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Energy-Oriented Maintenance Decision-Making for Sustainable Manufacturing Based on Energy Saving Window

In recent years, the industry's responsibility to join in sustainable manufacturing becomes huge, while innovating sustainability has been a new trend. Industrial enterprises are pursuing energy reduction to meet future needs for sustainable globalization and government legislations for green manufacturing. To run a manufacturing line in an energy-efficient manner, an energy-oriented maintenance methodology is developed. At the machine layer, the multi-attribute model (MAM) method is extended by modeling the energy attribute. Preventive maintenance (PM) intervals of each machine are dynamically scheduled according to the machine deterioration, maintenance effects, and environmental conditions. At the system layer, a novel energy saving window (ESW) policy is proposed to reduce energy for the whole line. Energy consumption interactivities, batch production characteristics, and system-layer maintenance opportunities are comprehensively considered. Real-time choice of PM adjustments is scheduled by comparing the energy savings of advanced PM and delayed PM. The results prove the energy reduction achieved by this MAM-ESW methodology. It effectively utilizes standby power, reduces energy consumption, avoids manufacturing breakdown, and decreases scheduling complexity. Furthermore, this energy-oriented maintenance framework can be applied not only in the automotive industry but also for a broader range of manufacturing domains such as the aerospace, semiconductor, and chemical industries.

[DOI: 10.1115/1.4038996]

Keywords: opportunistic maintenance, sustainable manufacturing, energy saving window, standby power

1 Introduction

For today's competitive market and variable demands, many enterprises have been pursuing the highly efficient batch production and cost-effective maintenance policies. A lot of studies have been devoted to reduce cost by integrating production characteristics [1]. In recent years, to meet future needs for sustainable globalization and government legislations for green manufacturing, energy control has become another research hotspot in industry and academy. Energy wastes lead to more carbon emissions, higher production cost, and contaminated natural environment. This urges enterprises to apply new green and sustainable technologies [2–4]. Thus, the energy-efficient health management will be urgently required to avoid environmental taxes and penalties [5–8]. For sustainable manufacturing, an innovative maintenance methodology should increase energy efficiency at the machine/system layer by real-time maintenance scheduling. This

framework should comprehensively consider diverse machine deteriorations, batch production characteristics, and energy consumption interactivities.

This energy-oriented maintenance methodology can be designed for series machining lines in batch production pattern. For example, automotive engine manufacturing involves die casting, machining, cutting, drilling or milling, where a large amount of energy is required. These manufacturing lines, such as engine block, cylinder head, crankshaft, and camshaft lines, should be kept in good conditions. Sequential batch orders are processed through different machines connected in series according to customer demands [9–12]. It is important to enable manufacturers to implement optimal energy efficiency practice and control the carbon production. Thus, the following issues need to be considered in the maintenance scheduling for each series system (such as a crankshaft line) as the batch production characteristics: (1) The series system structure causes energy consumption interactivities among the machines connected in series; (2) The standby power of every machine during each changeover activity between two batch cycles is much less than the working power; (3) Each batch order is independent with random lot size (different working

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Manuscript received June 1, 2017; final manuscript received December 28, 2017; published online February 15, 2018. Assoc. Editor: Karl R. Haapala.

durations of sequential batch cycles) according to variable market requirements. When machines are available and no maintenance action happens, the system provides stable production throughput for each batch cycle. Thus, batch production prefers no interruptions within each cycle to break the production of the whole line; and (4) The system-layer maintenance decision-making should respond rapidly to each batch ordered only a short time beforehand.

Our developed maintenance scheduling needs to fill the knowledge gap by understanding the interrelation of energy efficiency across different layers of each manufacturing line, both the machine layer and the system layer. We first analyze the machine-layer maintenance models for individual machines. For example, an engine crankshaft line consists of many different machines. It is essential to perform preventive maintenance (PM) actions to keep these machines in good condition [13–15]. Recently, sensor techniques of prognostic and health management provide real-time deterioration data [16–18]. Many valuable studies have been published on single-machine maintenance models, see, e.g., Elwany and Gebraeel [19], Liao et al. [20], and Xia et al. [21]. However, existing efforts mainly focus on maintenance cost, machine availability, or production time, while few of them pay attention to energy consumption. Thus, a machine-layer multi-attribute model (MAM) integrating energy attribute, besides cost and availability attributes, is required to dynamically schedule maintenance intervals. Individual machine deteriorations and different maintenance power values need to be integrated. In addition, maintenance effects and environmental conditions are taken into consideration. Furthermore, the sequential machine-layer PM scheduling should be interactive with the system-layer optimization for the whole manufacturing line.

Compared with the energy-efficient PM scheduling at the machine layer, the system-layer maintenance policy for reducing energy consumption is much more sophisticated. The machine interactions (economic, stochastic, and structural dependences) are considered to optimize PM intervals [22–24]. During the past several decades, many researchers have proposed maintenance strategies for multi-unit systems, see, e.g., Li et al. [25], Xia et al. [26], Ni and Jin [27], and Gu et al. [28]. These studies have played their important roles in promoting system-layer maintenance optimization. However, there are still some issues need to be addresses for novel sustainable manufacturing. First, few of existing strategies have focused on energy consumption interactivities via the system-layer view. Second, other than classical flow-line production, the random lot sizes in batch production should be considered for the industry. Third, most existing strategies suffer from the intractability when the number of machines grows. This implies that each maintenance opportunity at the system layer could be dynamically analyzed to achieve rapid decision-making.

In sum, an energy-oriented maintenance methodology not only considers individual machine deteriorations at the machine layer but also focuses on energy consumption interactivities, batch production characteristics, and system-layer maintenance opportunities at the system layer. Opportunistic maintenance policies have the advantage of adjusting PM actions to decrease system downtime and reduce maintenance cost, see, e.g., Chang et al. [29], Derigent et al. [30], and Ni et al. [31]. Traditional opportunistic maintenance policies focus on opportunities caused by maintenance actions. However, new challenges from batch production lines are not considered. That is, an incredible amount of energy is required and most of this demand is met by electricity. Only a few groundbreaking works have been devoted to maintenance policies for sustainable manufacturing, see, e.g., Sun and Li [32], Sari et al. [33], and Ye et al. [34]. Hoang et al. [35] investigated the energy efficiency indicator concept as a new indicator to be integrated in the maintenance decision-making process to support sustainability requirements. Xu and Cao [36] developed an average energy efficiency model and an average productivity model based on renewal reward theorem to analyze the energy and productivity performances of the deteriorating machine tool with

periodic maintenance. Different from previous studies, this study focuses on the following key improvements in the bi-layer maintenance decision-making for sustainable manufacturing: (1) Flexible machine-layer PM intervals are dynamically scheduled by integrating energy attribute according to machine deteriorations, other than periodic maintenance; (2) Each changeover activity between two batch cycles is utilized as the maintenance opportunity in a machining line, as a new kind of opportunistic maintenance; (3) The standby power at changeover times, much lower than the working power, is utilized to discover energy consumption interactivities in batch production, other than flow-line production; and (4) The designed mechanism of this energy-oriented opportunistic maintenance based on energy-saving maximizations in each cycle can ensure the total energy reduction and simplify the system-layer PM optimizations, even facing sequential batches with variable lot sizes.

