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Preventive maintenance optimization for a multi-component system under changing job shop schedule

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ABSTRACT

Variability and small lot size is a common feature for many discrete manufacturing processes designed to meet a wide array of customer needs. Because of this, job shop schedule often has to be continuously updated in reaction to changes in production plan. Generally, the aim of preventive maintenance is to ensure production effectiveness and therefore the preventive maintenance models must have the ability to be adaptive to changes in job shop schedule.

In this paper, a dynamic opportunistic preventive maintenance model is developed for a multi-component system with considering changes in job shop schedule. Whenever a job is completed, preventive maintenance opportunities arise for all the components in the system. An optimal maintenance practice is dynamically determined by maximizing the short-term cumulative opportunistic maintenance cost savings for the system. The numerical example shows that the scheme obtained by the proposed model can effectively address the preventive maintenance scheduling problem caused by the changes in job shop schedule and is more efficient than the ones based on two other commonly used preventive maintenance models.

1. Introduction

PM (preventive maintenance) optimization is an interesting field to many scholars and researchers. During the past several decades, PM problems for single-component deteriorating systems have been extensively studied in the literature [1–3]. These research results play a great role in lowering maintenance cost, improving operational safety and reducing system failures. However, as production systems become increasingly automated and complex, more and more attention is being directed to the PM scheduling for multi-component systems. This has given rise to a number of creative works, and the focus of which is to understand the interaction between the components using single-component PM technique as the basis for multi-component PM optimizing [4,5].

In general, the more interaction there is, the more complex the model will become. Therefore most of the earlier researches only take economic dependence into account in modeling the interaction between components [1]. For example, the maintenance of a system component usually requires preparatory or set-up work. This set-up work can be shared when several components are maintained simultaneously. The cost of this set-up work is called the set-up cost which may include the down-time cost due to production loss if the system cannot be used during maintenance, or the preparation cost associated with erecting a scaffolding or disassembling a machine. More often than not, when PM activities for different components are executed simultaneously, only one set-up is needed, which means lower set-up cost. Therefore, grouping PM activities can create significant cost savings opportunities.

Group maintenance is one of the earliest strategies studied in multi-component PM modeling which considers the economic dependence between components. This strategy is usually used to deal with the system in which parallel components or units exist and all the components or units are failure independent [6–10].The common feature shared by these studies is that no PM activities will be carried out unless the number of the failed parallel components or units goes beyond the given number n, or the PM interval reaches the threshold T. Once the PM begins, the failed components or units will be maintained as a group, which reduces the set-up cost.

However, for most of the multi-component systems, a single failure usually causes the stop of the whole system. In such a system, especially in a serial one, then components usually depend upon mutually not only in economic aspect but also in failure aspect. In order to decrease the number of the system stop and then reduce the downtime cost, a PM combining process is necessary for the system components. This implies whenever one of the system components fails or is preventive maintained, PM opportunities will arise for all the other components in the

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system. Different such opportunistic PM policies have been developed to decide which of the system components will be maintained together. Gurler [11] proposes an opportunistic PM policy for a series system with identical items. The effort is an extension of the work by Frank [12], who also proposes an opportunistic policy for such a system. In their models, the lifetime of the components is described by several stages defined as good, doubtful, PM due and failed. A replacement is suggested whenever a component enters a PM due or a down state and the number of the components in the doubtful states is at least N. Zhou [13] proposes an opportunistic PM model combined with dynamic programming, in which the potential cost savings under different opportunistic PM alternatives are carefully evaluated. Giacomo[14] investigates a system whose major components can be maintained only during a planned system downtime. An exact algorithm is proposed in order to single out the set of components that must be maintained to guarantee a required reliability level up to the next planned stop with the minimum cost.

