a multi-phase model that better integrates degradation information, dependencies and maintenance at the tactical level.

Design/methodology/approach – This paper proposes first a maintenance optimization model for multi-component systems with economic dependence and structural dependence. The cost of combining maintenance activities is lower than that of performing maintenance on components separately, and the downtime cost can be reduced by considering structural dependence. Degradation information and multiple maintenance actions within scheduling horizon are considered. Moreover, the maintenance resources can be integrated into the optimization model. Then, the optimization model adopting one maintenance activity is extended to multi-phase optimization model of the whole system lifetime by taking into account the cost and the expected number of downtime.

Findings – The superiority of the proposed method compared with periodic maintenance is demonstrated. Thus, the values of both integrated degradation information and considering dependencies are testified. The advantage of the proposed method is highlighted in the cases of high system utilization, long maintenance durations and low maintenance costs.

Originality/value – Few studies have been carried out to integrate decisions on degradation, dependencies and maintenance. Their considerations are either incomplete or not realistic enough. A more comprehensive and realistic multi-phase model is proposed in this paper, along with an iterative solution algorithm for it.

Keywords Scheduling, Maintenance, Degradation, Multi-component manufacturing system, Weibull distribution, Genetic algorithm

Paper type Research paper

1. Introduction

Modern machinery systems such as aircrafts and manufacturing systems involve interdependent components. The systems need to operate at high reliability, low environmental risks and human safety. The maintenance plays a critical role in their efficient usage in terms of cost, available and safety, and it involves maintenance actions carried out to retain a system in or restore it to a better health state. Maintenance models of multi-component systems are concerned with optimal maintenance policies for sets of

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components that may be dependent on each other (Thomas, 1986; Zhao *et al.*, 2014). Generally, the maintenance can be classified into corrective maintenance (CM) and preventive maintenance (PM). The CM involves the repair or replacement of components which have failed or broken down (Kenne and Nkeungoue, 2008). The PM is a schedule of planned maintenance actions aimed at the prevention of system breakdowns and failures (Baraldi *et al.*, 2013; Sanchez *et al.*, 2009). Recently, condition-based maintenance (CBM) becomes more desirable in many application domains where safety, reliability and availability of the system are considered critically. It has attracted researchers in recent years by aiming to balance the maintenance cost, which is high in PM, with failure cost, which is high in CM. In addition, CBM can also increase productivity, efficiency and availability of systems (Makis *et al.*, 1998).

Three kinds of dependencies of a multi-component system are described, including economic dependence, structural dependence and stochastic dependence. For the three dependencies, economic dependence indicates that the maintenance cost performing maintenance activities to a group of components does not equal the total cost of individual maintenance of components, structural dependence describes when maintenance of one component takes maintenance of other components, and stochastic dependence shows that the faults of components are not independent and are interactional (Dekker, 1996). In this paper, economic dependence and structural dependence can be considered.

For multi-component systems, it is possible to use the existence of economic dependence and structural dependence to maintenance costs and models in some cases, for example, due to economic dependence among components, the cost of combining maintenance activities is lower than that of performing maintenance on components separately (Zhou *et al.*, 2012; Galante and Passannanti, 2009). Due to structural dependence among components, the maintenance of one component may lead to the downtime of multiple components and the downtime cost can be reduced by considering structural dependence. On the other hand, the present paper also considers maintenance resource restrictions, including spare parts, maintenance personnel and tools.

Maintenance models are used to find optimal maintenance schedules for a variety of systems. And it has been studied extensively (Fitouhi and Nourelfath, 2012; Bartholomew-Biggs *et al.*, 2009; Farnoosh and Makis, 2015; Tong *et al.*, 2004). Fitouhi and Nourelfath (2012) dealt with the problem of integrating non-cyclical PM and tactical production planning for a single machine. Bartholomew-Biggs *et al.* (2009) considered the optimal PM scheduling and dealt with the problem of scheduling imperfect PM for equipment. Tong *et al.* (2004) presented an optimal PM model for a nuclear power-plant. The above literatures mainly focus on minimizing system cost and identifying the PM period. For the multi-component maintenance scheduling approaches, two categories of approaches can be classified: opportunistic maintenance and group maintenance. For opportunistic maintenance (Dagpunar, 1996; Farrero *et al.*, 2002), the maintenance actions can be performed when the system is downtime due to a failure. The maintenance can include PM and CM. For group maintenance (Sheu and Jhang, 1997; Khamseh *et al.*, 2015), the components of a system can be grouped. And when one component in the group fails, the whole group needs to be maintenance, and maintenance actions can be adopted, including repair and replacement. However, the maintenance scheduling in these two approaches, is performed based on already occurred failure. Degradation information is not considered. In this paper, the maintenance strategy will consider not only the degradation information, but also the dependencies among components.

The study of maintenance can also concern resource management, maintenance strategy optimization and evaluation. Recently, mathematical models have been established to describe predictive maintenance with consideration of spare parts inventory (Park and Lee, 2011; De Smidt-Destombes *et al.*, 2006). For example, Basten *et al.* (2012) designed an optimal solution algorithm for joint problem of level of repair analysis (LORA) and spare parts stocking. Wang (2012) presented a joint optimization method for both spare parts inventory control and PM inspection interval. All these studies entail the joint optimization of maintenance and spare parts inventory. Thus, in current literatures, the maintenance mainly focussed on the optimization of spare parts inventory and maintenance strategies is developed only with consideration of system states. In this paper, the maintenance focusses on the optimization of spare parts, maintenance personnel and tools. The paper proposes a multi-phase maintenance scheduling model using degradation information with consideration of resources planning.

These studies are of interest and could be applied in a wide variety of multi-component systems such as semiconductor manufacturing, transportation and power generation (Ding and Kamaruddin, 2015; Yalaoui *et al.*, 2014; Huynh *et al.*, 2012). However, it can be found that there is a few works in the integration of resources, system degradation and multi-phase maintenance optimization.

The implementation of maintenance actions may require different resources such as spare parts, maintenance personnel and tools. This paper provides a new method that incorporates degradation information with available resources to obtain the optimal maintenance strategy. Thus, an integrated decision model for both maintenance optimization and resource planning is presented. The contributions of the paper can be summarized as follows. First, system degradation information based on Weibull distribution is integrated into the proposed system maintenance scheduling model, and based on the actual maintenance effect, two adjustment factors are developed. Second, the maintenance optimization model of one system maintenance activity is developed, and the multi-phase maintenance model of the whole system lifetime can be proposed. By considering structural dependence of systems, the number of expected downtime is integrated into the maintenance model. Then, in the process of maintenance scheduling, it is important for maintenance model to able to incorporate resources information, and maintenance scheduling without considering available resources to be used in maintenance may not be practical. Moreover, some maintenance actions of multi-component systems cannot be performed at the same time due to lack of enough maintenance resources. The proposed maintenance method incorporates failure probability with other system information such as maintenance resources to obtain the optimal maintenance schedule. Finally, GA is used to solve the proposed model, and an example illustrates its performance. The overall optimal maintenance scheduling strategy is obtained.

This paper is organized as follows. Section 2 describes system degradation, maintenance actions and adjustment factors. Section 3 focusses on the development of the proposed maintenance scheduling approach, including one maintenance scheduling activity and multi-phase maintenance scheduling model. A numerical example is introduced in Section 4, and some results are discussed. Section 5 presents the conclusions drawn from this work.