In this paper, an energy-oriented maintenance methodology for sustainable manufacturing is proposed by enabling technologies both at the machine layer and at the system layer. For each machine in a series machining line, the MAM method with energy, cost, and availability attributes dynamically schedule PM intervals cycle by cycle ($i = 1, 2, 3, \dots$), while machine deteriorations, maintenance effects and environmental conditions are taken into consideration. By pulling these machine-layer PM intervals, the energy saving window (ESW) policy is proposed to achieve energy-efficient PM schemes for the whole line by utilizing each changeover duration ($k = 1, 2, 3, \dots$). Each changeover activity between two batch cycles is employed as a system-layer opportunity for performing PM actions on the machines that are originally not scheduled to be performed maintenance actions at this moment. The corresponding standby power can be utilized to reduce energy consumption. ESW optimization dynamically maximizes the energy saving of each machine in each cycle to obtain the real-time optimization of advanced PM, delayed PM or in situ PM. Meanwhile, the system-layer ESW results will be fed back to schedule the subsequent PM cycle in real time. Its aim is to help manufacturing companies to efficiently utilize standby power, reduce energy consumption, avoid manufacturing breakdown, and decrease scheduling complexity.

The remainder of this paper is organized as follows: Section 2 discusses the design framework of this MAM-ESW methodology. In Sec. 3, the MAM method integrating energy consumption is illustrated at the machine layer. In Sec. 4, the ESW policy is presented for maximizing the energy savings in a batch production line. Section 5 investigates case studies by applying the proposed methodology to demonstrate its effectiveness. Finally, some concluding remarks and future works are provided in Sec. 6.

2 Methodology Design

The research aims to develop a framework for energy-efficient maintenance management by integrating multilayer modeling and optimization methods. MAM-ESW methodology is designed to improve energy efficiency and reduce energy consumption, while high manufacturing quality and system throughput are maintained. PM is imperfect maintenance performed at the end of each PM interval. A PM action reduces the hazard rate of the machine, but not to be as good as new. Corrective repair (CR) is used if a machine fails during the PM interval. A CR action only recovers the machine to the failure rate it had when it failed. Traditional maintenance-driven opportunistic maintenance policies for flow-line production (e.g., maintenance time window policy [26]) utilize a PM action as the opportunity for other machines. In practice, the low standby power of each machine between successive batches can be used to reduce energy consumption. Therefore, each changeover activity can be considered as the new opportunity to maximize the energy saving. The design of this energy-oriented opportunistic maintenance methodology for batch production is illustrated and compared with maintenance time window policy in Fig. 1.

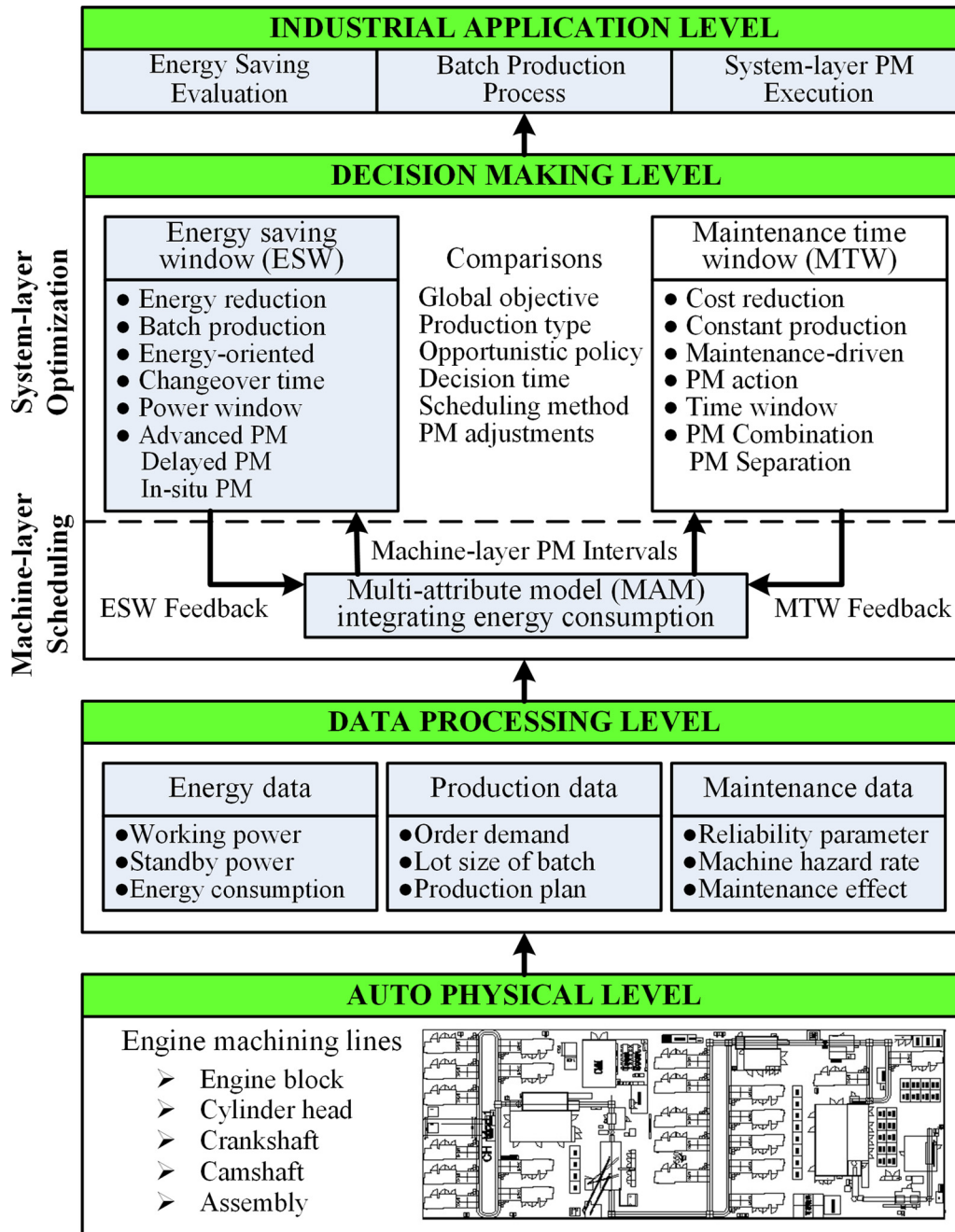


Fig. 1 Design of MAM-ESW methodology

The proposed MAM-ESW methodology consists of four levels: (1) Auto physical level describes and characterizes the scheduling object of a series batch production line. This methodology can be applied to each manufacturing line of engine block, cylinder head, crankshaft or camshaft. (2) Data processing level communicates energy data (working power, standby power, energy consumption), production data (order demand, batch duration, production sequence), and maintenance data (reliability parameter, maintenance effect, environmental condition) to support decision-making in real time. (3) Decision-making level is the core level that interactively performs the machine-layer scheduling and the system-layer optimization. Real-time PM intervals are pulled from the MAM method. ESW programming dynamically identifies energy saving opportunities and enhances energy efficiency by comparing the energy savings. (4) Industrial application level

executes the system-layer ESW results into the batch production and evaluates the overall energy saving.