Because of the complexity of PM modeling, most of the above researches are focused on the maintenance optimization only and usually do not consider other factors. However, maintenance activity is an integral part of a production process and it is important to consider production demand (i.e. job shop schedule) in developing optimal PM policies. As a result, we have seen a growing number of studies in the joint optimization of maintenance and production. In this new research area, the initial efforts are mainly focused on the PM modeling for single-component systems [15–19]. There are only few papers which discuss maintenance and production simultaneously on multi-component systems. Sun [20] deals with the problem of processing a set of n jobs on two identical machines, in which the machines need to be maintained regularly and the largest consecutive working time for each machine cannot exceed an upper limit T. Wang [21] deals with a flexible job-shop scheduling problem for multiple parallel machines with availability constraints considered. Each machine is subject to PM during the planning period and the starting times of PM activities are either flexible in a time window or fixed beforehand. Lee [22] develops a model to solve multi-machine scheduling problem with deteriorating job processing time and periodic maintenance. Other research efforts can be seen in Ref [23,24]. All these creative works are greatly promoting the development of research on maintenance policies for multi-component systems. However, in most of the studies, the PM plan is usually predetermined and it is always seen as a constraint of production scheduling. Furthermore, few of these studies take the PM grouping problems into account. It is always assumed that the PM activities for different components are mutually independent and each component is given PM individually. In fact, the grouping of the system PM activities could lead to a substantial reduction in the maintenance cost for the whole system [25].

In this paper, an opportunistic PM model is proposed for multi-component systems to group the PM activities of the system components with the integration of production demand (i.e. changes in job shop schedule caused by unpredictable market fluctuations) into the maintenance decisions. An optimal PM practice is dynamically determined by minimizing the short-term cumulative opportunistic PM cost for the whole system. The rest of the paper is organized as follows. Section 2 gives a detailed problem description. Section 3 is devoted to the PM optimization modeling for the multi-component systems, which includes the component level PM modeling and the system level PM modeling. In Section 4, a decision rule is obtained to simplify the PM decision process. Finally, a numerical example and a result analysis are provided in Section 5 for the proposed PM model.

2. Problem description

In response to fierce competition in the global market and fast-changing customer needs, companies and businesses all over the world have worked hard to produce a large variety of products in small batch sizes. Market fluctuations often lead to the adjustment of production plans and subsequently the changes in job shop schedule. To ensure production quality, the PM activities are normally prohibited throughout a job and usually performed in between the jobs. As the changes in job shop schedule inevitably affect the arrangement of the PM activities, a short-term PM optimization is obviously necessary. Fig. 1 gives the relationship between the PM activities and the job shop schedule under such a circumstance. In this figure, the PM activity for component 1 is originally planned to be preformed during Job $k+1$. This is not permitted. Therefore the PM activity has to be moved to the time t_k or t_{k+1} to ensure a smooth production process.

On the other hand, the components in a multi-component system always interact with and support each other. Whenever one of the components stops to perform a PM action, the whole system must be stopped. At that time, PM opportunities arise for the other components in the system because combining PM activities can reduce the system-dependent cost (i.e. downtime cost) which is called "set-up cost" [25]. In Fig. 1, the PM actions of component 1, 2 and j originally occur in job $k+1$ and therefore they can be preventive maintained at time either t_k or t_{k+1}. If they are preventive maintained together at time t_k or t_{k+1}, the number of system stop may decrease, which can yield a considerable saving in the downtime cost of the whole system.

Based on the above consideration, this paper tries to propose a dynamic opportunistic PM policy for a multi-component system under the constraint of frequently changing job shop schedule. Whenever a job finishes, PM opportunities arise for the components whose PM activities are originally scheduled to be implemented during the next job. Since the job information is only available in the short-term, which is caused by the changes in job

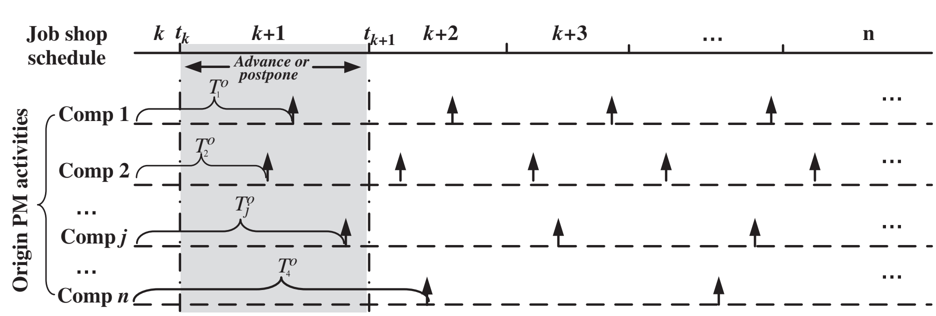

Fig. 1. Relationship between PM activities and job shop schedule.

shop schedule, it is supposed that the decision interval depends on the duration of the next job. Thus the decision process can be described as follows.