2. System degradation and maintenance description

2.1 System degradation

The system performance degradation affects the adopting maintenance actions and the maintenance effect. In the present paper, the failure rate (*FR*) is used to denote the system degradation. *FR* is bigger, then, the system degradation is more serious and the system failure probability will be increased. Based on the analysis of system failure rate, the failure rate of general system has shown the "bathtub curve" distribution shape. Thus, it is assumed that the failure behavior of component i ($i = 1, \ldots, n$) is described by a Weibull distribution with shape parameter $\beta_i > 0$, and scale parameter $\eta_i > 0$.

Weibull distribution is extremely flexible and can fit an extremely wide range of empirical observations very well. Moreover, it is especially useful as a failure model in analyzing the reliability of different types of systems. Application of Weibull distribution depends on having reliable estimates of the parameters. The parameters of Weibull distribution can be calculated based on system failure data and maximum likelihood estimation (Melchor-Hernández *et al.* 2015). The failure rate of component i is then:

$$FR(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \tag{1}$$

Where, β_i and η_i is shape and scale parameters of component i, respectively.

Weibull distribution can exactly describe the system failure rate corresponding to different parameter value. In the process of system operation, the failure rate gradually rise with the increase of system running time, thus, the maintenance scheduling can be adopted before the failure in order to length the system useful lifetime.

2.2 Maintenance actions

For maintenance scheduling of multi-component systems, the different maintenance actions need to be adopted in order to decrease system degradation. Each maintenance action corresponds to different system degradation state. Thus, the available maintenance actions set can be expressed as follows.

2.2.1 Minor repair (denoted as M). Adopt some minor maintenance actions such as lubrication, adjustment and cleaning. The purpose is to keep the system staying at the current health state as long as possible, and the system degradation can acquire a little improvement. F_M is described as the failure threshold of minor repair.

2.2.2 Imperfect repair (denoted as I). Adopt some imperfect maintenance actions such as repairing the internal loss of parts. The maintenance goal is to restore the system from current health state to a better health state, and the system degradation can be improved. F_I is described as the failure threshold of imperfect repair.

2.2.3 Replacement (denoted as R). Adopt replacement by directly using new parts to replace the old ones. The system health state will be restored to the initial health state h_1, and the system can restore the new state. F_R is described as the failure threshold of replacement.

By adopting maintenance actions, system can have recovery of different degrees. The changing trend of failure rate can be used to analyze the system recovery status, and the detailed maintenance effect can be shown as Figure 1. In Figure 1, the failure rate curve of time (t_M, t_I) deno*t*es the system maintenance effect adopting minor repair, the current system failure rate is not changed and the system degradation speed has slowed. The failure rate curve of time (t_I, t_R) deno*t*es the system maintenance effect adopting imperfect repair, the system operational performance obtains the obvious recovery and the system degradation speed is reduced. The failure rate curve after time t_R denotes the system maintenance effect adopting replacement, the system operational performance obtains the complete recovery and the system degradation speed is reduced.

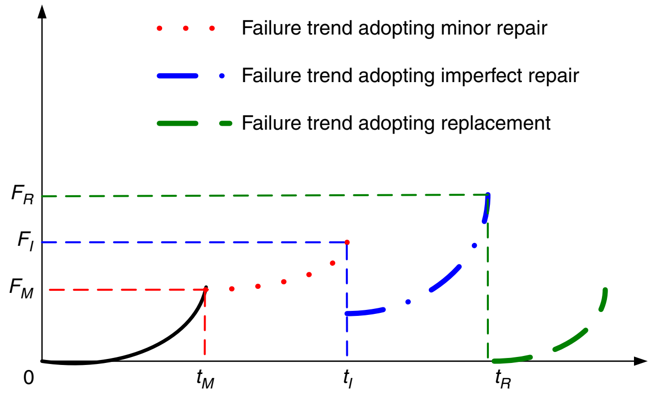

Figure 1.
Maintenance effect for different maintenance action

In the process of system operation, the imperfect repair can be adopted when the failure rate of one component achieves F_I, however, other components can also adopt the corresponding maintenance actions when they also achieve the maintenance threshold in order to decrease system maintenance time and improve system utilization. The component failure rate can be obtained based on the Weibull parameters from Table I with the degradation of system performance.

2.3 Adjustment factors

In the process of production, the actual effect of maintenance actions will decrease gradually with the increase of the number of adopting maintenance actions, and system degradation speed will increase. Thus, the adjustment factors of the component are integrated into the proposed maintenance scheduling model, including the degradation factor and the recovery factor. The degradation factor can accelerate the degradation rates of the component. If it is introduced into the minor repair, then, the component will significantly accelerate the degradation with the increase of the number of adopting minor repair. The recovery factor can calculate the original failure rate after adopting maintenance actions. Thus, it is introduced into the imperfect repair, and the component degradation speed will continuously increase with the increase of the number of adopting imperfect repair and the failure rate will also recover less and less. The adjustment factors effect can be shown in Figure 2.

Table I.
Maintenance action cost and time

Component no.	Minor maintenance		Imperfect maintenance		Replacement	
	Cost	Time	Cost	Time	Cost	Time
1	6	3	14	11	26	19
2	8	5	16	13	31	24
3	9	6	18	15	28	21
4	8	5	17	14	33	26
5	8	5	14	12	27	20
6	7	4	19	16	32	25
7	10	7	20	17	30	23
8	8	5	15	12	30	23

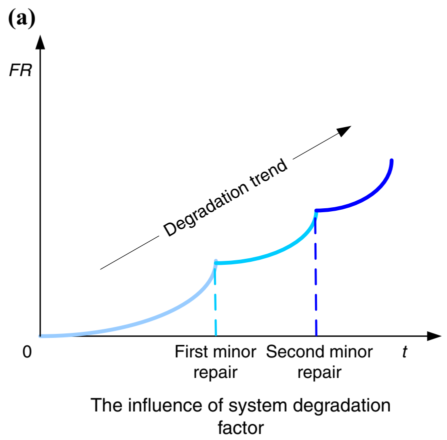

Figure 2.
Adjustment factor effect for different maintenance action

By considering the degradation factor, the minor repair failure model of ith component of a system at time t can be shown as follows:

$$FR_M(t) = FR_M(t_0) + FR_M\left(t, \beta_{i,M}, \eta_{i,M} \times \theta\right) \tag{2}$$

Where, $FR_M(t_0)$ is the failure rate before adopting minor repair. θ is the degradation factor $(0 < \theta < 1)$.

In order to describe the component degradation, θ can be shown as:

$$\theta = a^{MN}$$

Where, a can be obtained based on history data of the component $(0 < a < 1)$, MN is the number of adopting minor repair until the current time.

It can be seen that θ will become smaller with the increase of the number of minor repairs. And the failure rate curve of the component will become steeper. In addition, MN equals 0 when the first minor repair is adopted.

By considering the recovery factor, the imperfect repair failure model of i-th component of a system at time t can be shown as follows:

$$FR_I(t) = (1-\phi)FR_I(t_0) + FR_I\left(t, \beta_{i,I}, \eta_{i,I} \times \theta\right) \tag{3}$$

where, $FR_I(t_0)$ is the failure rate before adopting imperfect repair. φ is the recovery factor $(0 < \varphi < 1)$.

