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Manufacturing paradigm-oriented PHM methodologies for cyber-physical systems

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Abstract In today's competitive environment of Industry 4.0, cyber-physical systems (CPS) of various advanced manufacturing paradigms have brought new challenges to maintenance managements. Efficient prognostics and health management (PHM) policies, which can integrate both individual machine deteriorations and different manufacturing paradigms, are urgently needed. Newly proposed PHM methodologies are systematically reviewed in this paper: as the decision basis, an operating load based forecasting algorithm is proposed for machine health prognosis; at the machine level, a dynamic multi-attribute maintenance model is studied for diverse machines in CPS; at the system level, novel opportunistic maintenance policies are developed for complex flow-line production, mass customization and reconfigurable manufacturing systems, respectively. This framework of PHM methodologies has been validated in industrial implementations.

Keywords Maintenance · Dynamic programming · Manufacturing paradigms · Cyber-physical system

Introduction

In the global competition and technique innovation, many manufacturing enterprises are pursuing a shift to cyber-physical systems (CPS) of advanced manufacturing paradigms (Lee et al. 2014a). In practice, complex flow-line production, mass customization and reconfigurable manufacturing paradigms have been applied to satisfy changeable customer demands and keep enterprise core competitiveness (Al-Zaher and ElMaraghy 2013; Lin et al. 2015; Jardim-Goncalves et al. 2016). However, these CPS systems, machines and accessorial sensors have also become technologically more advanced, and more difficult to manage. This transformation provides motivation for improving maintenance methodologies. It is important to efficiently predict machine health statuses, eliminate unnecessary production breaks, achieve maintenance cost reduction and decrease systemic decision-making complexity (Rafiee et al. 2014; Benkedjouh et al. 2015).

In the recent decades, numerous valuable studies have been devoted to the maintenance scheduling (Arab et al. 2013; Mirabi et al. 2013; Zied et al. 2014). Prognostics and health management (PHM) has been crucial to keep CPS systems and their machines in good condition (Liu et al. 2013). Cyber-physical systems usually consist of diverse machines, which have different degrading processes that will finally lead to failures and interrupt the normal production (Sheikhalishahi et al. 2014; Chouikhi et al. 2014; Ebrahimipour et al. 2015). Considering CPS characters of integrated computational and physical capabilities such as actuation, sensing and communication to physical world, PHM should provide a systematical view of the machine health prognosis, the machine-level maintenance scheduling and the system-level maintenance optimization. To develop proper PHM methodologies for advanced manufacturing paradigms, it is necessary to comprehensively consider maintenance opportunities and manufacturing characters to make maintenance schedules in a cost-effective manner. However, classical opportunistic maintenance policies are insufficient to provide feasible solutions because of complex series-parallel structures, changeable batch orders and open-ended

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system reconfigurations (Chang et al. 2007; Derigent et al. 2009; Zhou et al. 2009; Lee et al. 2013). Thus, PHM policies that can decrease decision-making complexity, avoid breakdowns of batch production, and adapt to diverse reconfigurations are urgently needed.

PHM methodologies for advanced manufacturing paradigms are complex due to the hierarchical levels of systematical maintenance decision-making: (a) accurate machine health prediction at the physical level; (b) dynamic maintenance scheduling at the machine level; (c) effective opportunistic maintenance policies at the system level. In a CPS system, recent advances in sensing and information technologies enable enterprises to on-line collect, store and process information that characterizes machine health statuses (Lee et al. 2014b). Thus, these statuses are utilized to predict machine deteriorations for supporting PHM decision-making. Furthermore, designed information transfer between the machine level and the system level should not be a "push" process, but a "pull" process. By pulling machine-level outputs, this interactive scheduling mode promotes opportunistic maintenance policies to dynamically optimize system-level schedules by integrating maintenance opportunities and manufacturing paradigms.

The remainder of this paper is organized as follows: "A systematical framework of PHM methodologies" section presents a systematical PHM framework for advanced manufacturing paradigms. "WFRGM algorithm for machine health prognosis" section proposes the W-variable forecasted-state rolling grey model (WFRGM) by considering the effect of operating loads. "MAM method for machine-level maintenance scheduling" section develops the multi-attribute model (MAM) by utilizing the multiple attribute value theory and imperfect maintenance. "Opportunistic maintenance for various cyber-physical systems" section discusses the maintenance time window (MTW) for complex flow-line production, the advance-postpone balancing (APB) for mass customization, and the reconfigurable maintenance time window (RMTW) for reconfigurable manufacturing, respectively. Finally, conclusions and perspectives are drawn in "Case study of PHM methodologies" section.

A systematical framework of PHM methodologies

Cyber-physical systems (CPS) are defined as transformative technologies for managing interconnected systems between its physical assets and computational capabilities (Lee et al. 2015). Recent advances in manufacturing industry have paved way for a systematical deployment of CPS, within which information from all related perspectives is closely monitored and synchronized between the physical factory floor and the cyber computational space. Moreover, by utilizing advanced information analytics, networked machines will be able to perform more efficiently, collaboratively and resiliently. Cyber-physical systems are ubiquitous in power systems, transportation networks, industrial control processes, and critical infrastructures. These systems need to operate reliably in the face of unforeseen failures (Pasqualetti et al. 2013).

For understanding the impact of CPS and the relation to the manufacturing field, Monostori et al. (2016) comprehensively studied cyber-physical systems in manufacturing. This important survey can help us: (1) to identify potentially impactful articles that are related to CPS and (2) to find out how CPS has evolved with respect to problems, applications and techniques. Wang et al. (2015) presented the current status and advancement of cyber-physical systems and their future research directions when applied to manufacturing. The characteristics of CPS were outlined together with those of Systems of Systems (SoS), Internet of Things (IoT), Big Data and Cloud technology. Like cloud-enabled prognosis can leverage advanced manufacturing by using data and information from across the manufacturing hierarchy (Gao et al. 2015), PHM methodologies for CPS have been designed to improve efficiency, productivity, and profitability by integrating monitored information, failure prediction, system structure and manufacturing characteristics.

In industry, modern manufacturing systems with CPS technologies could be widely used in advanced manufacturing paradigms, such as complex flow-line production, mass customization and reconfigurable manufacturing paradigms. Since machine statuses are available from sensors within the cyber computational space, PHM decisions to optimize maintenance arrangements should be made in the physical factory floor by considering different manufacturing characters. Without properly integrating the special characters of advanced manufacturing paradigms, valuable information collected by CPS technologies can achieve rapid responsiveness and cost effectiveness for modern manufacturing systems. At this point, several key issues need to be addressed in the developed PHM methodologies for CPS:

(1) Based on monitored and synchronized information, it will improves forecast accuracy by incorporating real-time influencing factors (i.e., operating load) for machine health prognosis; (2) with failure frequency predictions, it is important to accurately describe hazard rate evolutions of individual machines and model machine-level maintenance operations with multiple objectives; (3) by pulling machine-level outputs, cost-effective system schedules should be studied to avoid decision-making complexity caused by series-parallel structures for complex flow-line paradigm; (4) for mass customization paradigm, an opportunistic maintenance strategy is required to handle changeable batch orders due to customer demands and eliminate unnecessary production breaks; (5) for reconfigurable manufacturing paradigm, real-time maintenance schedules should be made to respond