Step 1: Original PM interval calculation—component level. Calculate the PM interval for each component individually by using the single-component PM model given in Section 3.1.

Step 2: Opportunistic PM cost determination for each component of the system—system level. When job k (k=1,2,…,n) finishes, all the PM activities originally scheduled to be performed during job $k+1$ will have the opportunities to be advanced or postponed, resulting in the opportunistic PM cost savings for all the components involved.

Step 3: PM activity grouping and decision making—system level. The cumulative cost savings of the opportunistic PM are determined for every possible PM grouping alternatives. The maintenance decision is based on the most cost-effective opportunistic PM group.

Step 2 and Step 3 will be repeated whenever a job finishes.

3. PM optimization modeling

3.1. Original PM interval calculation–component level

As illustrated in Fig. 1, the number of the components considered in each decision cycle depends on the original PM interval of each component which can be determined based on the single-component PM models.

Commonly, the reliability of the system component j can be defined as

$$R=\exp\left(-\int_0^{T_j^o} h_j(t)\mathrm{d}t\right) \tag{1}$$

where T_j^o and $h_j(t)$ are the original PM interval and the hazard rate function for component j , respectively. $\int_0^{T_j^o} h_j(t)\mathrm{d}t$ represents the cumulative failure risk in the PM cycle. Suppose the PM activity is perfect and it can restore the status of the component to as good as new, and all the failures that occur in the PM cycle are minimally repaired. Then the total maintenance cost per unit time for component j in every PM cycle can be evaluated as

$$c_j=\frac{(c^s+c_j^p)\tau^p+C_j^c\int_0^{T_j^o} h_j(t)\mathrm{d}t}{T_j^o+\tau^p} \tag{2}$$

where c^s is the system downtime cost per unit time, c_j^p is the PM cost per unit time for component j, C_j^c is the minimal repair cost caused by the breakdown of component j, and τ^p is the PM duration which is equal for every components. By minimizing c_j, the original PM interval T_j^o for component j can be obtained.

3.2. Opportunistic PM cost determination for each component–system level

For an n-component system, PM opportunities will arise for system components whenever a job finishes. As shown in Fig. 1, when job k finishes, component j has the opportunity to perform a PM action at $t=t_k$ or postpone its PM action until $t=t_{k+1}$ since its original PM action is scheduled to be performed during the next job. If component j is preventive maintained at $t=t_k$, the opportunistic PM cost savings can be evaluated as

$$C_{jk}^O=C_{jk}^D+C_{jk}^M-C_{jk}^P \tag{3}$$

where C_{jk}^D is the downtime cost savings, C_{jk}^M is the maintenance cost savings and C_{jk}^P is the punishment cost associated with the changing of the original PM schedule.

According to the single-component PM model proposed in Section 3.1, the downtime cost savings can be represented as

$$C_{jk}^D=\eta_{jk}c^s\tau^p \quad \text{for } \eta_{jk}\in(0,1) \tag{4}$$

where η_{jk}=1 if there are other PM actions scheduled at $t=t_k$, Otherwise η_{jk}=0. η_{jk}=1 means that component j will be performed the PM action together with other components. Consequently the number of system stop will decrease and the system downtime cost caused by the PM action of component j can be saved.

The advancement or postponement of the PM action may alter the cumulative failure risk for component j in the current PM cycle. Suppose the PM cost c_j^p remains unchanged, then the maintenance cost savings can be shown as

$$\begin{aligned} C_{jk}^M&=\underbrace{\left(c_j^p\tau^p+C_j^c\int_0^{T_j^o} h_i(t)\mathrm{d}t\right)}_{\text{orignal cost}}-\underbrace{\left(c_j^p\tau^p+C_j^c\int_0^{T_j^n} h_i(t)\mathrm{d}t\right)}_{\text{new cost}}\\ &=C_j^c\left(\int_0^{T_j^o} h_i(t)\mathrm{d}t-\int_0^{T_j^n} h_i(t)\mathrm{d}t\right)\\ &=C_j^c\int_{T_j^n}^{T_j^o} h_i(t)\mathrm{d}t \end{aligned} \tag{5}$$

where T_j^n is the new PM interval for component j after the advancement or postponement of the PM action.