In order to describe the component performance recovery, φ can be shown as:

$$\varphi = b^{IN}$$

where, b can be obtained based on history data of the component $(0 < b < 1)$, IN is the number of adopting imperfect repair until the current time.

It can be seen that φ will become smaller with the increase of the number of imperfect repairs. Thus, the failure rate recovery of the component is fewer when the original failure rate $(1-\varphi)FR_I(t_0)$ is higher after adopting imperfect repair. In addition, IN equals zero when the first imperfect repair is adopted.

3. Maintenance scheduling mathematical model

3.1 The mathematical model

In order to better analyze the maintenance scheduling strategies of multi-component systems, two failure models can be studied, one is the general failure model based on Equation (1), and the other is the improved failure model considering degradation factor and recovery factor based on Equations (2) and (3).

For multi-component systems, many maintenance actions can be adopted for each maintenance activity. Thus, the system total cost C_T is the summation of maintenance cost C_m, failure cost C_f and resource cost C_r. In addition, downtime cost C_d caused by maintenance actions is integrated into total cost by considering system utilization rate. Thus, the total cost of one maintenance activity can be shown as follows:

$$C_T = C_f + C_m + C_r + C_d \tag{4}$$

In Equation (4), the system failure cost is given as:

$$C_f = FF \times \bigcup_i^n FR(i,t) + \sum_{i=1}^{n} F_i \times FR(i,t) \tag{5}$$

where, FF represents the system fixed failure loss and has not relationship with maintenance actions. $FR(i, t)$ denotes the failure rate of component i at maintenance time t. The cumulative system failure probability $\cup_i^n FR(i,t)$ is the union of cumulative component failure probabilities. F_i is the failure dependent loss of component i. n is the number of components.

Failure cost consists of failure independent cost and failure dependent cost in Equation (5). Failure independent cost can be defined as the fixed cost due to any failure (cool down, start-up and warm up), and failure dependent cost is the repairing or replacement cost of failed components. The failure independent cost $\left(FF \times \cup_i^n FR(i,t)\right)$ is the product of fixed failure loss and the union of failure probabilities of system components. The failure dependent cost $\left(\sum_{i=1}^{n} F_i \times FR(i,t)\right)$ is the sum of the expected failure cost of components.

The system maintenance cost is written as:

$$\begin{aligned} C_m &= C_{M,m} + C_{I,m} + C_{R,m} \\ &= FM \times \left(\sum_{i=1}^{n} X_{M,i,t} + \sum_{i=1}^{n} X_{I,i,t} + \sum_{i=1}^{n} X_{R,i,t} \right) + \sum_{i=1}^{n} M_{M,i} \\ &\quad \times X_{M,i,t} + \sum_{i=1}^{n} M_{I,i} \times X_{I,i,t} + \sum_{i=1}^{n} M_{R,i} \times X_{R,i,t} \end{aligned} \tag{6}$$

where, $C_{M,m}$, $C_{I,m}$, $C_{R,m}$ denotes the maintenance cost of minor repair, imperfect repair and replacement of component i, respectively. FM describes system maintenance independent loss and has not relationship with maintenance actions. If minor repair is adopted for component i at time t, then $X_{M,i,t} = 1$, otherwise 0. If imperfect repair is adopted for component i at time t, then $X_{I,i,t} = 1$, otherwise 0. If replacement is adopted for component i at time t, the $X_{R,i,t} = 1$, otherwise 0. $M_{M,i}$, $M_{I,i}$, $M_{R,i}$ describes the maintenance dependent loss of minor repair, imperfect repair and replacement of component i, respectively.

The system resources play an important part to able to execute the maintenance actions. The maintenance actions can be adopted only if the required resources will be available at the time of the maintenance. Thus, it is important to incorporate available resource information into the system maintenance scheduling model. And in the proposed model, if the required parts, personnel or tools constraint is not satisfied, then a distinct penalty cost will be defined for one maintenance activity, which is calculated as the product of the number missing parts, personnel or tools and a penalty coefficient. So the system resource cost is described as:

$$\begin{aligned} C_r &= C_{r1}+C_{r2}+C_{r3} \\ &= c_s \times \mathrm{Max}\left(\left(\sum_{i=1}^{n}\left(Q_{M,s,i}\times X_{M,i,t}+Q_{I,s,i}\times X_{I,i,t}+Q_{R,s,i}\times X_{R,i,t}\right)-H_{s,t}\right),0\right) \\ &\quad + c_r \times \mathrm{Max}\left(\left(\sum_{i=1}^{n}\left(Q_{M,r,i}\times X_{M,i,t}+Q_{I,r,i}\times X_{I,i,t}+Q_{R,r,i}\times X_{R,i,t}\right)-H_{r,t}\right),0\right) \\ &\quad + c_g \times \mathrm{Max}\left(\left(\sum_{i=1}^{n}\left(Q_{M,g,i}\times X_{M,i,t}+Q_{I,g,i}\times X_{I,i,t}+Q_{R,g,i}\times X_{R,i,t}\right)-H_{g,t}\right),0\right) \end{aligned} \tag{7}$$

where, C_{r1}, C_{r2}, C_{r3} denotes the shortage cost of spare parts, maintenance personnel and tools, respectively. c_s represents the penalty coefficient when spare parts s is missing. $Q_{M,s,i}$, $Q_{I,s,i}$, $Q_{R,s,i}$ describes the number of the required spare parts s adopting minor repair, imperfect repair and replacement for component i, respectively. $H_{s,t}$ represents the number of available spare parts s in inventory at time t. Similarly, the subscripts r and g represent maintenance personnel and the required maintenance tools, respectively.

It is obvious that the maintenance needs to be waited due to lack of maintenance personnel and tools at a time. And the spare parts can be ordered when it is lacked. Thus, the penalty coefficient of maintenance personnel and tools is more than that of spare parts, respectively. The resources inventory information ($H_{q,t}$) in time t shows that the resources to be used in time t−1 is subtracted from the summation of available resources in time t−1 in inventory and resources to be delivered in time t. The resources inventory information ($H_{q,t}$) in time t is described as follows:

$$\begin{aligned} H_{q,t} = \mathrm{Max}\Bigg(\Bigg(H_{q,t-1}+A_{r,t}-\sum_{i=1}^{n}\big(Q_{M,q,i}\times X_{M,i,t-1} \\ +Q_{I,q,i}\times X_{I,i,t-1}+Q_{R,q,i}\times X_{R,i,t-1}\big)\Bigg),0\Bigg) \end{aligned} \tag{8}$$

where, $H_{q,t\text{-}1}$ denotes the number of available resources q in time t−1 in inventory. $A_{q,t}$ describes the number of resources q to be delivered in time t. q equals s, r, g, respectively.

The system will cause more downtime when more maintenance actions are performed. The corresponding downtime cost is related to the maintenance action time and downtime cost coefficient per unit time. Due to simultaneously performing maintenance actions for different components in a system, the system downtime can be decreased. Thus, the system downtime cost is the product of downtime cost coefficient per unit time and system downtime, and it is given as follows:

$$C_d = CA \times \sum_{i=1}^{n} \left[\begin{array}{l} X_{M,i,t}\left(T_{M,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right)+X_{I,i,t}\left(T_{I,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right) \\ +X_{R,i,t}\left(T_{R,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right) \end{array} \right] \quad (9)$$

where, CA represents the system downtime cost per unit time. $T_{M,i}$, $T_{I,i}$, $T_{R,i}$, respectively denotes the maintenance time of minor repair, imperfect repair and replacement of component i, respectively. N_i indicates the number of expected downtime of component i (it is the number of other downtime components when the component i is downtime). In order to calculate the number of expected downtime of component i, it is assumed that the status of other components can be favorable and no failure. T_{ij}^0 describes the saving time for component i and component j simultaneously performing maintenance actions.