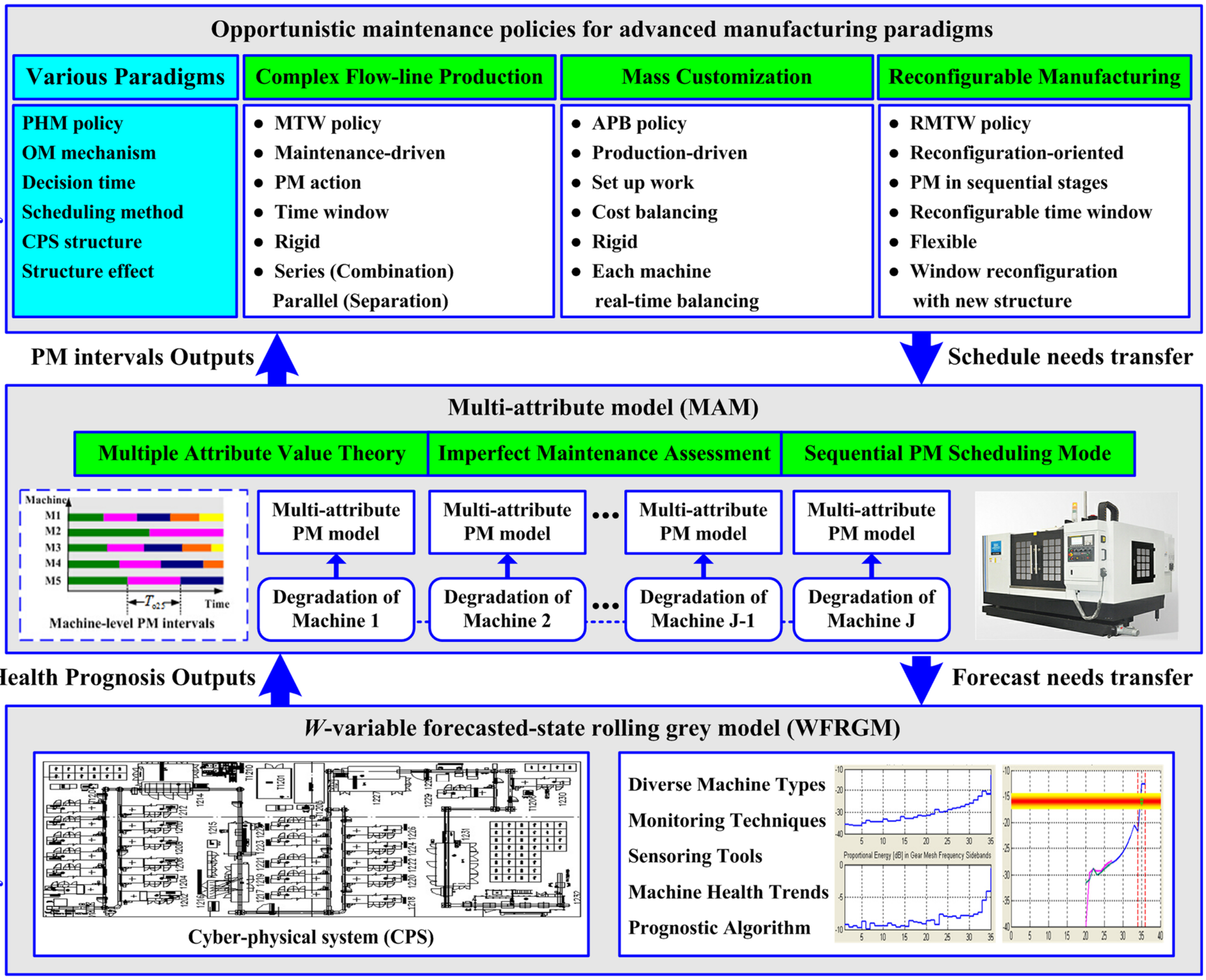

Fig. 1 Scheme of hierarchical PHM decision-making for CPS

rapidly to diverse open-ended reconfigurations and flexible system structures.

The designed PHM framework consists of three levels, where CPS maintenance decisions are dynamically made through the machine health prognosis, the machine-level maintenance scheduling and the system-level maintenance optimization. The hierarchical scheme is shown in Fig. 1.

- *Physical level* Cyber-physical systems of advanced manufacturing paradigms are defined as the decision objects. With rapid innovations of monitoring techniques and sensoring tools, efficient prognostic algorithm is developed to forecast accurate machine health trends for supporting the PHM decision-making process in real time, rather than over time.
- *Machine level* For each individual machine, preventive maintenance (PM) intervals are dynamically scheduled by considering multiple attribute value theory, imperfect maintenance assessment and sequential PM scheduling mode. If a machine fails between successive PM actions, minimal repair recovers it to the failure rate that it had when it failed.
- *System level* By pulling PM intervals, novel opportunistic maintenance policies are presented to utilize maintenance opportunities and manufacturing characters to make dynamic maintenance schedules in a cost-effective manner. The manufacturing characters of CPS are thoroughly investigated. Thus, the proposed PHM methodologies can adapt to advanced manufacturing paradigms and achieve significant reduction of maintenance cost, production downtime and decision-making complexity.

The notation used in this paper is listed in Table 1.

WFRGM algorithm for machine health prognosis

Machine health prognosis plays an important role in PHM methodologies. For complex CPS consisting of multiple machines, it is necessary to utilize maintenance opportunities

Table 1 Notation

W : Generating coefficient of grey model	L : Operating load change rate
$x^{(0)}$: Actual status of machine	$\hat{x}^{(0)}$: Forecasted status of machine
i : Index of PM cycles at machine level	j : Index of machine Mj
A_{ij} : Availability of the ith PM cycle for Mj	$c_{\mathrm{r}ij}$: Cost rate of the ith PM cycle for Mj
$T_{\mathrm{p}ij}$: Time duration of PM action	$T_{\mathrm{f}ij}$: Time duration of minimal repair
$C_{\mathrm{p}ij}$: Cost of PM action	$C_{\mathrm{f}ij}$: Cost of minimal repair
$\lambda_{ij}(t)$: Hazard rate function prior to the $i$thPM	$T_{\mathrm{o}ij}$: PM interval of machine level
a_{ij} : Age reduction factor	b_{ij} : Hazard increase factor
T_w : Maintenance time window	k : Index of PM cycles at system level
t_{jk} : PM time point of Mj at system level	t_k : PM execution point at system level
ETC : Excepted total system maintenance cost	$c_{\mathrm{d}j}$: Downtime cost rate
u : Index of batch Bu	TB_u : Time duration of batch Bu
t_{ij} : Time point of PM from machine level	tb_u : Set-up time point after Bu at system level
$\Theta(j, tb_u)$: Maintenance decision at tb_u	G_u : PM combination set after Bu
$SCA_{j(u+1)}$: Saved cost of PM advancement	$SCP_{j(u+1)}$: Saved cost of PM postponement
$APB_{j(u+1)}$: Advance-postpone balancing	$c_{\mathrm{s}j}$: Set-up cost rate
$T_{pu\,\max}$: Maximum duration for PM actions	h : Index of manufacturing stage MS_h
$T_{\mathrm{R}h}$: Time duration of the hth reconfiguration	$t_{\mathrm{R}h}$: Time point of the hth reconfiguration
$T_{\mathrm{W}h}$: Time width of RMTW in MS_h	$\Theta(j, t_k)$: Maintenance decision for Mj at t_k

and avoid production losses by forecasting machine degradations. Conventional forecasting methods can be categorized into quantitative forecasting and qualitative forecasting, including Delphi method, time series, exponential smoothing, linear regression, expert systems and neural networks (Wang and Hsu 2008; Yu and Xi 2008; Tian 2012). Generally, large amounts of machine statuses are required to construct prognosis models, which limit their practical uses for CPS. In recent decades, grey model (GM) forecasting has achieved good prognosis accuracy with limited statuses by using approximate differential equations to describe future tendencies for a time series (Akay and Atak 2007; Xia et al. 2015b). The GM method, which was first proposed by Deng (1982), focuses on information insufficiency and model uncertainty in analyzing future trends through studies on conditional analysis, prediction and decision making based on scarce and fuzzy information. This forecasting model is suitable for real-time prediction with limited data available.

