Joint Optimization of Condition-Based Operation and Maintenance for Continuous Process Manufacturing Systems Under Imperfect Maintenance

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For continuous process manufacturing systems (CPMSs) where the production process cannot be stopped, two popular performance evaluation metrics are production efficiency and stability. With the development of sensors and communication technologies, the condition-based decision can effectively coordinate the operation and maintenance (O&M) management of CPMSs to improve the production completion rate. However, most papers studied condition-based operation (CBO) and condition-based maintenance (CBM) separately which led to the inability to obtain optimal solutions. In addition, the effect of imperfect maintenance on production efficiency and stability has also been ignored. Therefore, this work develops an optimal condition-based operation and maintenance (CBOM) policy for CPMSs. CPMSs are required to complete a series of specified production batches within a finite horizon, and the optional maintenance actions include do nothing, imperfect maintenance, and replacement. The optimization objective to determine the optimal joint O&M policy by maximizing the average production completion rate. In the CBOM policy, the production completion rate of CPMSs under different missions is evaluated by a stochastic flow manufacturing network (SFMN). Since the CPMS has Markov property, we use the Markov decision process (MDP) framework to solve the CBOM optimization problem. The main contributions of this work include: (1) compared with existing studies, a more rational CBOM policy is proposed, which focuses on maximizing the production efficiency and stability of CPMSs; (2) the impact of imperfect maintenance on production efficiency and stability is considered in the CBOM, which makes the proposed policy has better applicability. Finally, the proposed approach is demonstrated in a hot rolling manufacturing system, and a sensitivity analysis of the relevant parameters is also performed. The results show that CBOM can improve the average production completion rate.

Keywords: continuous process manufacturing systems, joint operation and maintenance, condition-based decision, imperfect maintenance, Markov decision process, stochastic flow manufacturing network.

1. Introduction

The core objective of CPMSs (e.g., steel, pharmaceutical, chemical, etc.) is to maximize production efficiency and stability [1][2]. With the development of sensors and the IoT, condition-based decision making is gaining increasing interest. Condition-based decision enable manufacturers to develop more flexible O&M policy to improve the production completion rate of CPMSs.

In light of this, many scholars have undertaken research into CBM, which reduces unplanned downtime while avoiding wastage of remaining useful life through the development of flexible maintenance schedules. Liu et al. [3] developed a framework for CBM under periodical inspection, in which two degradation-dependent components are executed for preventive or corrective replacement depending on their state at inspection. To develop a more rational maintenance plan, Ma et al. [4] proposed a condition-based maintenance optimization model that considers imperfect maintenance and used accelerated degradation testing data and field data to construct the degradation model. A CBM policy with dynamic thresholds was proposed by Zheng et al. [5] where the hazard rate depends on age and covariate information from condition monitoring. Xu et al. [6] investigated the optimal CBM policy for a K-out-of-N: G system under periodic inspection, and used continuous state space discretization and value iteration algorithms to find the optimal inspection interval and the optimal CBM policy.

However, the above works only consider the improvement in performance due to maintenance actions and ignore the effect of production speed on performance deterioration. Different production speeds affect the failure risk [7] and the degradation rate [8] of machines. Based on the fact that machines usually deteriorate faster at higher production speed, it would make more reasonable to carry out a joint optimization of CBOM.

Nowadays, more and more researchers are focusing on the joint optimization of CBOM. For a joint optimization model of production lot sizing and condition-based maintenance for a multi-component production system, Cheng et al. [9] developed maintenance decision rules based on predicted reliability and structural importance of components. As the machine state cannot be perfectly observed, Celen and Djurdjanovic [10] proposed a CBOM decision method to find the optimal integrated policy in the realms of maintenance scheduling and production sequencing. Zheng et al. [11] developed a joint optimization model for economic production quantity and condition-based maintenance, which is based on a proportional hazard model with a continuous-state covariate process. A joint condition-based maintenance and production policy that takes into account economic dependence and load distribution was proposed by Broek et al. [12], which can achieve significant cost savings compared to separate condition-based decisions.