Based on Equations (5)-(9), the total cost C_T of one maintenance activity can be obtained:

$$\begin{aligned} C_T = {} & FF \times \bigcup_{i}^{n} FR(i,t) + \sum_{i=1}^{n} F_i \times FR(i,t) + FM \\ & \times \left(\sum_{i=1}^{n} X_{M,i,t} + \sum_{i=1}^{n} X_{I,i,t} + \sum_{i=1}^{n} X_{R,i,t} \right) + \sum_{i=1}^{n} M_{M,i} \times X_{M,i,t} + \sum_{i=1}^{n} M_{I,i} \\ & \times X_{I,i,t} + \sum_{i=1}^{n} M_{R,i} \times X_{R,i,t} + c_s \\ & \times \mathrm{Max}\left(\left(\sum_{i=1}^{n} \left(Q_{M,s,i} \times X_{M,i,t} + Q_{I,s,i} \times X_{I,i,t} + Q_{R,s,i} \times X_{R,i,t} \right) - H_{s,t} \right), 0 \right) + c_r \\ & \times \mathrm{Max}\left(\left(\sum_{i=1}^{n} \left(Q_{M,r,i} \times X_{M,i,t} + Q_{I,r,i} \times X_{I,i,t} + Q_{R,r,i} \times X_{R,i,t} \right) - H_{r,t} \right), 0 \right) + c_g \\ & \times \mathrm{Max}\left(\left(\sum_{i=1}^{n} \left(Q_{M,g,i} \times X_{M,i,t} + Q_{I,g,i} \times X_{I,i,t} + Q_{R,g,i} \times X_{R,i,t} \right) - H_{g,t} \right), 0 \right) + CA \\ & \times \sum_{i=1}^{n} \left[\begin{array}{l} X_{M,i,t}\left(T_{M,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right)+X_{I,i,t}\left(T_{I,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right) \\ +X_{R,i,t}\left(T_{R,i}(1+N_i)-\sum_{j=1}^{N_i} T_{ij}^0\right) \end{array} \right] \end{aligned} \quad (10)$$

In Equation (10), the total cost model of one maintenance activity can be described. However, one or more than one maintenance activity can be performed for the whole system lifetime. During the process of operation from system original health state, the system can trigger one maintenance activity when the failure rate of one component reaches or exceeds its failure threshold. The performance of the component is restored after performing maintenance, and it can be used to execute the task of production. However, the failure rate of the component continuously increases with the duration of operation and it re-reaches the threshold, the second maintenance activity can be triggered. The process will be continued until the termination of the whole lifetime. Thus, based on the total cost model of each maintenance activity, the total cost model of multi-phase maintenance optimization in the whole life can be considered, and the total cost rate can be obtained as follows:

$$C_{Total} = \left(\sum_{j=1}^{m} C_{j,T} + m \times c_q \right) / D \tag{11}$$

where, C_{Total} represents the total cost rate of system maintenance optimization. $C_{j,T}$ denotes the total cost of j-th maintenance activity. D is the whole system lifetime and m is the total number of maintenance activities in the whole system lifetime. c_q describes the system start-up cost when one maintenance activity is performed.

Based on Equation (11), in order to minimize the total cost rate of the whole system lifetime, the total cost of each maintenance activity can be considered and the number of maintenance activities of the whole lifetime needs to be minimized. The total cost rate can decrease by optimizing two objectives. Thus, the total cost rate of the whole system lifetime has overall characteristic. In the present paper, genetic algorithm (GA) is used to solve the maintenance scheduling model.

3.2 GA

GA is used in this paper to search for the optimal maintenance scheduling. Even though output of any GA-based optimization only approximates the optimal solution, it is a commonly used method giving one of the best results possible. The laws of natural evolution implemented through GA ensure a good approximation of the optimal solution, which is why GA is used in this paper rather than other approaches (Lu *et al.*, 2015; Yang *et al.*, 2008).

The basic elements of GA can be described as follows:

(1) Decoding: it is a way to convert the solution of GA, and performs a conversion of feasible solution of the optimization model from a solution space to a search space.

(2) Selection: the excellent individuals of population can survive by larger probabilities. It can prevent the effective gene disappearance, and improve the global convergence and computational efficiency of the iteration.

(3) Crossover: two individuals from the population are selected by larger probabilities in the iterative process, and they are performed the crossover to produce the offspring inheriting basic characteristics of the previous generation.

(4) Mutation: the mutation is random in the crossover process. In the process of producing new individuals, mutation affects the evolution ability of local optimal solution.

GA is a mature method utilizing heuristic rules to produce improved approximations of the objective function over a number of iterations. Thus, in this paper, it is used to solve the system maintenance scheduling problem.

4. Computational experiments

4.1 Experimental description

In this numerical example, the long-term wear test experiments were conducted at a research laboratory facility (Shanghai Pangyuan Machinery Co.). In the test experiments, one pump was worn by running it using oil containing dust. The degradation stages in this hydraulic pump wear test case study correspond to different stages of flow loss in the pump. As the flow rate of a pump clearly indicates pump's health state, the degradation stages corresponding to different degrees of flow loss in a pump were defined as the health states of the pump in the test.

The work of the hydraulic pump (system) needs eight components to cooperate with each other. Thus, maintenance optimization is executed to the eight components of the hydraulic pump. The health of the hydraulic pump will degrade gradually with the increase of time in the process of operation. In order to maintain its normal work and avoid high cost and risk, the pump needs to be executed maintenance activities. Moreover, the replacement can be adopted with the increase of operation cost and maintenance cost. The cost of each maintenance phase and the total cost rate are described as the optimization objective to make the maintenance scheduling strategy. Figure 3 shows the schematic diagram of the relationship among eight components (Component 1 is denoted as *C*1). GA is used to solve the problem. And all of the models and algorithm are coded in Visual *C#* and ran on a personal computer with a 2.10 GHz*2 CPU and 4.0 GB RAM.

4.2 Data preparation

4.2.1 Maintenance action cost and time. The maintenance costs and time of various maintenance actions are given in Table I.

4.2.2 System failure cost. The system failure cost is not related with different maintenance actions and is determined by different components. Thus, the failure cost of different components can be obtained in Table II.

4.2.3 Weibull parameters. In the process of system maintenance optimization, Weibull distribution is used to describe the system failure rate and obtain system degradation information. Its scale and shape parameter corresponding to different maintenance actions of different components are different. The Weibull parameter values can be

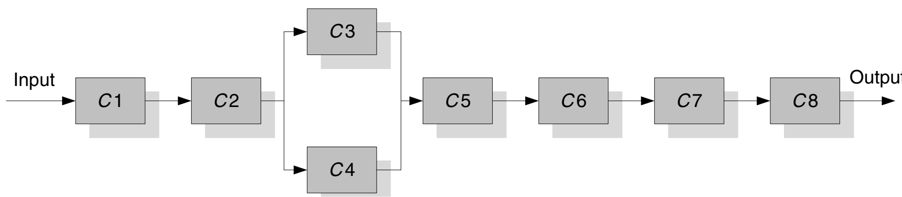

Figure 3. The relationship among eight components

Table II. Maintenance action failure cost

Component no.	1	2	3	4	5	6	7	8
Failure cost	15	18	18	19	16	19	20	17

calculated based on pump's failure data information from the literature (Liu *et al.*, 2012) and maximum likelihood estimation (Melchor-Hernández *et al.*, 2015) (see Table III).