To further increase GM accuracy, the novel philosophy comprising of utilizing practical industrial influencing factors, besides the time series itself, is needed. This study tries to achieve the following GM improvements: (1) incorporating real-time influencing factors (such as operating loads) that affect machine health trends; (2) taking new statuses into consideration and avoiding too old ones that cannot reflect current machine degradations; (3) dynamically evaluating the generating coefficient W values to overcome the shortage of static $W = 0.5$ in original GM(1,1). Thus, a W-variable Forecasted-state rolling grey model (WFRGM) is proposed to increase the accuracy of CPS health prognosis. This WFRGM algorithm includes the following steps:

(1) *Health data acquisition* With sensing technology of CPS, health statuses of machine failure frequency at sequential time d are collected online as the in-sample testing data $x^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(d), \ldots, x^{(0)}(p))$, $p \geq 4$.

(2) *Dynamic W fitting* In grey model, enumerate W values and select optimal ones $(W_1, W_2, W_3, \ldots, W_p)$ at time $d = 1, 2, 3, \ldots, p$. Evaluate the correlation coefficient (CR) of W values and corresponding operating load change rate Lvalues $(L_1, L_2, L_3, \ldots, L_p)$. Then construct the relationship of $W = f(L)$.

$$CR_{WL} = \frac{\sum_{d=1}^{p}\left(W_d - \overline{W}\right)\left(L_d - \overline{L}\right)}{\sqrt{\sum_{d=1}^{p}\left(W_d - \overline{W}\right)^2}\sqrt{\sum_{d=1}^{p}\left(L_d - \overline{L}\right)^2}} \quad (1)$$

(3) *WFRGM reconstruction* With forecasted W $(W_{p+1}, W_{p+2}, W_{p+3}, \ldots, W_{p+q})$ related to real-time $L(L_{p+1}, L_{p+2}, L_{p+3}, \ldots, L_{p+q})$, WFRGM is reconstructed by taking advantages of forecasted-state rolling and generated values calculating with dynamic W in Accumulating Generation Operation (AGO).

(4) *Health trend prediction* Then WFRGM is used to forecast the out-of-sample predictive data $(\hat{x}^{(0)}(p+1), \hat{x}^{(0)}(p+2), \hat{x}^{(0)}(p+3), \ldots, \hat{x}^{(0)}(p+q))$. Forecasted-state rolling process and dynamic W values ensure a high-precision prediction, which is essential for supporting PHM scheduling. The rolling process reconstructs the grey model whenever a new status rolls in. It takes newer information into consideration and eliminates older statuses that cannot show the new machine health trend. Furthermore, in original rolling GM, the generat-

ing coefficient W is customarily given as 0.5. The static W value does not consider real-time influencing factors. Therefore, by analyzing the relationship between dynamic W values and variable L data, WFRGM can generate better forecasts.

(5) *Performance evaluation and application* To evaluate the predicting performance, different error criteria are introduced and used, such as the mean absolute percentage error (*MAPE*) and the mean absolute error (*MAE*).

MAM method for machine-level maintenance scheduling

Based on the machine health prognosis, decision makers can make maintenance schedules. With age and usage, each machine undergoes increasing wear, which finally leads to a failure and breaks the normal production. Conventional maintenance models usually suffer from a critical problem of setting periodic intervals to perform PM actions. However, it has been noticed that insufficient maintenance inevitably leads to unnecessary downtime and huge cost; on the other hand, plethoric maintenance will increase maintenance cost and decrease manufacturing profit (Dekker et al. 1997). The innovative idea of this research is to incorporate the multiple attribute value theory, the imperfect maintenance assessment and the sequential PM scheduling mode. Proper machine-level PM intervals of diverse machines will be the solid base for the opportunistic maintenance policies at the system level (Xia et al. 2013).

This research focuses on three crucial questions for optimally scheduling PM intervals: firstly, the traditional assumption of perfect PM that covers a machine to the “as good as new” status is plausible (Wang and Tsai 2014). For most machines, even though some components are replaced, the cumulative wear on adjacent components may deteriorate unnoticed. This leads to the imperfect effects of maintenance activities. In practice, a machine after PM is not as good as brand new one, that is, the hazard rate value is decreased while always greater than zero. Simultaneously, each machine tends to have more frequent maintenance since the hazard rate increases more quickly than it did in the previous PM interval. To sum up, PM not only decreases the hazard rate to a certain value but also changes the slope of the hazard rate function. Secondly, most existing maintenance models were concerning cost. In fact, it should consider other machine-level PM objectives according to practical requirements. Thus, this study utilizes the multiple attribute value theory in building the PM model. Last but by no means the least, for responding quickly to system-level PHM pulling, a dynamic model-iteration mode is proposed to output PM intervals cycle by cycle. Since conventional static long-time planning focuses on the maintenance modelling and analysis for the whole designed lifetime and arranges PM actions in advance without considering the real-time machine degradation, which is usually not applicable in a practical factory. In our dynamic model-iteration mode, sequential PM intervals are obtained according to the real-time hazard rate evolution of the current cycles, not being relative to the whole lifetime.

The multi-attribute model (MAM), which is illustrated in Fig. 2, provides real-time PM intervals T_{oij}, even if there are L objectives $(O_{1ij}, O_{2ij}, \ldots, O_{Lij})$. The comprehensive objective function is minimized to schedule optimal PM intervals. If a smaller O_{lij} (such as the maintenance cost c_{rij}) is preferred, $\Delta_l = 0$; if a larger O_{lij} (such as the machine availability A_{ij}) is preferred, then $\Delta_k = 1$.

$$V_{ij} = w_{1ij}\frac{(-1)^{\Delta_1} O_{1ij}}{O_{1ij}^*} + w_{2ij}\frac{(-1)^{\Delta_2} O_{2ij}}{O_{2ij}^*} + \cdots + w_{Lij}\frac{(-1)^{\Delta_L} O_{Lij}}{O_{Lij}^*} \tag{2}$$

In this model, the machine availability A_{ij} and the maintenance cost rate c_{rij} may be considered as two objectives related to the efficiency and the economy, respectively:

$$A_{ij} = \frac{T_{aij}}{T_{aij} + \left(T_{pij} + T_{fij}\int_0^{T_{aij}} \lambda_{ij}(t)\mathrm{d}t\right)} \tag{3}$$

$$c_{rij} = \frac{C_{pij} + C_{fij}\int_0^{T_{cij}} \lambda_{ij}(t)\mathrm{d}t}{T_{cij} + \left(T_{pij} + T_{fij}\int_0^{T_{cij}} \lambda_{ij}(t)\mathrm{d}t\right)} \tag{4}$$

For each next PM cycle, with the actual interval T_{ij} from the system-level feedback, the relationship between hazard rates of consecutive cycles can be defined as:

$$\lambda_{(i+1)j}(t) = b_{ij}\lambda_{ij}(t + a_{ij}T_{ij}), t \in (0, T_{(i+1)j}) \tag{5}$$

In imperfect maintenance effects, the age reduction factor a_{ij}, $a_{ij} \in (0, 1)$indicates that imperfect PM causes the machine’s initial failure rate to become $\lambda_{ij}(a_{ij}T_{ij})$; meanwhile, the hazard increase factor $b_{ij} > 1$ reflects that PM increases the failure rate $b_{ij}\lambda_{ij}(t)$.