In essence, this energy-oriented opportunistic maintenance focuses on the novel method of real-time maintenance adjustments for future sustainable globalization. The proposed ESW policy is designed not only to reduce energy consumption for governmental green legislations but also to ensure system throughput for variable batch orders. To avoid the breakdown caused by in situ PM during a batch production, ESW programming comprehensively analyzes the energy savings (breakdown energy saving, PM energy saving, and CR energy saving) of PM adjustments (advanced PM and delayed PM). It should be noticed that compared with the original scheme, in situ PM without PM adjustments cannot reduce energy consumption. And what is worse is, in situ PM during a batch production will interrupt the system

production and decrease the system throughput. Thus, the energy consumption of in situ PM is considered as the baseline to assess a larger energy saving of advanced PM and delayed PM. Each changeover opportunity with low standby power is utilized as the energy saving window, which can avoid production losses and reduce energy consumption simultaneously.

3 Multi-Attribute Model Method Integrating Energy Consumption

Within the machine-layer scheduling for each individual machine, a PM cycle is defined as the duration between two successive PM actions. The actual power of a PM action and the actual power of a CR action are analyzed to evaluate the maintenance energy consumption. The MAM method is proposed to output PM intervals cycle by cycle by integrating attributes of energy conservation, manufacturing costs, and production availability. Thereby, sequential PM intervals are obtained by solving the multi-attribute model consisting of maintenance energy rate, maintenance cost rate, and machine working rate according to the hazard rate evolution of the current cycle. Implementation of the machine-layer MAM scheduling involves the following procedures:

Procedure 1 (Data input): Assess energy parameters (P_{Pij}, P_{Rij}), maintenance parameters ($T_{Pij}, T_{Rij}, C_{Pij}, C_{Rij}$), imperfect maintenance effects ($a_{ij}, b_{ij}, \varepsilon_{ij}$) and the initial hazard rate function $\lambda_{ij}(t)$ from the data processing level for M_j . Start from the first PM cycle $i = 1$.

Procedure 2 (Single-attribute scheduling): Solve the energy model, the cost model and the availability model separately. The solutions are W_{ij}^* , T_{Wij}^* , C_{ij}^* , T_{Cij}^* , A_{ij}^* , T_{Aij}^* .

In the sustainable aspect, the energy consumption consists of the energy of a PM action and the possible energy of CR actions. Let T_{Wij} be the PM interval of the energy model, the maintenance energy rate of the i th PM cycle for M_j can be developed as

$$W_{ij} = \frac{P_{Pij} \cdot T_{Pij} + P_{Rij} \cdot T_{Rij} \int_0^{T_{Wij}} \lambda_{ij}(t) dt}{T_{Wij} + \left(T_{Pij} + T_{Rij} \int_0^{T_{Wij}} \lambda_{ij}(t) dt \right)} \quad (1)$$

where the numerator equals to the total maintenance energy; and the denominator equals to the total duration of this PM cycle, including the PM interval (i.e., the working duration), the duration of a PM action and the duration of expected CR actions. $\int_0^{T_{ij}} \lambda_{ij}(t) dt$ is the expected failure frequency during the PM interval. The optimal T_{Wij}^* corresponding to the minimum W_{ij}^* can be determined by $(dW_{ij}/dT_{Wij})|_T = 0$.

In addition, the economical aspect and the production aspect can also be considered in the sustainable manufacturing. The cost model (maintenance cost rate) and the availability model (machine working rate) of the i th PM cycle can be separately represented as

$$C_{ij} = \frac{C_{Pij} + C_{Rij} \int_0^{T_{Cij}} \lambda_{ij}(t) dt}{T_{Cij} + \left(T_{Pij} + T_{Rij} \int_0^{T_{Cij}} \lambda_{ij}(t) dt \right)} \quad (2)$$

$$A_{ij} = \frac{T_{Aij}}{T_{Aij} + \left(T_{Pij} + T_{Rij} \int_0^{T_{Aij}} \lambda_{ij}(t) dt \right)} \quad (3)$$

Similarly, the optimal T_{Cij}^* with the minimum C_{ij}^* is determined by $(dC_{ij}/dT_{Cij})|_T = 0$; while the optimal T_{Aij}^* with the maximum A_{ij}^* is determined by $(dA_{ij}/dT_{Aij})|_T = 0$.

Procedure 3 (Multi-attribute scheduling): By integrating these single-attribute models, MAM is developed based on the multiple attribute value theory to form an overall objective. Substitute the solutions (W_{ij}^* , C_{ij}^* and A_{ij}^*) from Procedure 2 into MAM. Then solve it by minimizing O_{ij} , where T_{Oij} replaces T_{Wij} , T_{Cij} , and T_{Aij} in the function.

On the one hand, since single attributes are different in the unit and quantity, expressions of W_{ij}/W_{ij}^* , C_{ij}/C_{ij}^* , and A_{ij}/A_{ij}^* are defined as the value functions to eliminate these differences. These value functions are preferred to be 1, if the corresponding measure achieves the best level. On the other hand, since a large value of A_{ij} is preferred, the expression $-A_{ij}/A_{ij}^*$ is utilized. Thus, the overall objective function of the machine-layer MAM is built as

$$\min O_{ij} = \gamma_{1ij} \frac{W_{ij}}{W_{ij}^*} + \gamma_{2ij} \frac{C_{ij}}{C_{ij}^*} - \gamma_{3ij} \frac{A_{ij}}{A_{ij}^*} \quad (4)$$

where γ_{1ij} , γ_{2ij} , and γ_{3ij} ($0 \leq \gamma_{ij} \leq 1, \gamma_{1ij} + \gamma_{2ij} + \gamma_{3ij} = 1$) are the weights of energy, cost, and availability, respectively. T_{Oij}^* is dynamically determined by $(dO_{ij}/dT_{Oij})|_T = 0$.

Procedure 4 (Lifetime check): Identify whether the cumulative PM interval $\sum T_{Oij}^*$ is beyond the machine lifetime. If no, turn to Procedure 5 and schedule the next PM cycle. Otherwise, turn to Procedure 6 and end the scheduling for M_j . The designed lifetimes of various machines can be obtained from their OEMs (original equipment manufacturers). The designed lifetime of M_j is just used as a measurable horizon to prove the effectiveness of this improved MAM method via the energy comparison.