Furthermore, since a perfect PM can restore the status of the component to as good as new, it is obvious that the change of the current PM interval will not affect the later PM intervals. This implies that the later PM intervals for component j are still equal to T_j^o. Thus, if the current PM action is advanced or postponed $\Delta t=T_j^o-T_j^n$, all the later PM actions will be advanced or postponed Δt too. This may result in an increase or decrease of the number of PM in the later time horizon and subsequently an increase or decrease of the maintenance cost of the system. Therefore the punishment cost can be constructed on the increased or decreased maintenance cost in the later time horizon because of the change of the current PM action. Based on the above consideration, in this paper the punishment cost for component j is defined as

$$C_{jk}^P=\int_{T_j^n}^{T_j^o} c_j(t)\mathrm{d}t \tag{6}$$

where $c_j(t)$, which can be deduced from Eq. (2), is the total maintenance cost per unit time in every PM cycle and it can be evaluated as

$$c_j(t)=\frac{\left(c^s+c_j^p\right)\tau^p+C_j^c\int_0^t h_j(t)\mathrm{d}t}{t+\tau^p} \tag{7}$$

3.3. PM activity grouping and decision making—system level

Suppose when job k finishes at time $t=t_k$, there are m ($m\in$(1,2,&…,n)) components whose PM activities will be performed during job $k+1$ according to the original PM schedule. At that time, all these components have the opportunities to be preventive maintained at time $t=t_k$ or at time $t=t_{k+1}$, depending on the cumulative opportunistic PM cost savings of the PM combination G. Assume that r($r\in$(1,2,&…,m)) components, forming the PM combination G^a, are preventive maintained at time $t=t_k$, and s($s\in$(1,2,&…,m)) components, forming the PM combination G^b, are preventive maintained at time $t=t_{k+1}$. s, r, G^a and G^b satisfy

$$\begin{cases} r+s=m \\ G^a\cup G^b=G \end{cases} \tag{8}$$

Then the cumulative opportunistic PM cost savings for PM combination G is

$$C_G^O = C_{G^a}^o + C_{G^b}^o = \sum_{j=1}^{r} C_{jk}^o + \sum_{j=1}^{s} C_{j(k+1)}^o = C_G^D + \sum_{j=1}^{r}(C_{jk}^M + C_{jk}^P) + \sum_{j=1}^{s}(C_{j(k+1)}^M + C_{j(k+1)}^P) \quad (9)$$

where C_G^D is the cumulative downtime cost savings for PM combination G. C_G^D satisfies

$$C_G^D = \sum_{j=1}^{r} \eta_{jk} C_{jk}^D + \sum_{j=1}^{s} \eta_{j(k+1)} C_{j(k+1)}^D = (r-1+\eta)c^s\tau^p + (s-1+\mu)c^s\tau^p \quad \textit{for } \eta \in (0,1)\ u \in (0,1) = (m-2+\eta+\mu)c^s\tau^p \quad (10)$$

where $\eta = 1$ if there are PM activities postponed to the end of job k in the former decision cycle, otherwise $\eta = 0$. $u = 1$ if $s = 0$, otherwise $u = 0$.

With the change of r and s, all the alternatives for the PM combinations can be determined. The decision making is based on the optimal PM combination G which can be obtained by maximizing the cumulative opportunistic PM cost savings C_G^O. All the PM activities in the combination G^a will be performed in the interval of job k and job $k+1$, and those in the combination G^b will be implemented after job $k+1$ finishes.

4. Model simplification

The proposed PM model in Section 3 gives a dynamic PM scheduling technique under the constraint of changing job shop schedule. However, as the number of system components increases, the number of the PM group G will increase exponentially and the decision process will become more and more complex. Therefore it is necessary to simplify the proposed PM model.

According to the original PM schedule illustrated in Fig. 2, the PM moment of component 1 is very close to the PM moments of other components. In such an instance, these components can be treated as a component group, and the PM activities for all the components in this group can be advanced or postponed simultaneously. Thus the number of the PM group G will decrease.