Opportunistic maintenance for various cyber-physical systems

Nowadays, there has been a growing interest in PHM methodologies of multi-unit systems for leading enterprises. It is essential to investigate and model the complicated machine interactions and the diverse manufacturing characters, which provide maintenance opportunities for CPS of advanced manufacturing paradigms. Opportunistic maintenance refers

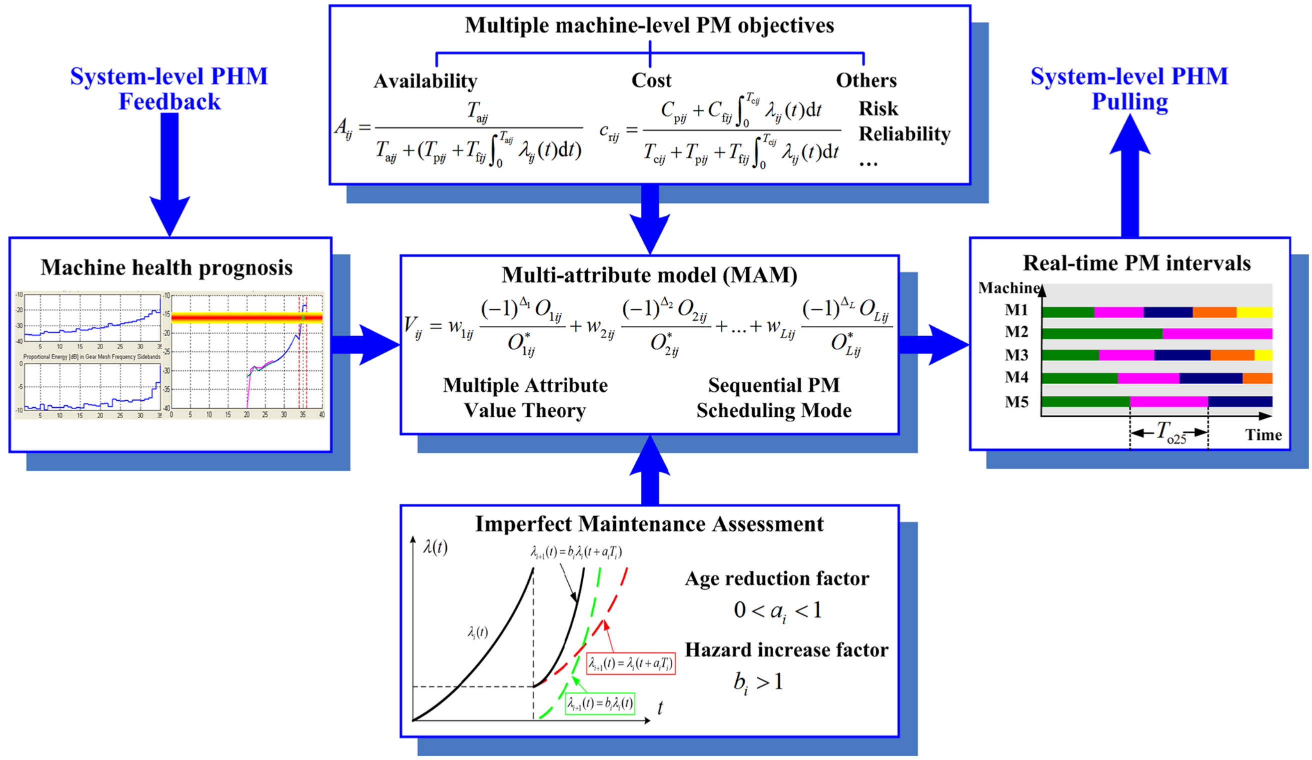

Fig. 2 Illustration of machine-level MAM method

to the scheme where PM can be performed at opportunities with the advantages of combining individual PM actions and saving much group maintenance cost (Xia et al. 2012; Gu et al. 2015). To overcome the exponential decision-making complexity with machine number increasing and apply the system-level PHM methods to advanced manufacturing paradigms, novel opportunistic maintenance policies will be presented in detail.

MTW policy for complex flow-line system

Complex series-parallel cyber-physical systems have been widely used to satisfy flow-line productions. In this article, a general PHM decision-making policy is proposed by considering both machine degradation and system structure. This maintenance time window (MTW) policy can help enterprise managers to make dynamic maintenance schedules based on not only single-machine plans, but also the whole-system global programming. MTW programming is applied by pulling real-time machine-level PM intervals. A breakdown caused by one machine is utilized to carry out PM actions on non-failed ones, thus unnecessary breakdown of CPS could be avoided. This maintenance-driven opportunistic maintenance policy aims to systematically obtain system-level maintenance schedules in a cost effective manner:

(1) *MTW-separation in parallel subsystem* According to machine-level PM intervals, the MTW value T_w provides a criterion to separate PM actions in subsystems. MTW-separations can avoid the unnecessary downtime of upstream and downstream machines.
(2) *MTW-combination in series subsystem* Pulling the outputs from MAM and MTW-separations cycle by cycle, MTW is defined as the criterion to combine PM actions within $[t_k, t_k+T_w]$. The time point t_k is when one machine is preformed PM, which also means maintenance opportunities for other machines in series.
(3) *System performance evaluation* The total system maintenance cost (*ETC*) by using MAM policy can be evaluated based on system-level maintenance schedules. The total maintenance cost of the kth cycle for machine j can be evaluated by:

$$ETC_{kj} = \begin{cases} c_{dj} \cdot T_{pk\max} & \Theta(j, t_k) = 0 \\ C_{pij} + C_{fij} \int_0^{T^*_{oij}-(t_{jk}-t_k)} \lambda_{ij}(t)\mathrm{d}t + c_{dj} \cdot T_{pk\max} & \Theta(j, t_k) = 1 \\ 0 & \Theta(j, t_k) = 2 \end{cases} \quad (6)$$