Procedure 5 (Hazard rate evolution): Assess an imperfect PM based on internal factors (maintenance effects) and external factors (environmental condition) to describe the hazard rate of the next PM cycle. Then assign $i = i + 1$ and turn back to Procedure 2 to schedule the next PM cycle.

On the one hand, a PM action not only reduces the hazard rate to a lower value, other than to be as good as new, but also changes the slope of the hazard rate function. On the other hand, if a machine is working in poor environmental conditions, it degrades faster. Therefore, the relationship of the hazard rates before and after the i th PM action is defined as

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

where T_{ij} is the actual PM interval of the last PM cycle after the system-layer ESW optimization. The age reduction factor $0 < a_{ij} < 1$ indicates that each imperfect PM makes this machine's initial failure rate become $\lambda_{ij}(a_{ij} T_{ij})$ for the next cycle. The hazard rate increase factor $b_{ij} > 1$ indicates that imperfect PM magnifies the failure rate along with the deterioration process. Meanwhile, the environmental factor $\varepsilon_{ij} > 1$ reflects that the hazard rate is affected by external factors such as temperature, humidity, climate, and so on. These factors can be extracted and predicted based on historical maintenance data and online monitoring information [37,38].

Procedure 6 (Result output): The sequential PM scheduling for M_j has been complete. PM intervals T_{Oij}^* are pulled to support system-layer ESW optimization in real time. Based on these inputs from each machine, ESW programming dynamically identifies energy saving opportunities and enhances overall energy efficiency for the whole line.

4 Energy Saving Window Programming for Batch Production Systems

At the system layer, sequential batch orders and real-time machine-layer PM intervals are pulled as the inputs. ESW programming dynamically identifies energy saving opportunities and enhances overall energy efficiency by comparing the energy savings of advanced PM and delayed PM. In essence, this policy is

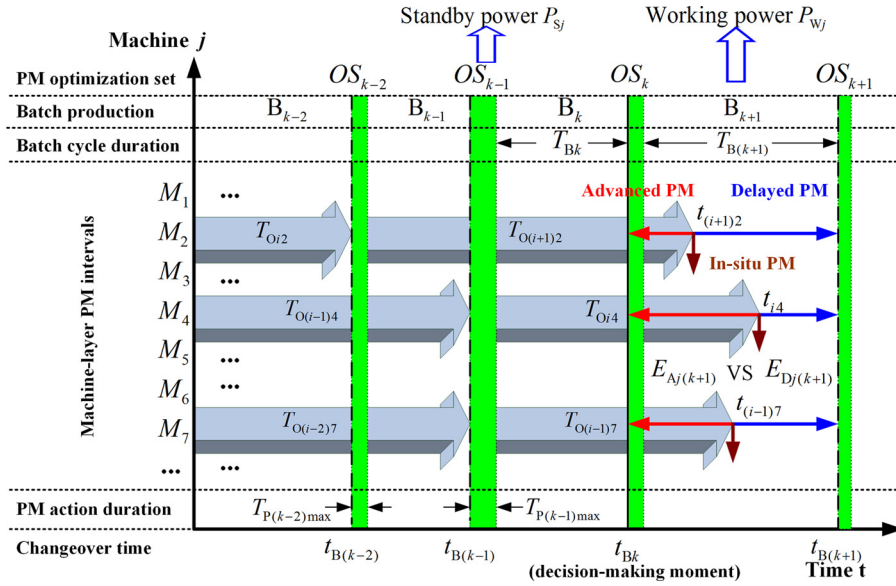


Fig. 2 Illustration of ESW programming

designed to avoid PM interruptions within each cycle to ensure the system throughput, and thus reduce energy consumption due to unnecessary system breakdown and extra maintenance actions. These system-layer PM optimizations aim to efficiently utilize standby power, reduce energy consumption, avoid manufacturing breakdown, and decrease scheduling complexity.

4.1 Mechanism of Energy-Oriented Opportunistic Maintenance. For a batch production line, variable batch orders are processed through diverse machines sequentially. In practice, the standby power values of the machines during each changeover activity are much less than their working power values. In addition, the series structure of a machining line causes energy consumption interactivities among individual machines. During a batch cycle, one machine's breakdown will interrupt the normal production. Unnecessary downtime of other machines in this line results in the energy waste of production losses. Therefore, the mechanism of energy-oriented opportunistic maintenance is designed as follows: Each changeover activity between two batch cycles is taken as a system-layer opportunity for performing PM on nonfailure machines. That is, corresponding standby power values are utilized to reduce energy consumption. Thereby, ESW programming dynamically maximizes the energy saving of each machine in each batch cycle. This optimization process can be illustrated in Fig. 2.

This ESW policy is performed as follows: A manufacturing line of engine crankshaft is taken as an example. The changeover time t_{Bk} ($k = 1, 2, 3, \dots$) before the next batch B_{k+1} is defined as the decision-making moment. The standby power P_{Sj} of every machine between two batch cycles is much less than its working power P_{Wj} . Thus, energy saving opportunities for PM adjustments arise, while the time duration of next batch production $T_{B(k+1)}$ can be pulled for decision-making. If expected PM times t_{ij} for machines M_j (such as $j = 2, 4, 7$) are originally scheduled in B_{k+1} according to machine-layer outputs, ESW programming will compare the energy savings at the changeover time. Then, PM actions can be adjusted to the current PM optimization set OS_k at t_{Bk} (advanced PM), to the next OS_{k+1} at $t_{B(k+1)}$ (delayed PM) or still at t_{ij} (in situ PM, negative energy savings). The corresponding expressions of the energy saving of advanced PM $E_{Aj(k+1)}$ and the energy saving of delayed PM $E_{Dj(k+1)}$ will be presented to decide the real-time system-layer optimization $\Psi(j, t_{Bk})$ for each machine.

4.2 Energy Saving Maximization of Preventive Maintenance Adjustments. At each new changeover time, the system-layer optimization of advanced PM, delayed PM, or in situ PM for each machine is decided dynamically according to $E_{Aj(k+1)}$ and $E_{Dj(k+1)}$.