However, the above works focused on maintenance cost rather than production completion rate. Since the production process of CPMSs cannot be stopped, unplanned downtime can cause huge economic losses [13]. Therefore, the production completion rate is more important compared to the maintenance cost. In addition, existing studies ignored the effects of imperfect maintenance and different production missions on the production completion rate.

Therefore, this paper develops a CBOM policy for CPMS with the objective of maximizing the average production completion rate in an finite horizon. The downtime opportunities between production batches are used to inspect the machine state, select the maintenance actions and the production mission for the next production batch. And by constructing a SFMN to analyse the production completion rate under imperfect maintenance and different production missions.

2. Problem statements

2.1. *CBOM policy of CPMSs*

We investigate the joint optimization of condition-based operation and maintenance for a multi-machine CPMS. The performance level of the machine is divided into several discrete states, which are used to characterize the production capacity of the machine. The state of machine l at time t within the G-th production batch is $W_{l,G}(t)$. $W_{l,G}(t) \in S_l = \{s_{l,1}, \cdots, s_{l,N_l}\}$. $s_{l,1}$ and s_{l,N_l} are the fault and optimal states, respectively. The most distinctive feature of CPMSs is that the production process cannot be stopped. Therefore, the interval between two adjacent production batches is used as an opportunity for inspection and maintenance. Based on this feature, the CBOM policy proposed in this paper is shown in Fig. 1.

The studied CBOM is a combination of CBM and CBO, where the maintenance action and the production mission for the (G+1)-th production batch are selected at the end of the G-th production batch based on the state of the machine that was checked.

CBM policy: CBM is a flexible maintenance policy that allows the operator to plan maintenance interventions based on condition information. The inspection cost is c_i. In addition, the inspection time is considered to be negligible.

This is because the time required for modern monitoring technology is negligibly short compared to maintenance time and operation time. Depending on the current state of the machine, it is determined which maintenance action to choose. Alternative maintenance actions include a_1 (do nothing), a_2 (preventive maintenance), and a_3 (replacement).

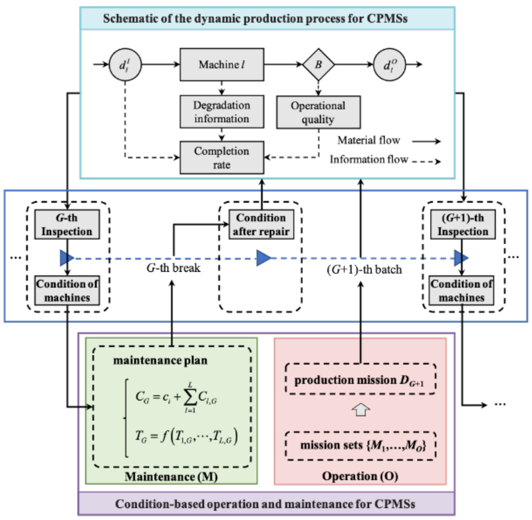

Fig. 1. The diagram of CBOM for CPMSs.

CBO policy: CPMSs are able to perform different production missions (production rate and quality). At the end of the (G-1)-th production batch, the operator selects the mission D_G to be performed for the G-th production batch from the missions set $M = \{M_1, \cdots, M_O\}$ according to the current state of machines. M_O means the most rigorous mission. In this paper, the production completion rate is proposed to quantify the production efficiency and stability of CPMSs, which is defined as the probability that CPMSs successfully complete the production mission.

CBOM policy: CPMSs execute H production batches sequentially within a finite horizon. Each batch is of length L_{pb}. At the end of (G-1)-th production batch, a maintenance action set $Ma_{G-1} = \{ma_{1,G-1}, \cdots, ma_{L,G-1}\}$ satisfying the cost constraint and a production mission D_G for the G-th batch are selected according to the machines' state. The goal of the CBOM policy is to maximize the average production completion rate. The average production completion rate is denoted as.

$$PCR_{ave} = \frac{\sum_{G=1}^{H} PCR_G \varpi(D_G)}{H} \tag{1}$$

where PCR_G is the production completion rate of the G-th production batch with known maintenance actions Ma_{G-1} and production mission D_G. $\varpi(D_G)$ is the weight of production mission D_G. And $\varpi(D_G) \in [0,1]$.