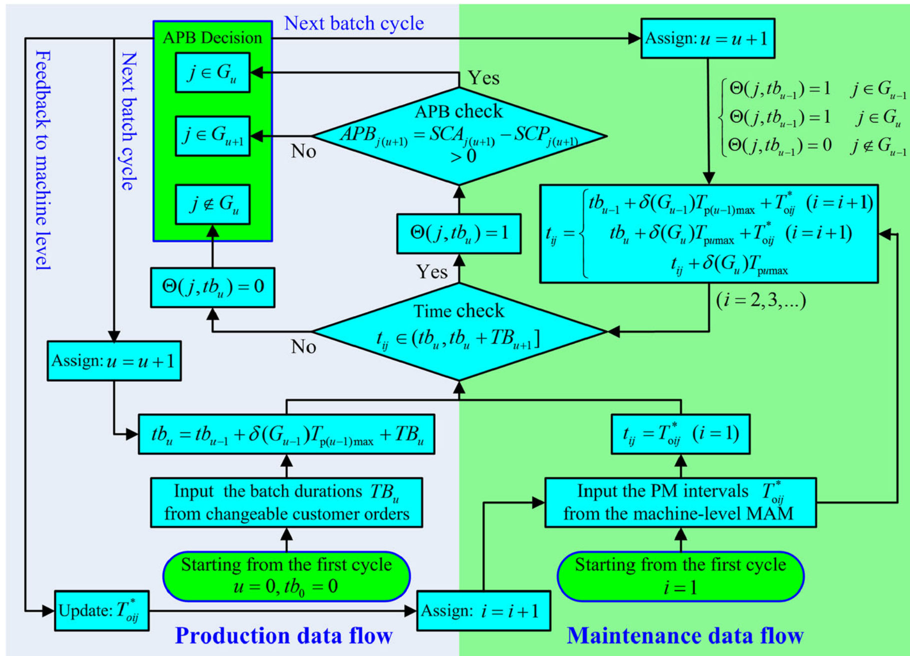

Fig. 3 Flowchart of APB policy for mass customization CPS

where $\Theta(j, t_k) = 0$ means no maintenance action is initiated on Mj at the time point t_k, but this machine will be down; $\Theta(j, t_k) = 1$ means the PM action is combined to be performed in advance; $\Theta(j, t_k) = 2$ means no maintenance action is initiated and the machine continues to operate. Thus, the total system maintenance cost for the CPS in its mission lifetime can be obtained by:

$$ETC = \sum_{k=1}^{K} \left(\sum_{j=1}^{J} ETC_{kj} \right). \tag{7}$$

APB policy for mass customization system

As one of advanced manufacturing paradigms, mass customization is widely used to response quickly to changeable customer demands. In mass customization, batch orders are processed through CPS with following production characteristics: (1) batch orders are independent with diverse lot size; (2) batches are sequentially ordered only a transient time beforehand; (3) one set-up work happens when a batch switches to another; (4) it prefers no interruptions in each batch cycle to ensure product quality. To meet the requirements of mass customization, there has been a great need to propose a new type of opportunistic maintenance that considers machine degradations and manufacturing characteristics (Xia et al. 2015a).

In this study, a production-driven opportunistic maintenance policy is presented to eliminate unnecessary production breaks and achieve significant cost reduction. According to sequential batch orders and machine-level PM intervals, the advance-postpone balancing (APB) policy utilizes the set-up works and analyzes the cost savings to schedule real-time PM adjustments. Each set-up time between successive batches is used to perform PM actions, thus unnecessary breakdown during batch productions can be avoided. We apply APB programming to analyze the cost savings of PM advancement and PM postponement, and then choose the better PM adjustment to ensure no-disruptions and reduce maintenance cost.

This production-driven APB policy has the advantages for the mass customization paradigm: (1) APB satisfies no-disruption requirements during changeable batch orders, other than traditional constant production assumption; (2) it utilizes planned production downtimes as maintenance opportunities to advance or postpone PM actions, which significantly reduces the complexity of system-level scheduling; (3) by choosing the greater cost savings between PM advancement and PM postponement at each set-up opportunity, APB ensures that the maximization of ETC-saving can be achieved. The procedure of APB programming is illustrated in Fig. 3.

When each batch B_u has been finished, and the next batch B_{u+1} has not started, this moment tb_u is utilized as the decision time to schedule APB. On the one hand, if machine M_j is prevented maintained now, the saved cost by advancing PM in batch B_{u+1} can be evaluated as:

$$\begin{aligned} SCA_{j(u+1)} &= SCA^{d}_{j(u+1)} + SCA^{f}_{j(u+1)} - SCA^{p}_{j(u+1)} \\ &= T_{\mathrm{p}ij}(c_{dj} - c_{sj}) \\ &\quad + \left[\int_0^{T^*_{\mathrm{o}ij}} \lambda_{ij}(t)dt - \int_0^{T^*_{\mathrm{o}ij} - (t_{ij} - tb_u)} \lambda_{ij}(t)dt \right] \end{aligned}$$

$$C_{\mathrm{f}ij} - \frac{t_{ij} - tb_u}{T^*_{\mathrm{o}ij} - (t_{ij} - tb_u)} C_{\mathrm{p}ij} \tag{8}$$

where $SCA^d_{j(u+1)}$ is the downtime cost saving, $SCA^f_{j(u+1)}$ is the minimal repair cost saving, $SCA^p_{j(u+1)}$ is the PM cost saving of PM advancement:

On the other hand, if PM of machine M_j is postponed to the next set-up time point tb_{u+1}, the minimal repair cost saving will be a negative value (prolonged PM interval leads to increasing cumulative failure risk and more minimal repair cost) and the PM cost saving will be a positive value (longer intervals mean that less PM actions would be needed in the same scheduling horizon). Therefore, the saved cost by postponing PM in batch B_{u+1} can be evaluated as:

$$\begin{aligned} SCP_{j(u+1)} &= SCP^d_{j(u+1)} - SCP^f_{j(u+1)} + SCP^p_{j(u+1)} \\ &= T_{\mathrm{p}ij}(c_{dj} - c_{\mathrm{s}j}) \\ &\quad - \left[\int_0^{T^*_{\mathrm{o}ij}+(tb_{u+1}-t_{ij})} \lambda_{ij}(t)dt - \int_0^{T^*_{\mathrm{o}ij}} \lambda_{ij}(t)dt \right] \\ &\quad C_{\mathrm{f}ij} + \frac{tb_{u+1} - t_{ij}}{T^*_{\mathrm{o}ij} + (tb_{u+1} - t_{ij})} C_{\mathrm{p}ij} \end{aligned} \tag{9}$$

where $SCP^d_{j(u+1)}$ is the downtime cost saving, $SCP^f_{j(u+1)}$ is the minimal repair cost saving and $SCP^p_{j(u+1)}$ is the PM cost saving of PM postponement:

According to the values of SCA and SCP, $APB_{j(u+1)}$ could be defined as the criterion to decide weather to advance or postpone this PM action:

$$APB_{j(u+1)} = SCA_{j(u+1)} - SCP_{j(u+1)}. \tag{10}$$

RMTW policy for reconfigurable manufacturing system

The system structure of reconfigurable manufacturing CPS can be adjusted to meet various future products and changeable market demands (Koren and Shpitalni 2010; Ni and Jin 2012). In other words, the main advantage of reconfigurable manufacturing is the adaptability to the uncertainties of the open system architecture with reconfigurable system structures. For the entire system, those different reconfigurations are caused by the changing needs in terms of capacity and functionality, while the production process will be separated into sequential manufacturing stages. Each manufacturing stage (MS_h) has its own system structure designed for its current production requirements. If the system-level maintenance policy has to be rebuilt according to each different structure, its responsiveness and flexibility will be obviously weakened (Xia et al. 2016).