4.2.1 Energy Saving of Advanced PM. The series structure of a machining line and the standby power values should be considered. Thus, the energy saving of advanced PM before the batch B_{k+1} (M_j is performed the PM action in advance at time t_{Bk}) consists of three sources:

$$E_{Aj(k+1)} = E_{Aj(k+1)}^B - E_{Aj(k+1)}^P + E_{Aj(k+1)}^C \quad (6)$$

(1) *Breakdown energy saving of advanced PM.* In a sustainable machining line, a breakdown of one machine caused by in situ PM during a batch production will cause the downtime of the whole system. It means in situ PM will affect the throughput of the normal system production. For ensuring this critical manufacturing performance, ESW programming utilizes maintenance adjustments to ensure the system production. Advanced PM or delayed PM is thus preferred to avoid production losses and reduce energy consumption. Without this production breakdown, all machines of the system can be working with their working power values P_{Wj} to ensure the throughput during sequential batches. We develop the breakdown energy saving of advanced PM measured by comparing the PM duration T_{Pij} (i.e., the system downtime). By advancing the PM action of the machine j to the changeover time, its power decreases from the working power P_{Wj} to 0. The energy saving of this machine j is $(P_{Wj} - 0) \cdot T_{Pij}$. For all other machines ($\forall J \neq j$), their power values decrease from individual working power values P_{Wj} to their standby power values P_{Sj} . The corresponding energy savings of these machines can be $\sum_{\forall J \neq j} (P_{Wj} - P_{Sj}) \cdot T_{Pij}$. Thus, the breakdown energy saving of avoiding production interruption can be represented as

$$\begin{aligned} E_{Aj(k+1)}^B &= \sum_{\forall J \neq j} (P_{Wj} - P_{Sj}) \cdot T_{Pij} + P_{Wj} \cdot T_{Pij} \\ &= \sum_J (P_{Wj} - P_{Sj}) \cdot T_{Pij} + P_{Sj} \cdot T_{Pij} \end{aligned} \quad (7)$$

(2) *PM energy saving of advanced PM.* To analyze the PM energy saving of advanced PM, we use the additional PM

frequency caused by advancing a PM action before the batch B_{k+1} (M_j performed the PM action in advance at time t_{Bk}). It is because that all advanced PMs (shorter PM intervals) will cause more PM actions and correspondingly more PM energy consumption within a time horizon. For example, within the same time horizon T_H , the original total PM frequency N will be T_H/T_{Oij}^* . If each PM interval is shortened by ΔT , the total additional PM frequency ΔN will be $T_H/(T_{Oij}^* - \Delta T) - T_H/T_{Oij}^*$; thus, we can measure the expected additional PM frequency $\Delta n = \Delta N/N = [T_H/(T_{Oij}^* - \Delta T) - T_H/T_{Oij}^*]/(T_H/T_{Oij}^*) = T_{Oij}^*/(T_{Oij}^* - \Delta T) - 1 = \Delta T/(T_{Oij}^* - \Delta T)$. Thus, for each changeover time, if an advanced PM is performed on M_j , its current PM interval will be reduced to a shorter interval $T_{Oij}^* - (t_{ij} - t_{Bk})$, while the PM interval change is $t_{ij} - t_{Bk}$. We can measure the addition of PM frequency for one advanced PM by the ratio of PM interval change and the actual PM interval $(t_{ij} - t_{Bk})/[T_{Oij}^* - (t_{ij} - t_{Bk})]$. Therefore, with the energy consumption of a PM action ($P_{Pij} \cdot T_{Pij}$), the PM energy saving of advanced PM (minus) can be defined as

$$E_{Aj(k+1)}^P = \frac{t_{ij} - t_{Bk}}{T_{Oij}^* - (t_{ij} - t_{Bk})} \cdot P_{Pij} \cdot T_{Pij} \quad (8)$$

(3) *CR energy saving of advanced PM.* In contrast to the PM energy saving, the CR energy saving can be achieved by advancing a PM action. ESW programming uses each changeover activity as the system-layer opportunity for adjusting PM. This sequential and dynamic decision-making mode requires energy saving analysis of each PM adjustment in real time, other than static long-periodic scheduling. It means we should measure the energy saving of each PM adjustment. For each advanced PM, CR energy saving is calculated based on the adjusted PM interval to measure the reduction of the expected CR frequency. Since the change of expected CR frequency $\int_0^{T_{Oij}^*} \lambda_{ij}(t)dt - \int_0^{T_{Oij}^* - (t_{ij} - t_{Bk})} \lambda_{ij}(t)dt$ can be calculated by the change of the PM interval $t_{ij} - t_{Bk}$ of this cycle, the CR energy saving can be obtained by directly comparing the original PM interval and the shortened PM interval. Obviously, a shorter interval $T_{Oij}^* - (t_{ij} - t_{Bk})$ reduces the cumulative failure risk. It means unnecessary energy of CR actions for unexpected machine failures can be reduced. Thus, the CR energy saving of advanced PM is evaluated as

$$E_{Aj(k+1)}^C = \left[\int_0^{T_{Oij}^*} \lambda_{ij}(t)dt - \int_0^{T_{Oij}^* - (t_{ij} - t_{Bk})} \lambda_{ij}(t)dt \right] \cdot P_{Rij} \cdot T_{Rij} \quad (9)$$

4.2.2 *Energy Saving of Delayed PM.* Similarly, the energy saving of delayed PM after the batch B_{k+1} (M_j performed the PM action at time $t_{B(k+1)}$) consists of three sources. A longer interval $T_{Oij}^* + (t_{B(k+1)} - t_{ij})$ causes higher cumulative failure risk and corresponding more CR energy. And less PM actions during the lifetime can save PM energy. Therefore, the energy saving of delayed PM is shown as

$$E_{Dj(k+1)} = E_{Dj(k+1)}^B + E_{Dj(k+1)}^P - E_{Dj(k+1)}^C \quad (10)$$

In this equation, $E_{Dj(k+1)}^B$ is the breakdown energy saving, $E_{Dj(k+1)}^P$ is the PM energy saving, and $E_{Dj(k+1)}^C$ is the CR energy saving of delayed PM. These three energy saving sources can be formulated as follows:

$$E_{Dj(k+1)}^B = \sum_j (P_{wj} - P_{sj}) \cdot T_{Pij} + P_{sj} \cdot T_{Pij} \quad (11)$$

$$E_{Dj(k+1)}^P = \frac{t_{B(k+1)} - t_{ij}}{T_{Oij}^* + (t_{B(k+1)} - t_{ij})} \cdot P_{Pij} \cdot T_{Pij} \quad (12)$$

$$E_{Dj(k+1)}^C = \left[\int_0^{T_{Oij}^* + (t_{B(k+1)} - t_{ij})} \lambda_{ij}(t)dt - \int_0^{T_{Oij}^*} \lambda_{ij}(t)dt \right] \cdot P_{Rij} \cdot T_{Rij} \quad (13)$$

4.2.3 *Energy-Oriented Choice of PM Adjustments.* Sequential PM adjustments are obtained according to the real-time calculations of the energy savings of the current cycles, not being relative to the future batch orders. The ESW policy dynamically maximizes the energy saving of advanced PM and delayed PM. It ensures the energy-efficient maintenance management. Based on the calculations of $E_{Aj(k+1)}$ and $E_{Dj(k+1)}$, system-layer optimizations can be made in real time:

- (1) $E_{Aj(k+1)} < 0$ & and $E_{Dj(k+1)} < 0$ means neither advanced PM nor delayed PM reduces energy. In situ PM still at t_{ij} will be chosen.
- (2) $E_{Aj(k+1)} > 0$ & and $E_{Dj(k+1)} < 0$ means advanced PM can reduce energy consumption, while delayed PM cannot. Advanced PM will be performed at t_{Bk} .
- (3) $E_{Aj(k+1)} < 0$ & and $E_{Dj(k+1)} > 0$ means energy can be reduced by delayed PM, nor by advanced PM. Delayed PM will be performed at $t_{B(k+1)}$.
- (4) $E_{Aj(k+1)} > 0$ & and $E_{Dj(k+1)} > 0$ causes a merit-based PM selection: $E_{Aj(k+1)} - E_{Dj(k+1)} > 0$ means advanced PM is the choice; Otherwise, delayed PM will be chosen when $E_{Aj(k+1)} - E_{Dj(k+1)} < 0$.