2.2. *Imperfect maintenance model*

At each interval, maintenance actions can be classified according to their efficiency as replacement (as good as new), imperfect maintenance and do nothing (as bad as old). In contrast to replacement and do nothing, many maintenance actions in engineering practice can be considered as imperfect maintenance, which restores the machine to between the two extremes mentioned above. And, a more efficient maintenance action consumes more maintenance resources (cost and time). The maintenance cost and maintenance time of machine l in the G-th interval are.

$$C_{l,G} = \begin{cases} 0, & ma_{l,G} = a_1 \\ c_{IM,l}, & ma_{l,G} = a_2 \\ c_{R,l}, & ma_{l,G} = a_3 \end{cases} \tag{2}$$

$$T_{l,G} = \begin{cases} 0, & ma_{l,G} = a_1 \\ t_{IM,l}, & ma_{l,G} = a_2 \\ t_{R,l}, & ma_{l,G} = a_3 \end{cases} \tag{3}$$

where $c_{IM,l}$ and $t_{IM,l}$ are the cost and time required when machine l is executed with imperfect maintenance. $c_{R,l}$ and $t_{R,l}$ are the cost and time required when machine l is replaced, respectively. The total maintenance cost and time during the G-th interval are:

$$C_G = c_i + \sum_{l=1}^{L} C_{l,G} \tag{4}$$

$$T_G = f\left(T_{1,G}, \cdots, T_{L,G}\right) \tag{5}$$

The Eq. (5) is the general form of the total maintenance time. In this paper, all maintenance actions are performed in sequence. Therefore, the total maintenance time is the sum of the maintenance time of all machines.

Furthermore, quasi-renewal process is used in this paper to characterize imperfect maintenance [14]. Both replacement and imperfect maintenance can restore the machine to perfect state. However, the time to degrade the machine to a worse state after an imperfect maintenance has been performed is reduced. It is assumed that the state probability function of the machine l being in state i at the G-th production batch is $p_{l,i}^{G}(t)$. According to the quasi-renewal process,

$$p_{l,i}^{G+1}(t) = p_{l,i}^{G}(\alpha_l t) \tag{6}$$

where α_l is the parameter of quasi-renewal process. The number of imperfect maintenance times of CPMSs before the G-th interval is K_G ={ $k_{1,G}$,⋯, $k_{L,G}$ }. And, X_G ={ $x_{1,G}$,⋯, $x_{L,G}$ } denotes the state of the CPMS at the end of the G-th production batch. Thus, $p_{l,i}^{G+1}(t)$ depends on X_G, K_G, and Ma_G.

3. Condition-based operation and maintenance decision model

To achieve the maximum average production completion rate for the total missions, the maintenance actions for each interval and the production mission for the next batch should be dynamically selected based on the state and the number of imperfect maintenance times of all machines. This CBOM strategy is denoted as π. (Ma_G, D_G)= π (X_G, K_G). In this section, the production process of CPMS is first described by building a SFMN. Further, the production completion rate of CPMS is evaluated. Finally, the discrete-time finite horizon Markov decision process and its Bellman equation resulting from CBOM strategy are formulated.

3.1. *Stochastic flow manufacturing network*

Based on the network theory [15-16], SFMN is constructed to describe the dynamic production process of CPMS. The topology of SFMN is shown in Fig. 2.

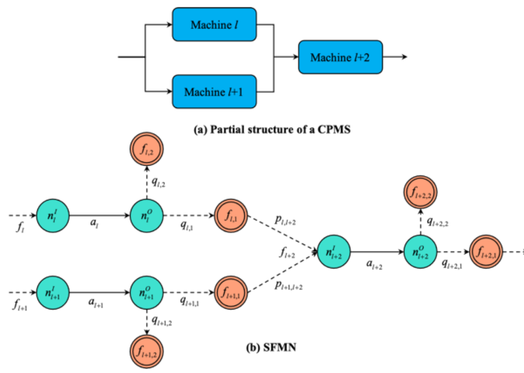

Fig. 2. The topological structure of the SFMN.