4.2.4 Maintenance resource cost. For maintenance optimization, spare parts, maintenance personnel and maintenance tools can be considered. The total number of each resource is given in Table IV. And spare parts, maintenance personnel and maintenance tools are denoted as *Sp*, *Pe* and *Mt*, respectively. The number of each resource corresponding to minor maintenance, imperfect maintenance and replacement of each component is given in Table V.

4.2.5 Other parameters. Based on Figure 3, the number of expected downtime of each component can be obtained and is shown in Table VI.

The values of parameters related to resources and other parameters are given in Table VII.

Component no.	Minor repair		Imperfect repair		Replacement	
	$\beta_{i,M}$	$\eta_{i,M}$	$\beta_{i,I}$	$\eta_{i,I}$	$\beta_{i,R}$	$\eta_{i,R}$
1	5.00	4.00	2.30	2.95	4.24	3.80
2	5.25	4.53	2.88	3.12	4.21	3.98
3	5.50	4.60	2.95	3.20	4.28	4.25
4	4.93	4.12	2.40	2.73	4.05	3.87
5	5.15	3.91	2.55	2.92	4.24	3.81
6	4.00	2.96	1.89	2.01	3.10	2.75
7	4.50	3.51	2.16	2.42	3.50	3.21
8	4.85	3.95	2.34	2.95	4.15	3.74

Table III. Weibull parameters of maintenance actions

Resource	Spare parts (*Sp*)	Personnel (*Pe*)	Maintenance tools (*Mt*)
Resource quantity	14	13	13

Table IV. Total resource quantity of maintenance actions

Component no.	Minor repair			Imperfect repair			Repair		
	Sp	*Pe*	*Mt*	*Sp*	*Pe*	*Mt*	*Sp*	*Pe*	*Mt*
1	1	3	3	2	6	5	4	4	6
2	1	0	2	2	4	5	4	5	6
3	1	3	2	2	4	3	5	5	6
4	2	2	4	3	5	6	5	6	7
5	1	4	3	2	5	4	3	7	6
6	2	3	4	3	6	5	4	6	7
7	2	2	3	3	1	4	5	4	7
8	1	3	3	3	5	5	6	5	6

Table V. Resource demand for different maintenance actions

N_i	1	2	3	4	5	6	7	8
Values	7	6	0	0	3	2	1	0

Table VI. The number of expected downtime

4.3 GA design

First, the input parameters of the proposed model can be obtained, including failure rate, the number of resources, the number of expected downtime, maintenance threshold, maintenance time and cost of each maintenance action, system running time, resources needed by each maintenance action. Then, the system maintenance record is cleared, and maintenance indicator sets zero. For a component, when the failure rate achieves imperfect repair threshold, the imperfect repair is adopted. In this process of maintenance, for other components, if the failure rate achieves minor repair or replacement threshold, then they need to adopt the corresponding maintenance action. Meanwhile, the system maintenance resources limit to simultaneously perform multiple maintenance actions, the corresponding maintenance cost is different due to the different maintenance order. The detailed GA structure can be shown in Figure 4.

In addition, for GA parameters can be shown as follows:

(1) the component numbers are used to encode for GA;

(2) the total cost rate is used as fitness function;

(3) the evolutionary population is 30;

Table VII.
Other parameters

Parameter name	*FF*	*FM*	c_s	c_r	c_g	*CA*	c_q	F_M	F_I	F_R	*D*
Parameter value	200	100	450	550	500	50	1,000	0.3	0.5	0.7	1,400

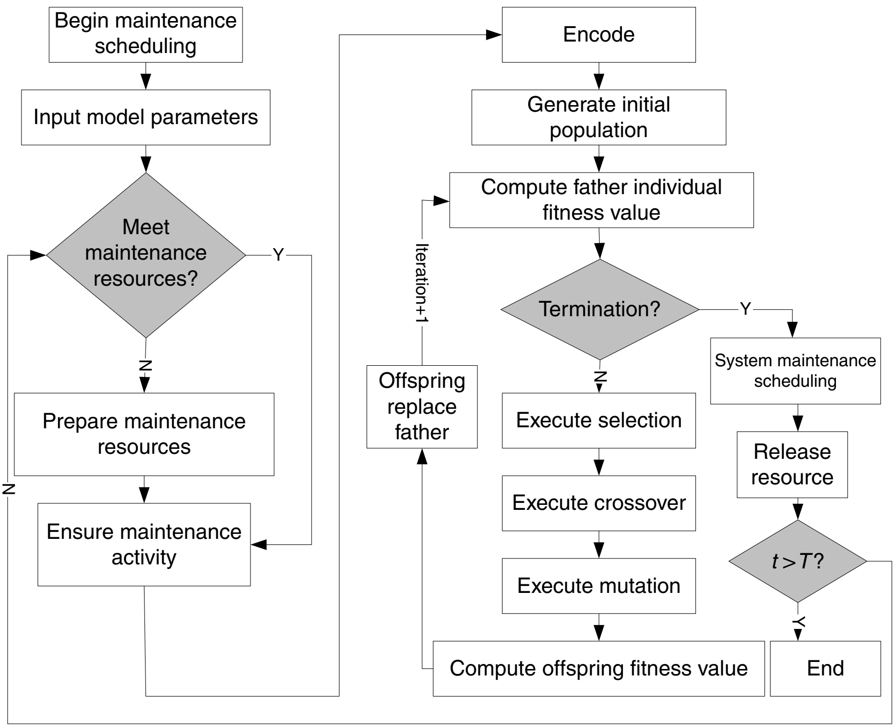

Figure 4.
The structure of maintenance scheduling

(4) the largest iteration is 300;

(5) the selection probability and the crossover probability are 0.8, respectively; and

(6) the mutation probability is 0.1.

The GA parameters defining the size of the evolutionary population, the largest allowed iteration and the mutation probability are chosen after several trial runs.

4.4 Maintenance scheduling strategy comparison

First, the performance of the proposed maintenance optimization model without considering adjustment factors is analyzed. Nowadays, periodic maintenance, defined as significant activities carried out regularly to maintain the condition or operational status of the system, is a common maintenance strategy. In this paper, periodic maintenance aims to obtain the optimal maintenance strategies in one life-cycle of the system. And the one life-cycle of the system can be divided into 20 maintenance cycles (i.e. $T = 20$). Based on failure rate of each component, the adopting maintenance actions of each component can be computed and obtained. The results are shown in Table VIII.

Figure 5 shows the periodic maintenance optimization status of four components and their failure rate changing condition. Each component has different degradation performance, and its failure rate can be changed with the increase of the number of maintenance after adopting periodic maintenance. Thus, it can be seen from Figure 5 that the failure rate changing trends of four components are different.

For the proposed maintenance scheduling model, based on Equations (10) and (11), the maintenance optimization of each component can be computed. The system adopts ten maintenance activities in the entire life-cycle of the system. The maintenance scheduling time and maintenance actions can be shown in Table IX.