In sum, the system-layer ESW policy dynamically makes the real-time optimization of advanced PM, delayed PM or in situ PM. It ensures the total energy reduction and simplifies the system-layer PM adjustments. The maintenance decision for M_j at t_{Bk} can be obtained by

$$\Psi(j, t_{Bk}) = \begin{cases} 0 & \text{(in situ PM)} & E_{Aj(k+1)} < 0 \ \& \ E_{Dj(k+1)} < 0 \\ 1 & \text{(advanced PM)} & E_{Aj(k+1)} - E_{Dj(k+1)} > 0 \\ 2 & \text{(delayed PM)} & E_{Aj(k+1)} - E_{Dj(k+1)} < 0 \end{cases} \quad (14)$$

4.3 *Energy Saving Window Programming in Batch Production.* Above is the ESW programming for one machine in one system-layer batch cycle. In this section, the procedures of energy-oriented opportunistic maintenance for sequential batches B_k ($k = 1, 2, 3, \dots$) will be presented in detail.

Procedure 1 (Machine-layer PM input): Start the system-layer optimization from the first cycle $i = 1$. Pull real-time PM intervals T_{Oij}^* from the MAM scheduling and input expected PM times of each machine M_j

$$t_{ij} = T_{Oij}^* \quad (j = 1, 2, 3, \dots) \quad (15)$$

Procedure 2 (Batch production input): At each changeover time t_{Bk} ($k = 1, 2, 3, \dots$), pull the new batch B_{k+1} (production duration $T_{B(k+1)}$). Start from the beginning time $t_{B0} = 0$. Every machine will be checked that based on machine-layer expected PM times t_{ij} , whether M_j is originally scheduled to be performed a PM action in the new batch production

$$\Phi(j, t_{Bk}) = \begin{cases} 0 & t_{ij} \notin (t_{Bk}, t_{Bk} + T_{B(k+1)}) \\ 1 & t_{ij} \in (t_{Bk}, t_{Bk} + T_{B(k+1)}) \end{cases} \quad (16)$$

Procedure 3 (Energy saving calculation): For $\forall \Phi(j, t_{Bk}) = 1$, calculate energy savings of advanced PM $E_{Aj(k+1)}$ and delayed PM $E_{Dj(k+1)}$ of each machine. Their breakdown energy saving, PM energy saving, and CR energy saving can be obtained via Eqs. (6)–(13).

Procedure 4 (ESW PM adjustment): Take each changeover activity as a system-layer opportunity. For $\forall \Phi(j, t_{Bk}) = 1$, ESW programming makes real-time optimizations of advanced PM (in

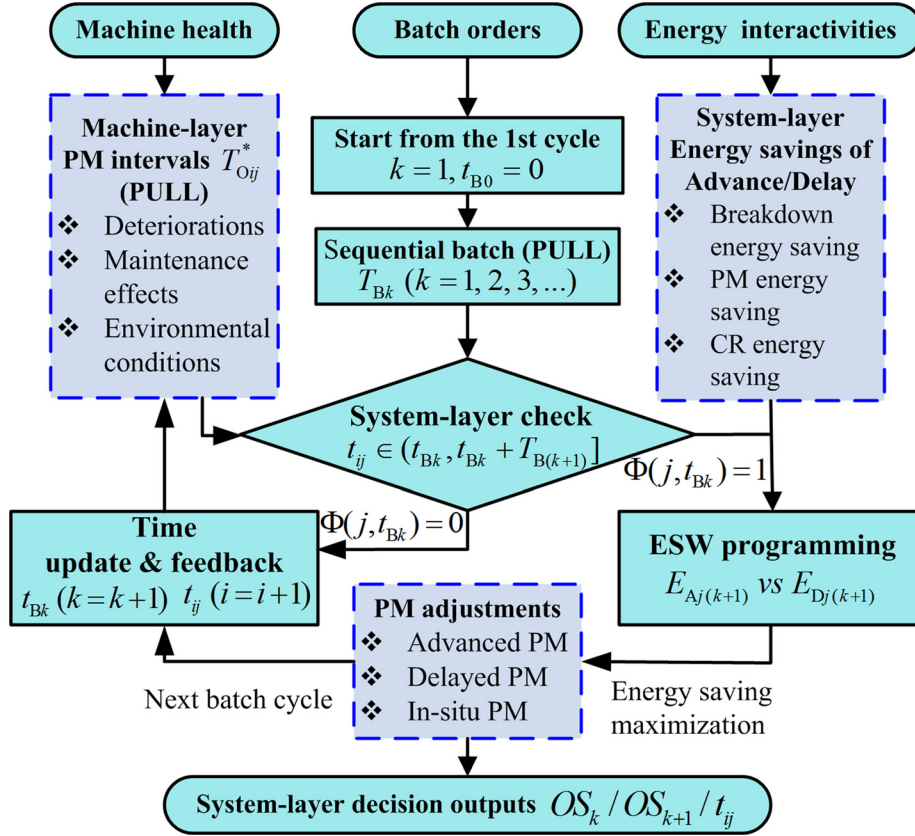


Fig. 3 Flowchart of energy-oriented maintenance decision-making

the current PM optimization set OS_k), delayed PM (in the next set OS_{k+1}), or in situ PM. The real-time PM adjustment $\Psi(j, t_{Bk})$ for M_j at t_{Bk} can be obtained by Eq. (14). It is worth noting that no PM action is adjusted to be performed at $t_{B0} = 0$.