By extending the previous research from both reconfigurable structure and manufacturing paradigm aspects, this study presents a reconfiguration-oriented opportunistic maintenance policy to achieve rapid responsiveness and cost effectiveness for future reconfigurable manufacturing. Other than rebuilding new system-level policies for different stationary structures, the developed reconfigurable maintenance time window (RMTW) focuses on the structure analysis to extract reconfigured parallel subsystems and series subsystems in each manufacturing stage. Faced with different system structures, the RMTW policy utilizes reconfiguration characters and maintenance opportunities to constantly redefine reconfiguring scheduling criteria within a uniform method. This manner is more suitable for rapidly adapting to new system structures in reconfigurable manufacturing systems (RMS).

The production scenarios in Fig. 4 can be taken as an example to illustrate the RMTW scheduling for system-level reconfigurations. After the original design, the RMS enters service at time $t = t_{\mathrm{R}1} = 0$ with its initial system structure (5 machines). In the first manufacturing stage MS_1, the time width value of RMTW $T_{\mathrm{W}1}$ is defined as a criteria to separate PM actions in parallel subsystems and combine PM actions in series subsystems based on machine-level PM intervals.

At the reconfiguration time $t_{\mathrm{R}2}$, the structure is redesigned for the second manufacturing stage MS_2. In the time duration of this reconfiguration $T_{\mathrm{R}2}$, M1 is replaced with a new M6, and M7 is added in parallel with M5. Then, the RMS continues production with a new structure, while a redefined time width of RMTW $T_{\mathrm{W}2}$ is applied for reconfigured parallel/series subsystems to minimize the total system maintenance cost.

Similarly, in the next reconfiguration before MS_3, M3 is removed, while M8 is added in parallel with M2 and M4. In contrasted to the traditional manner of rebuilding new system-level policies for different structures, RMTW scheduling focuses on reconfiguring scheduling criteria $T_{\mathrm{W}h}$ within a uniform method for rapidly adapting to new structures. Above structure analysis of each manufacturing stage is essential for RMTW scheduling. Then, the process flowchart of the proposed RMTW programming is shown in Fig. 5.

Case study of PHM methodologies

Effectiveness of WFRGM algorithm

To prove the prognosis accuracy of the proposed WFRGM algorithm, the increasing health statuses of a monitored machine's deterioration during a maintenance interval are collected. The twelve status data points of failure frequency from monitoring points 1–12 are regarded as the in-sample test data, which reflects the increasing failure risk. The

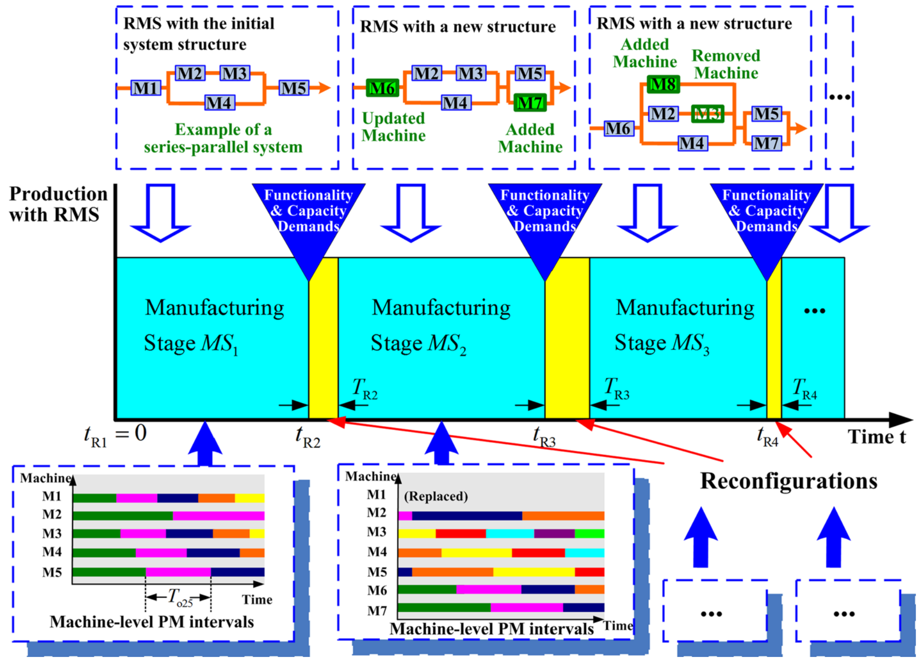

Fig. 4 Production scenarios of reconfigurable manufacturing CPS.

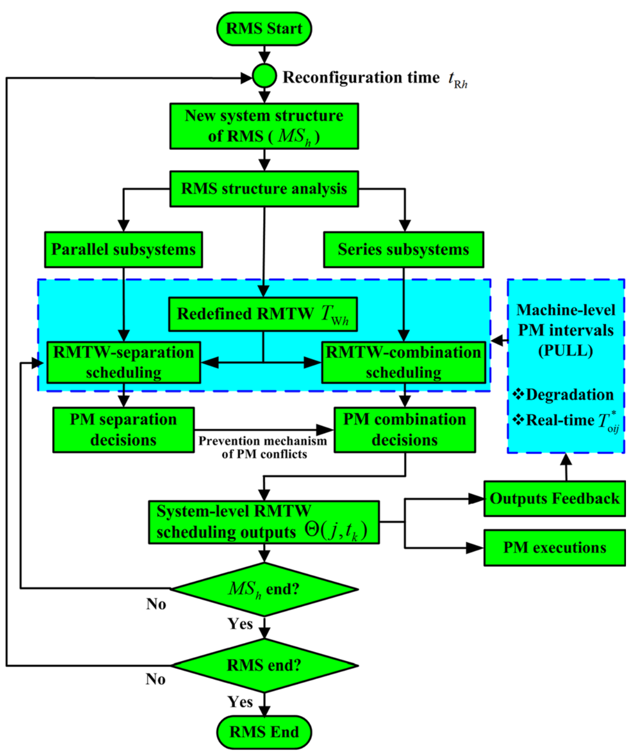

Fig. 5 Flowchart of RMTW policy for reconfigurable manufacturing CPS

remaining six states from cycles 13–18 are used for out-of-sample forecasting.

Results of the linear regression model (LRM) with $\hat{x}^{(0)}(d) = 0.0362d + 0.0211$, the original GM(1,1) model with $\hat{x}^{(0)}(d) = \left(1 - e^{-0.147}\right)\left(x^{(0)}(1) + \frac{0.0951}{0.147}\right)e^{0.147(d-1)}$, the actual-state rolling grey model (ARGM), the forecasted-state rolling grey model (FRGM) and the proposed WFRGM algorithm have been presented in Table 2. The plot of actual versus forecasted machine states from above five models is shown in Fig. 6.

From the result comparisons in Table 2, it can found that the *MAPE* (5.19%) and *MAE* (0.0395) of WFRGM are all lower than LRM (*MAPE* = 21.26%; *MAE* = 0.1608), GM (*MAPE* = 17.74%; *MAE* = 0.1415), FRGM (*MAPE* = 15.73%; *MAE* = 0.1263) and ARGM (*MAPE* = 9.80%; *MAE* = 0.0729), indicating the highly accurate forecasting ability. Thus, WFRGM algorithm can provide real-time machine health information to dynamic PHM decision-making.