Figure 6 shows the proposed maintenance scheduling optimization status of eight components and their failure rate changing condition in the entire life-cycle of the system. It can be seen from Figure 6 that the failure rate changing trends of eight components are different due to different failure rate changing trend of each component by adopting maintenance scheduling strategy. Based on the proposed maintenance scheduling model, each component has a lower failure rate level by executing least maintenance actions, and the system can be ensure to stably work in a long time.

Based on Equations (5)-(9), the failure cost, maintenance cost, resources cost and downtime cost of performing one maintenance activity can be obtained, respectively. Thus, based on Equation (10), the total cost of performing one maintenance activity can be calculated. Finally, based on Equation (11), the total cost rate of the periodic maintenance scheduling optimization and the proposed maintenance scheduling optimization can be calculated, and it is 109.08 and 89.21, respectively. Thus, the proposed maintenance scheduling model has a better performance than periodic maintenance scheduling, including the number of adopting maintenance scheduling and the total cost rate.

Then, in order to illustrate the convergence and effectiveness, Figure 7 is used to describe the system maintenance scheduling cost changing trend when the second system maintenance scheduling activity is adopted. The maintenance scheduling cost of the system reduces gradually with the increase of GA iterations, and finally converges at a stable level. The optimal cost adopting second maintenance scheduling activity can be obtained, and the result verifies the convergence and effectiveness of GA in the optimization process.

Table VIII. Maintenance scheduling of periodic maintenance

Component no.	*M*1	*M*2	*M*3	*M*4	*M*5	*M*6	*M*7	*M*8	*M*9	*M*10	*M*11	*M*12	*M*13	*M*14	*M*15	*M*16	*M*17	*M*18	*M*19	*M*20
1	*M*			*M*		*I*		*M*		*I*	*M*		*I*		*M*			*R*		*M*
2					*I*		*M*			*M*	*I*		*M*		*M*		*M*	*I*		*R*
3			*M*		*M*		*M*		*I*			*M*		*I*		*M*	*M*		*I*	
4		*M*				*I*		*M*		*M*			*M*		*I*		*I*			*M*
5				*M*		*R*			*M*		*M*		*I*		*M*			*I*		
6	*M*			*M*		*I*		*R*		*I*		*M*		*I*		*R*		*M*		*I*
7			*M*		*I*			*M*		*M*		*R*		*M*	*I*		*M*		*R*	
8		*M*			*I*		*M*		*I*		*M*		*M*	*M*		*I*		*R*		*M*

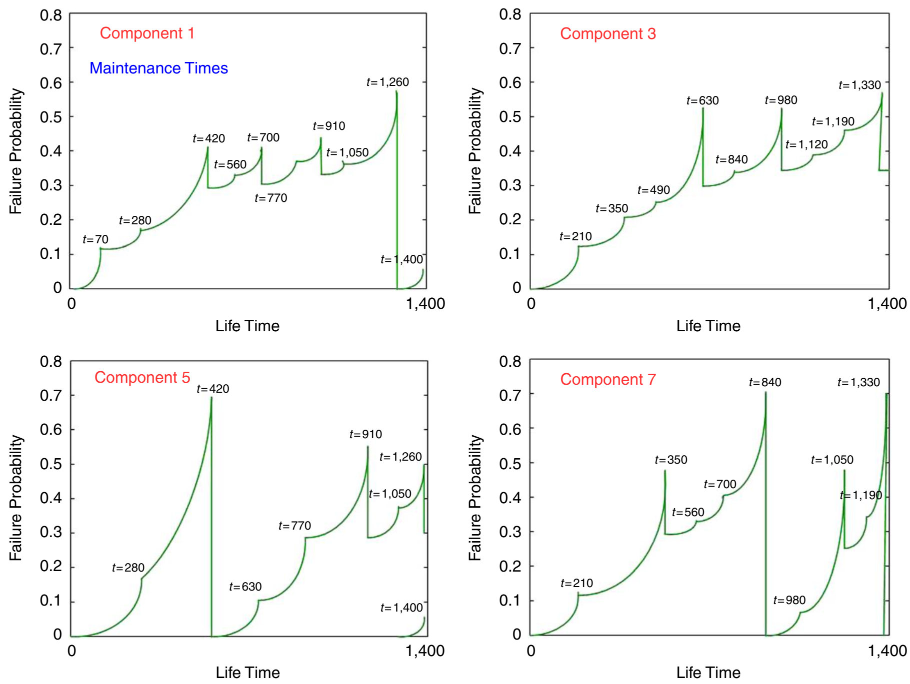

Figure 5. Failure probability of periodic maintenance scheduling model

Table IX. Maintenance scheduling of proposed maintenance scheduling model

Component no.	$M1$ $t=310$	$M2$ $t=409$	$M3$ $t=533$	$M4$ $t=621$	$M5$ $t=750$	$M6$ $t=860$	$M7$ $t=945$	$M8$ $t=1{,}104$	$M9$ $t=1{,}247$	$M10$ $t=1{,}352$
1		*I*	*M*	*M*	*I*	*M*	*M*	*I*	*M*	
2		*M*	*M*	*I*			*M*	*I*	*M*	*M*
3		*M*			*M*	*I*		*M*		*I*
4		*I*	*M*	*M*	*I*	*M*		*I*	*M*	
5		*R*		*M*		*M*	*M*	*R*		*M*
6	*R*		*R*			*R*			*I*	*M*
7	*M*	*I*	*M*	*M*	*R*			*I*	*M*	*R*
8		*I*	*M*	*M*	*I*		*M*	*I*	*M*	*I*

Finally, in order to describe the maintenance optimization process, for ten maintenance activities of the system, the second maintenance activity ($t=409$) is analyzed in details. For second maintenance activity, $C2$ and $C3$ adopt minor repair actions, $C1$, $C4$, $C7$ and $C8$ adopt imperfect repair actions, $C5$ adopts replacement, and $C6$ does not adopt maintenance action. In the process of maintenance optimization, resources need to be considered. Based on the optimization results of the proposed model, $C1$, $C2$ and $C5$ first adopt maintenance actions. Based on Tables VIII and IX, the required number of resources for $C1$, $C2$ and $C5$ adopting maintenance actions is (6, 13, 13). Then, the residual amount of resources is (9, 0, 0) after adopting maintenance actions. By analyzing resource demands of other components, the resource demands of $C3$, $C4$, $C7$ and $C8$ are (1, 3, 2), (3, 5, 6), (3, 1, 4) and (3, 5, 5), respectively. Thus, the residual amount