Procedure 5 (Time update and feedback): For the next batch cycle, we first assign $k = k + 1$. Then, update the changeover time t_{Bk} in the system-layer optimization and the expected PM

time t_{ij} of M_j ($j = 1, 2, 3, \dots$) based on the machine-layer scheduling, where new PM intervals are scheduled according to actual PM intervals from ESW feedback by Eq. (5)

$$t_{Bk} = t_{B(k-1)} + \sum_{\Psi(j, t_{B(k-1)})=0} T_{Pij} + \delta(OS_{k-1})T_{P(k-1)\max} + T_{Bk} \quad (17)$$

$$t_{ij} = \begin{cases} t_{ij} + \sum_{\Psi(j, t_{B(k-1)})=0} T_{Pij} + \delta(OS_{k-1})T_{P(k-1)\max} & \Phi(j, t_{B(k-1)}) = 0 \\ t_{(i-1)j} + \sum_{\Psi(j, t_{B(k-1)})=0} T_{Pij} + \delta(OS_{k-1})T_{P(k-1)\max} + T_{Oij}^* \quad (i = i + 1) & \Psi(j, t_{B(k-1)}) = 0 \\ t_{B(k-1)} + \sum_{\Psi(j, t_{B(k-1)})=0} T_{Pij} + \delta(OS_{k-1})T_{P(k-1)\max} + T_{Oij}^* \quad (i = i + 1) & \Psi(j, t_{B(k-1)}) = 1 \\ t_{Bk} + \delta(OS_k)T_{Pk\max} + T_{Oij}^* \quad (i = i + 1) & \Psi(j, t_{B(k-1)}) = 2 \end{cases} \quad (18)$$

$$\delta(OS_k) = \begin{cases} 0 & |OS_k| = 0 \\ 1 & |OS_k| > 0 \end{cases} \quad (19)$$

where $|OS_k| = 0$ means there is no PM action in the PM optimization set OS_k . Otherwise, define $|OS_k| > 0$.

It is worth noting that if an unscheduled failure happens on one machine M_j during a batch production, a CR action will be performed to recover this failed machine to its operational state. Since the machines are connected in series, the whole

manufacturing line will experience a downtime (time duration of this CR action). Thus, the following changeover time t_{Bk} and all the new PM time points t_{ij} for M_j ($j = 1, 2, 3, \dots$) will be added the CR time duration T_{Rij} .

Procedure 6 (System-layer decision output): Output and execute system-layer ESW results. If there is a new batch order coming, turn back for system-layer check $\Phi(j, t_{Bk})$ in Procedure 2. Then calculate the energy saving $E_{Aj(k+1)}$ and $E_{Dj(k+1)}$ in Procedure 3. Moreover, perform PM adjustments $\Psi(j, t_{Bk})$ for system-layer optimizations in Procedure 4. Then, time update and

Table 1 Energy and maintenance data of individual machines

j	$P_{Wj}(\text{kW})$	P_{Sj}	P_{Pij}	P_{Rij}	T_{Pij}	T_{Rij}	C_{Pij}	C_{Rij}	(m_j, η_j)	$(a_{ij}, b_{ij}, \varepsilon_{ij})$
1	48	20	400	280	18	60	6800	17,000	(3.0, 8000)	(0.03, 1.025, 1.032)
2	100	40	1100	700	24	70	9000	32,000	(1.6, 7200)	(0.018, 1.035, 1.01)
3	30	15	440	200	9	40	3000	8700	(2.2, 10,000)	(0.025, 1.05, 1.015)
4	70	30	850	250	10	45	6200	18,000	(1.8, 12,000)	(0.04, 1.011, 1.022)
5	95	40	920	400	16	64	9900	28,500	(2.6, 9600)	(0.02, 1.035, 1.015)
6	70	32	880	800	10	25	7200	21,400	(3.2, 15,000)	(0.015, 1.02, 1.025)
7	20	12	380	330	8	16	2700	5800	(1.3, 11,000)	(0.036, 1.01, 1.045)
8	42	18	500	260	18	64	5500	16,000	(2.5, 9400)	(0.05, 1.005, 1.035)
9	110	50	1400	760	30	85	8800	22,900	(2.8, 16,600)	(0.01, 1.025, 1.036)
10	6	2	100	50	6	30	2200	6000	(1.9, 7400)	(0.06, 1.018, 1.024)

Table 2 Production data of batch orders in sustainable manufacturing

B_k	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$
$T_{Bk}(\text{h})$	1500	3700	5600	2000	6000	1000	2500	2300	3400	2000

feedback will be carried out for the interactive bi-level scheduling in Procedure 5. This cyclic energy-oriented opportunistic maintenance scheduling is shown in Fig. 3.

5 Numerical Example and Discussion

To validate the developed MAM-ESW methodology, a production line of engine crankshaft is taken as an example. This series manufacturing system consists of ten individual machines, including Horkos RM80H-16, Boehringer CB320, Hegenscheidt MFD, Landis 5SE, Landis LT2, Boehringer NG200, and so on. The reliability of each machine is formulated by a Weibull function $\lambda_{1j}(t) = (m_j/\eta_j)(t/\eta_j)^{m_j-1}$, which has been widely used to fit repairable machines in mechanical engineering. For applying the energy-oriented maintenance decision-making, the energy and maintenance parameters are estimated by reliability engineers and shown in Table 1. Working/standby power values of individual machines and PM/CR power values of maintenance actions are essential to calculate the energy consumption with the corresponding durations. On the one side, working power values P_{Wj} of M_j ($j = 1, 2, 3, \dots$) are usually remarked on equipment nameplates and collected from the OEM, while standby power values P_{Sj} are also designed by OEM. On the other side, actual power values of corrective repairs P_{Pij} and actual power values of corrective repairs P_{Rij} are collected from reliability engineers, since it will be their duty to evaluate the energy consumption of each maintenance action within the plant. The production information of batch orders is pulled according to the market and shown in Table 2.

5.1 Effectiveness of Machine-Layer MAM Integrating Imperfect Maintenance Effects.

At the machine layer, MAM dynamically outputs PM intervals according to individual machine deteriorations. The case of $\gamma_{1ij} = 0.5, \gamma_{2ij} = 0.2, \gamma_{3ij} = 0.3$ is just taken as an example. It is worth noting that these objective weights reflect the enterprise attention of energy conservation, manufacturing costs, and production availability. The relative importance of these three objectives is measured by the weight ratio. In practice, there are lots of methods proposed to determine these objective weights, such as Delphi method, analytic hierarchy process, entropy method, and fuzzy cluster analysis [39]. In fact, no matter what value of γ_{1ij} is defined, MAM has already considered the energy attribute in its model. This ensures the lower maintenance energy rate than traditional cost and availability models. If the automobile company only considers the energy attribute at the machine layer, just assign $\gamma_{1ij} = 1$.

The designed experiment takes M_1 for the machine-layer example with the lifetime of 30,000 h. Its energy and maintenance

parameters can be seen in Table 1. For sustainable manufacturing, our MAM integrating imperfect maintenance effects aims to reduce the maintenance energy. The sequential PM intervals of this machine can be obtained by Eq. (4): $T_{O11}^* = 4758, T_{O21}^* = 4578, T_{O31}^* = 4408, T_{O41}^* = 4247, T_{O51}^* = 4093, T_{O61}^* = 3947, \dots$. Besides, three periodic single-attribute models are utilized to prove the effectiveness of MAM with imperfect maintenance effects. In these periodic models, internal factors (maintenance effects) and external factors (environmental condition) in Eq. (5) are not considered:

- (1) Periodic energy model ($\gamma_{1ij} = 1$) with constant $T_{W11}^* = T_{W21}^* = T_{W31}^* = \dots = 4791$ h from Eq. (1);
- (2) Periodic cost model ($\gamma_{2ij} = 1$) with $T_{C11}^* = T_{C21}^* = T_{C31}^* = \dots = 4681$ h from Eq. (2);
- (3) Periodic availability model ($\gamma_{3ij} = 1$) with $T_{A11}^* = T_{A21}^* = T_{A31}^* = \dots = 4251$ h from Eq. (3).