Effectiveness of MAM method

A 5-unit series-parallel system with the initial system structure in Fig. 4 is selected as an example for numerical experiments using the proposed MTW policy. In this manufacturing system, PM intervals of each machine are dynamically scheduled by the MAM method according to individual machine degradation. The reliability of each machine is formulated by a Weibull failure probability function: $\lambda_{1j}(t) = (m_j/\eta_j)(t/\eta_j)^{m_j-1}$, which has been widely used to fit repairable equipment in electronic and mechanical engineering. Machine e parameters are shown in Table 3.

From the results of industrial implementations (Xia et al. 2012), the proposed machine-level MAM method reveals following conclusions: (1) the PM interval decreases while PM cycle increases, since the underlying hazard rate evolution

Table 2 Forecasting results of different methods

Monitoring point	Actual status	LRM	GM	FRGM	ARGM	WFRGM
1	0.0837	0.0573	0.0837	0.0837	0.0837	0.0837
2	0.0864	0.0935	0.1157	0.1157	0.1157	0.1157
3	0.1705	0.1297	0.1340	0.1340	0.1340	0.1340
4	0.1732	0.1659	0.1552	0.1552	0.1552	0.1552
5	0.2110	0.2021	0.1798	0.1798	0.1798	0.1798
6	0.2122	0.2383	0.2082	0.2082	0.2082	0.2082
7	0.2388	0.2745	0.2412	0.2412	0.2412	0.2412
8	0.2448	0.3107	0.2794	0.2794	0.2794	0.2794
9	0.2856	0.3469	0.3236	0.3236	0.3236	0.3236
10	0.4144	0.3831	0.3749	0.3749	0.3749	0.3749
11	0.4219	0.4193	0.4342	0.4342	0.4342	0.4342
12	0.5318	0.4555	0.5030	0.5030	0.5030	0.5030
In-sample testing statuses (1–12)						
13	0.6316	0.4917	0.5827	0.5827	0.5827	0.6207
14	0.6401	0.5279	0.6749	0.6586	0.6857	0.6743
15	0.6812	0.5641	0.7818	0.7649	0.7762	0.7074
16	0.7483	0.6003	0.9056	0.8849	0.8421	0.8285
17	0.8540	0.6365	1.0490	1.0315	0.9130	0.8589
18	0.9026	0.6727	1.2151	1.1953	0.9976	0.9830
Out-of-sample forecasting statuses (13–18)						
MAPE (%)		21.26	17.74	15.73	9.80	5.19
MAE		0.1608	0.1415	0.1263	0.0729	0.0395

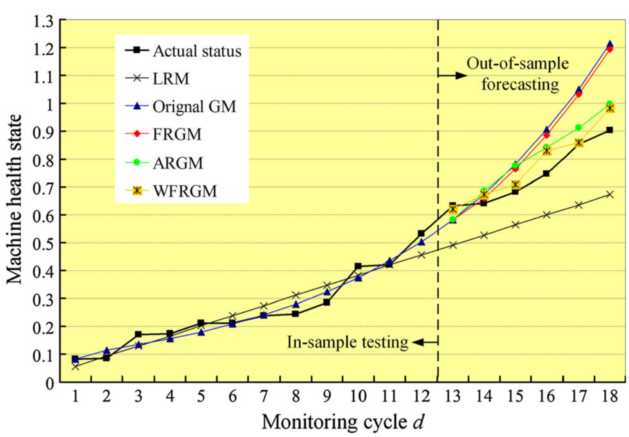

Fig. 6 Comparison of actual and forecast machine health states

becomes faster with the degradation process; (2) machine availability will be lower and maintenance cost will be higher as a machine ages due to the consideration of maintenance effects; (3) ignoring the effects of a maintenance activity will lead to less availability and extra cost, and MAM contributes to more practicality of PM intervals.

Effectiveness of MTW policy

To validate the MTW policy for complex flow-line systems, we program the system-level maintenance schedule with machine parameters in Table 3. Taken $T_w = 800$ h for the MTW programming as an example, the CPS mission lifetime is 25,000 h. Table 4 provides the system-level maintenance schedule results.

The influence of MTW-value and the effectiveness of MTW programming is shown in Fig. 7. It is proven that MAM policy can reduce *ETC* up to 27% comparing with Individual maintenance mode (IMM) of $T_w = 0$ and Simultaneous maintenance mode (SMM) of $T_w = 25{,}000$. Besides,

Table 3 Machine parameters

j	m_j	η_j	T_{pij}	T_{fij}	C_{pij}	C_{fij}	c_{dij}	a_{ij}	b_{ij}
1	3.0	8000	140	600	5000	35,000	80	$i/(15i+5)$	$(17i+1)/(16i+1)$
2	2.0	7000	120	200	6000	18,000	40	0.03	1.04
3	1.5	12,000	200	350	2000	15,000	30	$i/(20i+20)$	1.03
4	3.0	13,000	80	300	7500	22,000	45	0.025	$(16i+3)/(15i+3)$
5	2.5	16,000	300	800	2500	25,000	75	$i/(16i+14)$	1.05

Table 4 System-level maintenance schedule based on MTW

j	Time point of PM activity (h)											
1	3319		6911	10,020	13,121		15,134	17,940		20,212		22,789
2	3319		6911	10,020			15,134		19,105			22,789
3		5108		10,020			15,134			20,212		
4			6911			14,455					21,984	
5		5108		10,020			15,134			20,212		

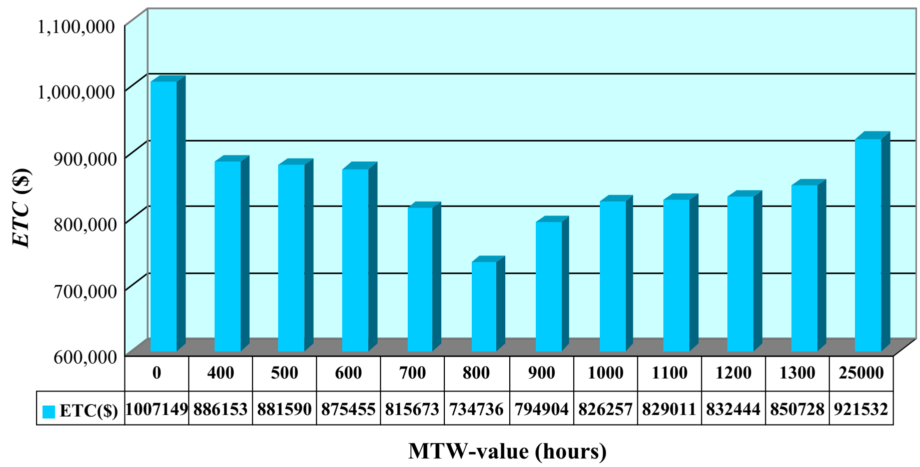

Fig. 7 *ETC* of the flow-line CPS with various MTW

it can be concluded that larger MTW value enables more machines to take advantage of maintenance opportunities, but too large MTW causes extra maintenance and more *ETC* will be needed for CPS.