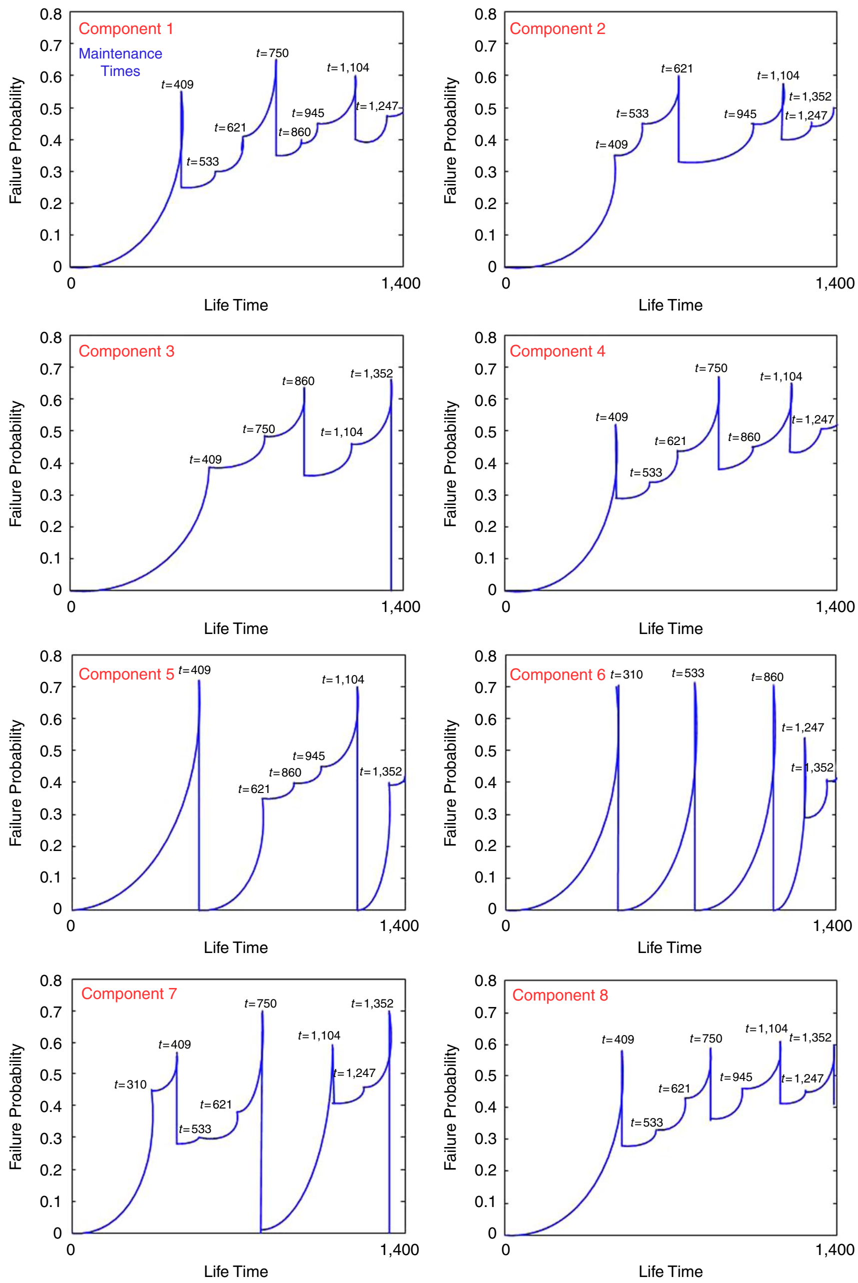

Figure 6.
Failure probability of proposed maintenance scheduling model

of resources cannot satisfy with the resource demands of the current other components. $C3$, $C4$, $C7$ and $C8$ need adopt maintenance actions after obtaining resources when the executing maintenance actions are completed. The Gantt chart of the second maintenance activity of the system can be shown as Figure 8.

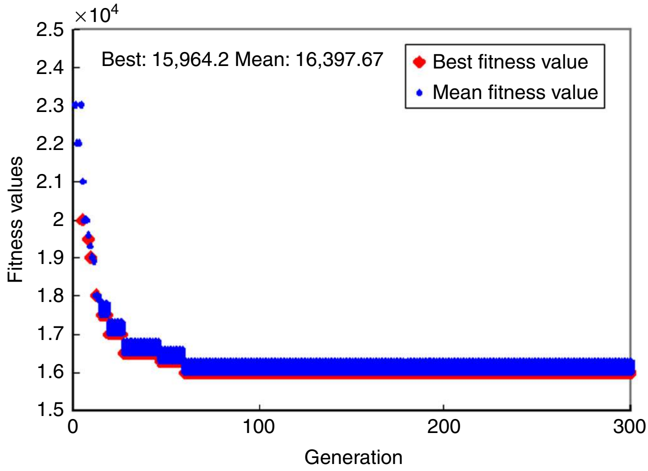

Figure 7. Cost changing trend of the second maintenance activity

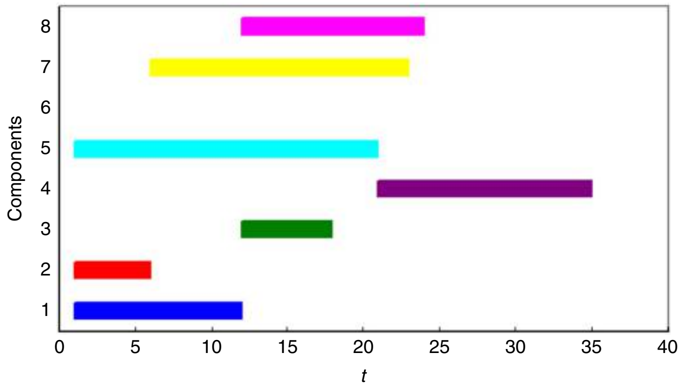

Figure 8. Gantt chart of the second maintenance activity

4.5 Maintenance scheduling analysis considering adjustment factor

Based on Equations (2) and (3), the maintenance scheduling optimization considering the degradation factor and recovery factor is analyzed. The parameter values can be obtained as follows:

(1) the degradation factor adopting minor repair: $\theta = 0.97^{MN}$;

(2) MN = the current number of minor repair−1;

(3) the degradation factor adopting imperfect repair: $\theta = 0.96^{IN}$;

(4) the recovery factor adopting imperfect repair: $\varphi = 0.97^{IN}$; and

(5) IN = the current number of imperfect repair−1.

By analyzing multi-phase optimization model, 12 maintenance activities can be adopted in the entire life-cycle of the system. The number of maintenance actions for each component in the entire life-cycle can be shown in Table X.

It can be seen from Table X that $C5$, $C6$ and $C7$ adopts replacement, and other components only adopt minor and imperfect repair. Although other components do not adopt replacement, their performance can be guaranteed by adopting minor and imperfect repair. For $C5$, $C6$ and $C7$, the number of minor and imperfect repair can be reduced after adopting replacement. The optimization strategy can improve the system utilization, decrease system failure rate and increase system lifetime by adopting corresponding maintenance actions based on system actual situation.

In order to illustrate the failure rate changing trend, Figure 9 showsthe failure rate changing trend of four components in the process of maintenance optimization. It can be seen from Figure 9 that the number of system maintenance considering adjustment factors is more than that of the proposed maintenance scheduling optimization model. Thus, the adjustment factor can influence on the system maintenance optimization.