For an n-component system, a component grouping activity can be implemented based on the following decision rule

$$\frac{T_j^o - \min\{T_1^o, T_2^o, \cdots, T_n^o\}}{\min\{T_1^o, T_2^o, \cdots, T_n^o\}} \le \varepsilon \quad (11)$$

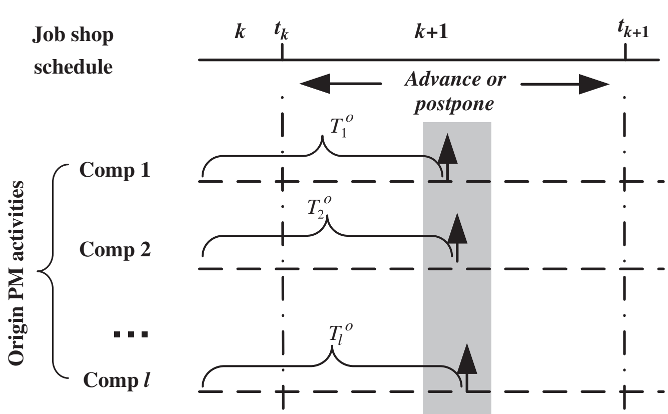

Fig. 2. Component grouping.

where $j \in (1,2,\ldots,n)$. The value of ε depends on the required precision of the decision process. Usually $0 \le \varepsilon \le 0.5$. Without loss of generality, here suppose $T_1^o \le T_2^o \le \cdots \le T_l^o \le \cdots \le T_n^o$ and component l is the first component which does not satisfy the above decision rule. Then the residue components $(l, l+1, \ldots, n)$ will begin a new component grouping activity. This process will not stop until all the components are grouped.

Based on this decision rule, the number of the PM group G will decrease and the whole decision process can be simplified.

5. Numerical example

An 8-component system is considered here. It is assumed that the hazard rate function for each component is a Weibull $h_j(t) = (\alpha_j/\beta_j)\ (t/\beta_j)^{\alpha_j - 1}$. A numerical simulation is implemented to do the optimization and the simulation software is Matlab. The original parameters and the optimal results for each single component are listed in Table 1.

Table 2 gives the original job shop schedule where T_k^{job} (unit in hours) represents the duration of job k. A PM optimization is implemented on these 8 components. Fig. 3 gives an example to show the application of the proposed PM model. The gray area implies that the decision cycles for these components in job 1 and job 2 have completed. The current decision interval is throughout job 3. There are five components whose PM activities are originally scheduled to be performed during job 3 as shown in Fig. 3, and they are component 1, 2, 3, 4, and 6. In order to simplify the decision process, a component grouping activity is implemented on these five components based on Eq. (11).

Here $T_1^o < T_2^o < T_3^o \le T_4^o \le T_6^o$. Suppose $\varepsilon = 0.15$. Component 1 and component 2 satisfy

$$\frac{T_2^o - \min\{T_1^o, T_2^o\}}{\min\{T_1^o, T_2^o\}} = \frac{49-43}{43} = 0.14 < \varepsilon = 0.15$$

and they form a component group. For component 3,

$$\frac{T_3^o - \min\{T_1^o, T_2^o, T_3^o\}}{\min\{T_1^o, T_2^o, T_3^o\}} = \frac{52-43}{43} = 0.21 > \varepsilon = 0.15$$

and therefore the residue components, including component 3, 4 and 6, will start a new grouping process. Component 3 and component 4 satisfy

$$\frac{T_4^o - \min\{T_3^o, T_4^o\}}{\min\{T_3^o, T_4^o\}} = \frac{56-52}{52} = 0.08 < \varepsilon = 0.15$$

and they form a new component group. For component 6

$$\frac{T_6^o - \min\{T_3^o, T_4^o, T_6^o\}}{\min\{T_3^o, T_4^o, T_6^o\}} = \frac{65-52}{52} = 0.25 > \varepsilon = 0.15$$

and therefore component 6 itself forms a component group.

Thus these five components form three component groups which are (1, 2), (3, 4) and (6). This means component 1 and 2 must advance or postpone their PM activities simultaneously in the current decision cycle and so must component 3 and 4 do.