Moreover, traditional opportunistic maintenance policies calculate the cost-savings of all possible combinations at each cycle with the exponential decision-making complexity of $O(2^{(J-1)})$. For example, Zhou et al. (2009) took a 3-unit system to illustrate the opportunistic PM scheduling algorithm, while the cost savings for 4 possible combinations were calculated at each opportunity. For our presented MTW policy, since the numbers of parallel/series subsystems and their respective machines are all smaller than J, the maximal decision-making complexity at each opportunity is less than $2J^2$. Thus, the MTW complexity is just polynomial with total machine number J, which means even a complex flow-line CPS with a large number of machines can be handled.

Effectiveness of APB policy

Faced with sequential batch orders, APB dynamically utilizes set-up works and analyzes the cost savings to reduce the total system maintenance cost. PM intervals and various batch orders are pulled to make opportunistic maintenances cycle by cycle. For a 7-unit mass customization CPS, results of production-driven opportunistic maintenance are presented in Table 5.

The results from mass customization CPS (Fig. 8) reveal that the mechanism of APB policy can ensure the lowest *ETC*. On the one hand, huge downtime cost saving ensures that *ETC* of APB policy is lower than those of

Table 5 APB results in sequential batch cycles

APB (cost)	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10
M1		−9204		−3269			−2725			4022
M2			2262	33	1865			1746		2790
M3			392	−6332				105		−902
M4			−110				4033			4555
M5		−78		5762	5934		3687	1758	−1640	
M6			526	−2332				336		151
M7				6490			1951			2250

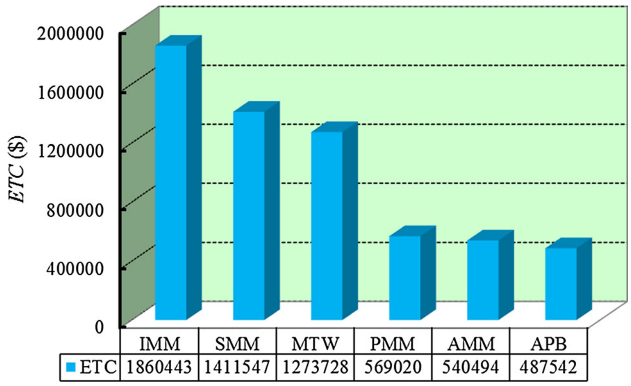

Fig. 8 Results comparison of opportunistic maintenance policies

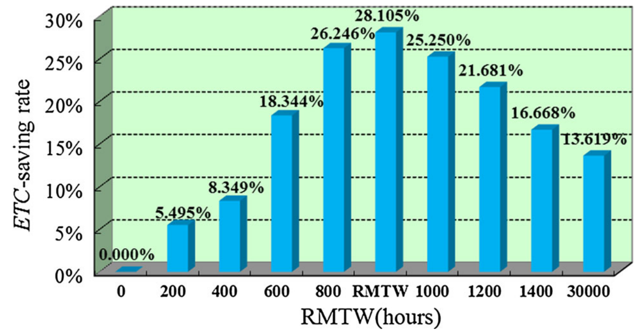

Fig. 9 ***ETC***-saving rate comparison with various methods

maintenance-driven opportunistic maintenance policies (e.g. IMM, SMM and MTW). On the other hand, APB dynamically compares cost savings and chooses PM adjustment with $Max\,\{SCA_{ju}, SCP_{ju}\}$, which is thus a more cost-effective policy than Advanced maintenance mode (AMM) and Postponed maintenance mode (PMM). Therefore, APB policy achieves significant cost reduction by considering batch characteristics and making PM adjustment based on maximum cost saving for each machine at each set-up time.

Effectiveness of RMTW policy

The RMTW policy is performed on a reconfigurable manufacturing CPS with changeable system structures shown in Fig. 4. In the first manufacturing stage ($MS1$), $T_{W1} = 800$ is applied for the RMTW programming as an example, while $T_{W2} = 600$ and $T_{W3} = 1000$ are taken for $MS2$ and $MS3$ separately. Table 6 shows the RMTW scheduling results for reconfigured system structures. At each system-level PM execution point t_k, $\Theta(j, t_k) = 0$ means no PM action but this machine will be down according to the system structure; $\Theta(j, t_k) = 1$ indicates a PM action is combined to be performed; while $\Theta(j, t_k) = 2$ evinces no PM and this machine continues working. Newly added or removed machines are considered in each manufacturing stage.

From the results of reconfigurable manufacturing CPS, we can find that different CPS structures with various machine reliabilities and changeable system-level reconfigurations would lead to different *ETC*-saving rates. However, RMTW policy is exactly designed to redefine the time width of T_{Wh} for minimizing the *ETC* in each manufacturing stage. Therefore, this optimization mechanism ensures that RMTW policy can not only be rapidly adapt to new diverse system structures, but also achieve cost effectiveness for the whole-CPS maintenance scheduling. In Fig. 9, results indicate that the*ETC*-saving rate (28.105% comparing to IMM) achieved by RMTW scheduling is much higher than traditional opportunistic maintenance policies (IMM, SMM and static MTW). It can be concluded that proposed RMTW policy is a viable and effective policy to achieve rapid responsiveness and cost reduction for future reconfigurable manufacturing.

Conclusions and perspectives

In this paper, we have presented systematic PHM methodologies for cyber-physical systems of three advanced man-

Table 6 RMTW results for reconfigurable manufacturing CPS

$\Theta(j, t_k)$	$MS1$				$MS2$					$MS3$		
t_k	4587	6042	9033	10251	12563	16012	18437	19147	19978	21955	24188	27538
M1	1	2	1	0	–	–	–	–	–	–	–	–
M2	1	0	0	1	0	1	2	0	0	1	0	1
M3	0	1	0	0	1	0	2	1	0	–	–	–
M4	0	2	1	0	2	0	1	2	0	2	0	1
M5	1	2	0	1	2	1	2	2	0	1	0	1
M6	–	–	–	–	2	1	2	2	1	2	1	1
M7	–	–	–	–	2	0	2	2	1	2	0	1
M8	–	–	–	–	–	–	–	–	–	2	0	1

ufacturing paradigms. With monitored and synchronized information from the cyber computational space, PHM methodologies integrating manufacturing characters in the physical factory floor can improve the health management. These developed prognosis algorithm, scheduling model and opportunistic maintenance policies achieve significant improvements in following aspects: (1) WFRGM algorithm provides real-time and accurate health predictions by incorporating updated information and influencing factors; (2) MAM method can output sequential PM intervals based on individual machine health for supporting the system-level opportunistic maintenance; (3) MTW policy schedules PM separations/combinations according to series-parallel structures for reducing maintenance cost and decision-making complexity; (4) APB policy achieves huge cost savings by utilizing set-up times to makes real-time PM optimizations and handle variable batch orders; (5) RMTW policy efficiently achieve rapid responsiveness and cost effectiveness for diverse open-ended reconfigurations and flexible system structures.

In sum, both cyber factors (information technologies) and physical factors (manufacturing paradigms) are essential for the health management of future CPS. Some industrial enterprises (i.e., port machinery manufacturers and automobile manufacturing companies) have already benefited from these novel PHM methodologies. Future work is needed to extending this hierarchical PHM framework to other burgeoning manufacturing paradigms, such as sustainable manufacturing, green production and cloud manufacturing.

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