The parameters in SFMN include:

(1) $Ar = \{ar_1, \cdots, ar_L\}$ is the set of arcs (machines). $S_l = \{s_{l,1}, \cdots, s_{l,N_l}\}$ is the capacity set of the arc ar_l, which represents the maximum flow (working load) that can be withstood. The capacities of the different arcs are independent.

(2) $N = \{n_l^I, n_l^O\}$, $l = 1, \cdots, L$, is the set of nodes. The node is fully reliable and it only inspects and stores WIP.

(3) $D = \{d_l^I, d_l^O\}$, $l = 1, \cdots, L$, is the set of demands. Demand includes quality and quantity of WIP. d_l^I and d_l^O denote the input and input demand of machine l, respectively.

(4) $F = \{f_1, \cdots, f_L\}$ is the set of flow. Flow is an abstract representation of the product. f_l is the flow into ar_l. The output flow of ar_l is divided into $f_{l,1}$ (meet the demand) and $f_{l,2}$ (does not meet demand). Only $f_{l,1}$ is transmitted to the downstream arc.

(5) $P=\left\{p_{l,1},p_{l,2},q_{l,j}\right\}$, $l,j=1,\cdots,L$, is the set of proportions. $p_{l,1}$ and $p_{l,2}$ denote the probability that ar_l outputs $f_{l,1}$ and $f_{l,2}$, respectively. $q_{l,j}$ denotes the proportion of $f_{l,1}$ that delivered into ar_l.

The transition of flow satisfies the flow conservation law. And, the change in flow in the SFMN is shown in Eq. (7).

$$\left(f_{l+1,1},f_{l+1,2}\right)=f_{l,1}\left(q_{l+1,1},q_{l+1,2}\right)p_{l,l+1} \tag{7}$$

3.2. *Production completion rate under given production mission*

In this paper, the production completion rate of a CPMS is defined as its capacity at the end of a mission without falling below that specified by the mission. The production completion rate of the CPMS at the *G*-th production batch, denoted as PCR_G, can be evaluated by the combination of the machine states at the end of *G*-th batch.

Considering the multi-state nature of the machine, its degradation process is assumed to obey the homogeneous continuous-time Markov process. The state set of machine *l* is $S_l=\left\{s_{l,1},\cdots,s_{l,N_l}\right\}$. The Markov transition intensity matrix of machine l is shown in Eq. (8).

$$\Lambda_l=\begin{pmatrix}\lambda^l_{N_l,N_l} & \cdots & \lambda^l_{N_l,1}\\ \vdots & \ddots & \vdots\\ \lambda^l_{1,N_l} & \cdots & \lambda^l_{1,1}\end{pmatrix} \tag{8}$$

where $\sum_{j=1,j\neq i}^{N_l}\lambda^l_{i,j}=-\lambda^l_{i,i}$. Moreover, let $P_l(t)$ ={ $p_{l,1}(t)$,⋯, $p_{l,N_l}(t)$ } denotes the set of state probabilities of machine *l* at time *t*. The Kolmogorov differential equations of Λ_l is:

$$\begin{cases}\dfrac{dp_{l,N_l}(t)}{dt}=-p_{l,N_l}(t)\sum_{j=1}^{N_l-1}\lambda^l_{N_l,j}\\ \dfrac{dp_{l,i}(t)}{dt}=\sum_{j=i+1}^{N_l}\lambda^l_{j,i}p_{l,j}(t)-p_{l,i}(t)\sum_{j=1}^{i-1}\lambda^l_{i,j},1<i<N_l\\ \dfrac{dp_{l,1}(t)}{dt}=\sum_{j=2}^{N_l}\lambda^l_{j,1}p_{l,j}(t)\end{cases} \tag{9}$$

Based on Laplace-Stieltjes theorem, the state probability $p_{l,i}(t)$, $i=1,\cdots,N_l$, at any time can be obtained. Combined with the quasi-renewal process, the state probability function of a brand-new machine *l* after being performed k_l imperfect maintenance is:

$$p_{l,i}(t\,|\,k_l)=p_{l,i}\left(\alpha_l^{-k_l}t\right) \tag{10}$$

where $p_{l,i}(\bullet)$ is the state probability function without considering imperfect maintenance effects.