Table 1
Original parameters and corresponding optimal results for each component.

j	(α_j,β_j)	c_j^p(¥/h)	c^s(¥/h)	τ^p(¥/h)	C_j^c(¥)	Tj(h)	cj(¥/h)
1	(2, 50)	10			200	43	1.711
2	(2.6, 112)	15			253	49	1.559
3	(2, 115)	15			225	52	1.778
4	(2.4, 125)	15			228	56	1.434
5	(2.4, 136)	17	10	2	180	61	1.427
6	(2.5, 118)	27			212	65	1.817
7	(1.8, 140)	20			240	71	1.791
8	(1.6, 135)	28			270	81	2.352

Table 2
Job shop schedule (unit in hours).

k	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
T_k^{job}(h)	50	33	39	45	24	41	33	20	40	37	35	27	30	38	34	24	50

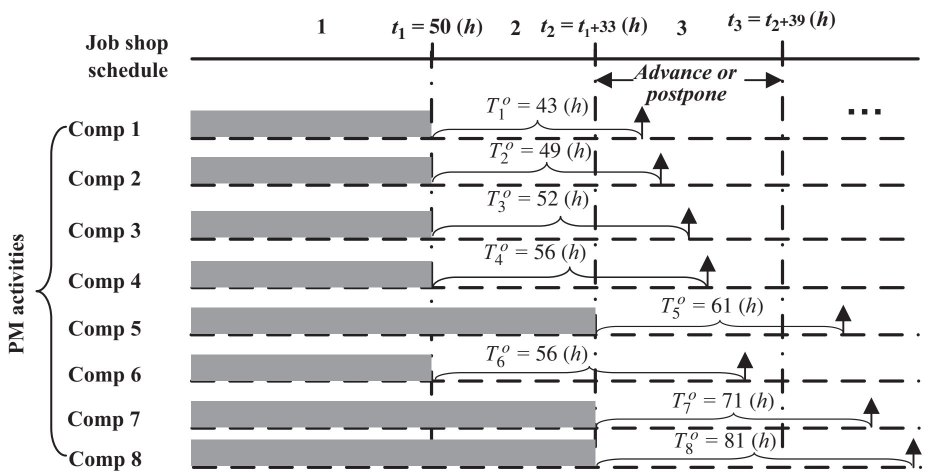

Fig. 3. Original PM activities in Job 3.

Table 3
Decision alternatives.

Alternative ID	Alternative	
	G^a	G^b
1	(1,2),(3,4),(6)	–
2	–	(1,2),(3,4),(6)
3	(1,2),(3,4)	(6)
4	(6)	(1,2),(3,4)
5	(1,2), (6)	(3,4)
6	(3,4)	(1,2), (6)
7	(1,2)	(3,4),(6)
8	(3,4),(6)	(1,2)

According to the PM activity grouping rule proposed in Section 3.3, the three component groups generate 8 decision alternatives as illustrated in Table 3.

Table 4 gives the cumulative opportunistic PM cost savings for each decision alternative.

In Table 4, the biggest cumulative opportunistic PM cost savings is 59.740 and therefore the optimal combination is $G^a=\{(1,2)\},G^b=\{(3,4),(6)\}$. This means component 1 and 2 will be preventive maintained at the beginning of job 3, and component 3, 4 and 6 will be preventive maintained at the end of job 3. Furthermore, the calculation of C_G^D is based on Eq. (10). For example, for alternative 1, all the PM actions of the components are advanced to the beginning of job 3, and therefore

$$\begin{aligned} C_G^D &= \sum_{j=1}^{r}\eta_{j2}C_{j2}^D+\sum_{j=1}^{s}\eta_{j3}C_{j3}^D \\ &=(m-2+\eta+\mu)c^s\tau^p \\ &=(5-2+1+1)\times 10\times 2 \\ &=100 \end{aligned}$$

The above decision process will be repeated whenever a job is completed. Table 5 gives the optimal PM schedule throughout the given job shop schedule which is illustrated in Table 2.

6. Discussion

In reality, there are two other common PM optimization methods for this kind of n-component systems. One is that all the PM activities originally scheduled in job k are performed simultaneously ahead of job k. This is referred to as model 1. The other, referred to as model 2, is that all these PM activities are postponed to the end of job k.

In order to prove the viability of the proposed PM model, a comparison is made between the three PM models in terms of the cumulative cost for maintenance per unit time throughout the given time interval [0, T]. The calculation of the total maintenance cost is based on the following rules.