Table X. Maintenance scheduling considering adjustment factor

Component No.	Minor repair	Imperfect repair	Replacement
1	7	4	0
2	8	3	0
3	9	2	0
4	7	4	0
5	5	2	1
6	1	0	5
7	5	4	1
8	7	4	0

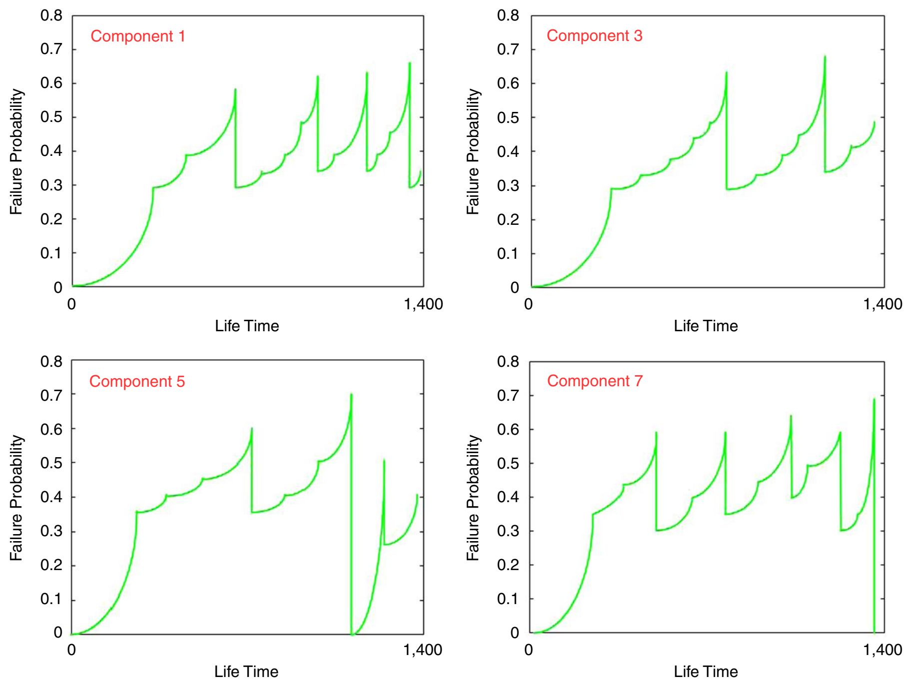

Figure 9. Failure probability considering adjustment factor

Based on Equations (5)-(11), the total cost rate of maintenance optimization strategy considering adjustment factor can be obtained and it is 97.79.

The comparison for the proposed maintenance scheduling optimization model with considering and without considering adjustment factors, periodic maintenance scheduling can be shown in Table XI. It can be seen from Table XI that the periodic maintenance scheduling strategy can improve the system utilization by adopting different maintenance activities, but the number of adopting maintenance activities is most in the process of maintenance optimization, it generates a long downtime and spends the high maintenance cost. For the proposed optimization model without considering adjustment factors, it can decrease the total cost rate, improve system utilization and reduce system downtime due to less maintenance actions. Thus, it has a better performance than periodic maintenance scheduling strategy, including total cost rate, the number of maintenance actions and system utilization.

For the proposed optimization model with considering adjustment factors, it also has a better performance than periodic maintenance scheduling strategy, including total cost rate, the number of maintenance actions and system utilization. By comparing with optimization model without considering adjustment factors, it has a higher total cost rate and the number of maintenance activities, and has better system utilization. And the maintenance effect can be reduced accordingly with the increase of maintenance activities. Thus, the proposed maintenance scheduling models with considering and without considering adjustment factors all have a better performance for multi-component systems.

4.6 Sensitivity and robustness analysis

In the experiment described above, problems are solved by GA. In order to analyze the sensitivity of GA, its convergence, search capabilities and timeliness stability are developed as performance evaluation indexes, and the initial population size, selection rate, crossover rate, mutation rate and termination conditions are selected as major factors. The orthogonal test method is used to carry out this test, and the range analysis method is used to determine the impact of factors on the performance of GA (Annibale *et al.*, 2015). And the results in Table XII show that the range sequence of initial population, termination condition and mutation probability always occupies the top three, thus, they are the most sensitive factors affecting the comprehensive performance of GA. Moreover, the GA's performance is more sensitive in parameters than operator selection.

In addition, the robustness coefficient (Guo, 2009) is used to analyze the parameters robustness affecting the output of the proposed methods. And the initial population size, selection rate, crossover rate, mutation rate and termination conditions are selected as major factors. And the results in Table XII show that the robustness

Evaluation criteria	Proposed model	Integrated adjustment factor	Periodic strategy	Optimal strategies
Total cost rate	89.21	97.79	109.08	Proposed model (decreased by 19.78)
Maintenance activities	10	12	20	Proposed model (decreased by 8)
System utilization (%)	93.18	97.92	87.67	Proposed model with factors (increased by 10.25%)

Table XI. Results comparison for different maintenance scheduling strategies coefficients corresponding to the initial population size, mutation rate and termination conditions are relatively small. Thus, it indicates that the three parameters have a greater impact on the output of the proposed methods, and need to be importantly considered in the model.

Based on the sensitivity and robustness analysis, the proposed method and GA have good robustness, and three parameters are full considered to solve the maintenance scheduling problem, including the initial population size, mutation rate and termination conditions.

5. Conclusions

This paper emphasizes the need of a maintenance optimization method of multi-component systems using degradation information and resource planning. For many industries, on one hand, the unavailability of resources is a major problem. On the other hand, the multi-component system degradation and dependencies are not described well in current literatures. Therefore, an effective framework to this problem is the integrated optimization of maintenance, degradation, dependencies and resource planning. In this paper, a multi-phase maintenance model of the whole system lifetime is proposed for this integrated maintenance optimization problem. And the GA is used to solve the maintenance model. Finally, a case is studied to validate the proposed methods. From the experiment results, the comparison of the method with periodical maintenance strategy reveals several benefits of the method, including lower total cost rate, higher system utilization and the less number of maintenance actions (see Table XI). And it indicates that the proposed method is effective for the multi-component systems considering degradation information and resource constraints.

The long-term wear test experiments are conducted at a research laboratory facility of Shanghai Pangyuan Machinery Co. Industrial implementation and demonstration of the newly proposed methods in a real factory environment remains to be doing, and the primary effect can be obtained. The further application needs to be done in the future.

Furthermore, a number of interesting directions for further research can be followed based on the ideas proposed in this study. For instance, the newly proposed strategy can be extended to address predictive maintenance in highly flexible by considering prognostics and diagnostics information. Moreover, based on the proposed methods, stochastic dependence among components in a system could be considered. Finally, extension of the methods proposed in this paper to service systems is another opportunity for further enhancing the benefits of maintenance operations through the usage of predictive condition information.

Table XII. The results of GA sensitive and robustness analysis

Factors/indexes		Initial population	Selection rate	Crossover rate	Mutation rate	Termination conditions
Convergence	Range	1,831	873	476	1,764	1,831
	Sequencing	2	4	5	3	1
Search capabilities	Range	324	113	186	277	306
	Sequencing	1	5	4	3	2
Timeliness stability	Range	5.624	1.408	1.191	1.705	4.021
	Sequencing	1	4	5	3	3
Robustness coefficient		0.23	0.36	0.51	0.08	0.15

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About the authors

Dr Qinming Liu (PhD) is a Lecturer in Industrial Engineering at the University of Shanghai for Science and Technology, China. His research interests include production management, semiconductor manufacturing planning and scheduling, maintenance optimization, management information systems and product design process innovation. He has published articles in *International Journal of Production Research*, *Mechanical Systems and Signal Processing*, *Mathematical Problems in Engineering*, *Journal of Mechanical Engineering Science*, *International Journal of Computer Integrated Manufacturing*. Dr Qinming Liu is the corresponding author and can be contacted at: lqm0531@163.com

Wenyuan Lv is a Professor in the University of Shanghai for Science and Technology, China. His research interests include equipment maintenance, data mining, decision making and management information systems. He has published articles in journals as *International Journal of Production Research*, *Mechanical Systems and Signal Processing*, *Maintenance and Reliability*.

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