On the other hand, when the mission demand for the *G*-th production batch is D_G, $d^I_{l,G}$ and $d^O_{l,G}$ for machine *l* can be obtained based on the flow change in SFMN [Eq. (7)] as follows:

$$d^I_{l,G}=D_G\Big/\prod_{j=l}^{L}p_{j,j+1}q_{j,1} \tag{11}$$

$$d^O_{l,G}=d^I_{l,G}q_{l,1} \tag{12}$$

Therefore, the PCR_G of CPMS at the *G*-th production batch is:

$$PCR_G=\prod_{l=1}^{L}\sum_{i=1}^{N_l}p^G_{l,i}\left(L_{pb}\right)1\left(s_{l,i}\geq d^I_{l,G}\right) \tag{13}$$

where $1(\bullet)$ is the judgement function, 1(true)=1 and 1(false)=0.

3.3. *MDP formulation*

The dynamic selection of the maintenance actions that satisfy the cost and time constraints at each interval and the production mission for the next production batch can be viewed as a Markov decision process. the state space, action space, and rewards of the MDP are as follows:

State space: The state space of the MDP consists of all possible combinations of the state and the number of imperfect maintenance times of each machine at the end of the production batch.

Action space: The action space is a set of production mission and feasible maintenance actions. For the G-th interval, the action space is:

$$S_G^{act} = \{M_1, \cdots, M_O\} \cup \{Ma_G \mid C_G \le C_{\lim}, T_G \le T_{\lim}\} \tag{14}$$

Reward: In the G-th interval, the reward is the weighted production completion rate for the (G+1)-th batch, namely $\frac{\varpi_G PCR_G}{H}$.

Given the X_G and K_G at the end of the G-th batch, the maximum average production completion rate of the remaining H-G batches can be viewed as a value function of MDP, namely $V(X_G, K_G, G)$.

$$\begin{aligned} V(X_G,K_G,G) &= \max_{\pi} E\left(\sum_{n=G+1}^{H} \frac{\varpi(D_n) PCR_n}{H} \mid X_G, K_G\right) \\ &= \max_{(D_{G+1}, Ma_G) \in S_G^{act}} \left\{ PCR_G(X_G, K_G, Ma_G) + \left[\sum_{x_{1,G+1}=1}^{N_1} \cdots \right.\right. \\ & \left.\left. \sum_{x_{L,G+1}=1}^{N_L} \left(p_{l,x_{l,G+1}}^{G+1}(L_{pb}) \bullet V(X_{G+1}, K_{G+1}, G+1)\right)\right]\right\} \end{aligned} \tag{15}$$

For a brand new CPMSs, it can be treated as if a batch 0 exists before the 1-st batch starts. It has Ma_0 for $ma_{l,0} = a_1$, $l = 1, \cdots, L$, namely "do nothing". And $D_1 = M_O$. The maximum average production completion rate can be addressed by the following:

$$\begin{aligned} PCR_{ave}^* &= V(X_0, K_0, 0) \\ &= \max_{\pi} E\left(\sum_{n=1}^{H} \frac{\varpi(D_n) PCR_n}{H} \mid X_0, K_0\right) \\ &= \max_{(D_1, Ma_G) \in S_G^{act}} \left\{ \frac{\varpi(M_O) PCR_1(X_0, K_0, Ma_0)}{H} + \right. \\ & \left. \left[\sum_{x_{1,1}=1}^{N_1} \cdots \sum_{x_{L,1}=1}^{N_L} \left(\prod p_{l,x_{l,1}}^{1}(L_{pb}) \bullet V(X_1, K_1, 1)\right)\right]\right\} \end{aligned} \tag{16}$$

For this MDP, the dynamic programming can be used to determine the maximum average production completion rate and the corresponding CBOM policy π^*.

4. Case study

In this paper, a hot rolling manufacturing system, a typical CPMSs, is used as an object to verify the effectiveness of the proposed method. A simplified hot rolling manufacturing system is studied, which consists of a roughing mill (Machine 1) and a finishing mill (Machine 2). Figure 3 shows a schematic diagram of the studied CPMSs. Next, a step-by-step application of the proposed method is presented.