1) Once component j is preventive maintained, the cumulative cost for maintenance increases $c_j^p\tau^p+C_j^c\int_0^{T_j^n}h_j(t)\mathrm{d}t$.
2) Whenever the multi-component system stops performing a PM action, the cumulative cost for maintenance increases $c^s\tau^p$.
3) If no PM action is performed on component j right at time t=T, the cumulative cost for maintenance increases $c_j\times T_j^*$ where T_j^* is the amount of time passed since the last PM action for component j. T_j^* satisfies

$$T_j^*=T-\sum_{i=1}^{N_j}(T_j^n+\tau_p) \tag{12}$$

where N_j is the number of the PM actions for component j throughout [0,T].

According to the above rules, the cumulative cost for maintenance per unit time throughout [0,T] can be evaluated as

$$c=\frac{\sum_{k=1}^{M}\left(\sum_{j=1,j\in G^a\cup G^b}^{r+s}\left(c_j^p\tau^p+C_j^c\int_0^{T_j^n}h_j(t)\mathrm{d}t\right)+\eta_k c^s\tau^p\right)+\sum_{j=1}^{n}c_j\left(T-\sum_{i=1}^{N_j}(T_j^n+\tau_p)\right)}{T} \tag{13}$$

where M represents the number of the jobs during [0, T] and $\eta_k\in(0,1)$. $\eta_k=1$ if there are PM activities at the end of job k, otherwise $\eta_k=0$. Eq. (13) can be used for the calculation of the cumulative cost for maintenance for all of the above three PM models.

Table 4
Cumulative savings of opportunistic PM cost.

Alternative ID	C_G^D(¥)	C_{j2}^M(¥)					C_{j2}^P(¥)					C_G^O(¥)
		$j=1$	$j=2$	$j=3$	$j=4$	$j=6$	$j=1$	$j=2$	$j=3$	$j=4$	$j=6$	
1	100	14.799	18.751	27.917	24.338	38.142	−16.873	−25.585	−35.245	−35.251	−62.213	48.780
2	80	−67.101	−50.906	−41.752	−27.001	−14.743	52.526	37.687	35.750	22.806	13.588	40.854
3	80	14.799	18.751	27.917	24.338	−14.743	−16.873	−25.585	−35.245	−35.251	13.588	51.696
4	80	−67.101	−50.906	−41.752	−27.001	38.142	52.526	37.687	35.750	22.806	−62.213	17.938
5	80	14.799	18.751	−41.752	−27.001	38.142	−16.873	−25.585	35.750	22.806	−62.213	36.824
6	80	−67.101	−50.906	27.917	24.338	−14.743	52.526	37.687	−35.245	−35.251	13.588	32.810
7	80	14.799	18.751	−41.752	−27.001	−14.743	−16.873	−25.585	35.750	22.806	13.588	59.740
8	80	−67.101	−50.906	27.917	24.338	38.142	52.526	37.687	−35.245	−35.251	−62.213	9.894

Table 5
Optimal PM schedule for each component.

j	PM activities at the end of job k																
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$	$k=11$	$k=12$	$k=13$	$k=14$	$k=15$	$k=16$	$k=17$
1	O	O	O	O	O	O		O	O	O	O		O	O	O	O	
2	O	O	O	O		O		O	O	O		O		O		O	O
3	O		O	O		O		O	O	O		O		O		O	
4	O		O		O	O		O	O		O		O		O		O
5		O		O		O		O		O		O		O		O	
6	O		O		O		O		O		O		O		O		O
7		O		O		O		O		O		O		O		O	
8		O		O			O			O			O		O		

Table 6
Comparison of the cumulative cost for maintenance for the three PM models.

PM method	T(h)	C(¥/h)
Model 1		15.117
Model 2	550	14.997
The proposed PM model		13.821

Table 6 gives a comparison of the cumulative cost for maintenance per unit time throughout [0, T] under these three maintenance scheduling models. Table 6 shows that the total cost for maintenance per unit time under the proposed PM model is lower than those under the other two maintenance models. This implies that the proposed model is effective in the PM optimization for multi-component systems under changing job shop schedule.

7. Conclusion

Most published researches on PM deal with the PM activities without considering the constraint of production needs. However, in reality, preventive maintenance is an indispensable part of a manufacturing process and it is important to integrate production decisions into developing optimal PM policies. This paper proposes an opportunistic PM model for the multi-component systems under changing job shop schedule. The proposed model is based on dynamic programming and on short-term optimization. The decision time interval of the model is consistent with the duration of the current job, which is adaptive to the changing of the job shop schedule. The numerical example implies the proposed PM model is better than the other two PM models.

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