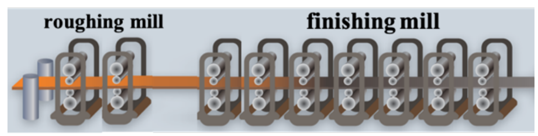

Fig. 3. Schematic diagram of hot rolling manufacturing system.

As a series system, $q_{1,2}=q_{2,3}=1$. The remaining parameters in SFMN are shown in Table 1. Then, the SFMN of the studied object is shown in Fig. 4.

Table 1. Parameters of studied SFMN.

machine	1	2
S_l	{0,20,40,60}	{0,20,40,60}
α_l	0.85	0.95
$\lambda_{2,1}^l$	0.022	0.015
$\lambda_{3,1}^l$	0	0
$\lambda_{3,2}^l$	0.014	0.017
$\lambda_{4,1}^l$	0	0
$\lambda_{4,2}^l$	0	0
$\lambda_{4,3}^l$	0.05	0.03
$p_{l,1}$	0.97	0.95

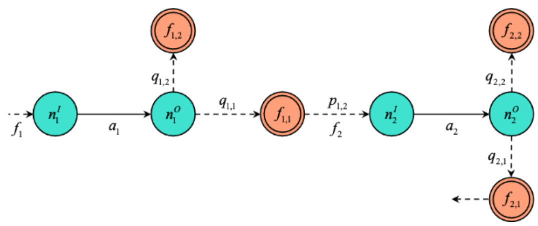

Fig. 4. The SFMN of studied hot rolling manufacturing system.

On the other hand, the set of optional missions is {30,15}. The sub-demands of the machines under each mission can be obtained by Eqs (11)-(12). The maintenance parameters associated with each machine are shown in Table 2.

Table 2. Maintenance parameters of machines.

machine	$c_{R,l}$	$c_{IM,l}$	$t_{R,l}$	$t_{IM,l}$	c_i
1	15	10	0.5	0.4	1
2	15	10	0.5	0.4	

(unit of cost: \$1,000, unit of time: hour)

The studied CPMSs execute 3 consecutive production batches. In other words, the number of breaks is 2. The duration of each production batch is 3 months. At each break, maintenance budget $C_{\lim} = 26\times10^3$ US dollars and limited duration $T_{\lim}$ =1 hour.

The expected average production completion rate of the three production batches is 0.9927 as evaluated by the dynamic programming.

Next, the effect of maintenance budget and break duration on the average production completion rate is analysed. Case 1: $C_{\lim} = 26\times10^3$ US dollars and $T_{\lim}$ =1 hour. Case 2: $C_{\lim}$ = 31×10^3 US dollars and $T_{\lim}$ =1.2 hours. Case 3: $C_{\lim} = 24\times10^3$ US dollars and $T_{\lim}$ =0.9 hours. Case 4: $C_{\lim} = 9\times10^3$ US dollars and $T_{\lim}$ =0.4 hours. The maximum average production completion rates for the four cases are shown in Table 3.

Table 3. Maximum average production completion rates for the different cases.

Case	$\boldsymbol{PCR_{ave}}$
1	0.9927
2	0.9949
3	0.9847
4	0.9782

As shown in Table 3, the average production completion rate gradually increases as the maintenance budget and break duration increase. The largest average production completion rate is 0.9949. And the smallest average production completion rate is 0.9782, which means that no machine is repaired at each break.

5. Conclusion

In this paper, a condition-based operation & maintenance method for CPMSs was discussed. Considering the continuity of the production process of CPMSs, all maintenance actions were performed during the breaks between adjacent production batches. The state of each machine was inspected at the end of the production batch. The maintenance plan and the production plan for the next batch were decided based on the machines‘ state. This problem of maximizing the average production completion rate was transformed into a Markov decision process. In the case study, a hot rolling manufacturing system was applied to verify the effectiveness of the proposed method, and the impact of the key parameters (maintenance budget and break duration) on the results was analysed.

It is worth noting that there are several interesting topics for our future work. (1) The tailored solution algorithms, such as deep reinforcement learning algorithms, for CBOM strategy should be developed. (2) The effect of imperfect observations should be considered when developing a CBOM strategy.

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