Figure 4 shows the energy comparison of various machine-layer models. This figure proves the effectiveness of the MAM integrating imperfect maintenance effects. The maintenance energy comparisons are calculated by $E = \sum_{i=1}^I (P_{P1i} \cdot T_{P1i} + \int_0^{T_{i1}^*} \lambda_{i1}(t) dt \cdot P_{R1i} \cdot T_{R1i})$. In this function, T_{i1}^* is replaced by $T_{O11}^*, T_{W11}^*, T_{C11}^*$, and T_{A11}^* for these four machine-layer models, and Eq. (5) are integrated to reflect the maintenance effects and environmental condition, whose values for M_1 are shown in Table 1.

Machine-layer PM intervals T_{O1i}^* from Eqs. (1) to (5) present the following performances:

- (1) When PM cycle i increases, T_{O1i}^* decreases. Because the underlying hazard rate increases faster when the machine

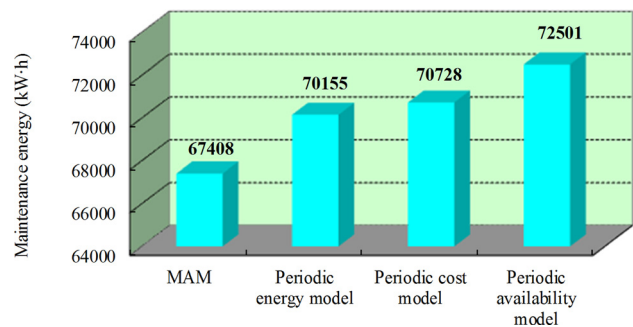


Fig. 4 Maintenance energy comparison with periodic machine-layer models

Table 3 ESW programming at second changeover time

M_j	t_{ij}	t_{B2}	T_{B3}	$\Phi(j, t_{B2})$	T_{Oij}^A	T_{Oij}^*	T_{Oij}^D	E_{Aj3}	E_{Dj3}	A-PM	I-PM	D-PM
M1	9778	5200	5600	1	0	4578	5600	-Inf	4716	-	-	Y
M2	6037			1	5200	6037	10,800	12,531	-36,209	Y	-	-
M3	6380			1	5200	6380	10,800	3303	-1756	Y	-	-
M4	10,305			1	5200	10,305	10,800	1331	3256	-	-	Y
M5	6118			1	5200	6118	10,800	6088	-14,505	Y	-	-
M6	8849			1	5200	8849	10,800	486	1934	-	-	Y
M7	17,367			0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M8	5929			1	5200	5929	10,800	6508	-7928	Y	-	-
M9	10,908			0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M10	9740			1	0	4540	5600	-Inf	1798	-	-	Y

Table 4 Energy saving calculation at second changeover time

M_j	E_{Aj3}^B	E_{Aj3}^P	E_{Aj3}^C	E_{Aj3}	E_{Dj3}^B	E_{Dj3}^P	E_{Dj3}^C	E_{Dj3}
M1	6336	Inf	3533	-Inf	6336	1314	2934	4716
M2	8928	4249	7852	12,531	8928	11,643	56,780	-36,209
M3	3123	898	1078	3303	3123	1621	6500	-1756
M4	3620	8345	6056	1331	3620	390	754	3256
M5	5952	2599	2735	6088	5952	6381	26838	-14,505
M6	3640	6175	3021	486	3640	1590	3296	1934
M7	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M8	6300	1262	1470	6508	6300	4059	18287	-7928
M9	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M10	2004	Inf	651	-Inf	2004	113	319	1798

ages. It reflects that the machine is subject to the degradation;

- (2) Ignoring the imperfect maintenance effects (a_{i1} , b_{i1} , and ϵ_{i1}) leads to extra energy consumption; thus MAM considering these effects can achieve more practical PM intervals T_{O1}^* ;
- (3) The comparison in Fig. 4 indicates that maintenance effects environmental condition should be considered in the hazard rate evolution to avoid extra energy consumption.

5.2 Analysis of System-Layer Energy Saving Window Utilizing Energy Saving. Energy saving window programming schedules energy-efficient PM adjustments at each changeover time. We start when the system enters operation $t_{B0} = 0$ ($k = 0$) with the first batch B_1 ($T_{B1} = 1500$ h). Expected PM times t_{ij} for machines M_j are scheduled based on machine-layer outputs: $t_{11} = T_{O11}^* = 4758$, $t_{12} = T_{O12}^* = 6037$, $t_{13} = T_{O13}^* = 6380$, $t_{14} = T_{O14}^* = 10,305$, $t_{15} = T_{O15}^* = 6118$, $t_{16} = T_{O16}^* = 8849$, $t_{17} = T_{O17}^* = 17,367$, $t_{18} = T_{O18}^* = 5929$, $t_{19} = T_{O19}^* = 10,908$, and $t_{1-10} = T_{O1-10}^* = 4770$. Since all $t_{ij} \notin (t_{B0}, t_{B0} + T_{B1}] = (0, 1500]$ ($\Phi(j, t_{B0}) = 0$), we just update $t_{B1} = t_{B0} + T_{B1} = 1500$. In the batch cycle $k = 1$ with a new B_2 ($T_{B2} = 3700$ h), t_{11} and $t_{1-10} \in (t_{B1}, t_{B1} + T_{B2}] = (1500, 5200]$. Since $E_{A11} = -5899$ and $E_{D11} = 5869$ and $E_{A1-10} = 1275$ and $E_{D1-10} = 1938$, these two machines are performed Delayed PMs at the next decision-making moment $t_{B2} = t_{B1} + T_{B2} = 5200$ (No PM at t_{B1} or in B_2). Their expected PM times are updated as $t_{21} = t_{B2} + T_{O21}^* = 5200 + 4578 = 9778$ and $t_{2-10} = t_{B2} + T_{O2-10}^* = 5200 + 4540 = 9740$. Then, ESW programming at second changeover time is taken as an example for energy saving calculating. Table 3 illustrates the decision-making process of expected PM actions at second changeover time, where “N/A” means the machine with $\Phi(j, t_{Bk}) = 0$ is not performed ESW programming. The changeover time $t_{B2} = 5200$ is defined as the decision-making moment, while the batch B_3 ($T_{B3} = 5600$ h) is obtained. $\Phi(j, t_{B2}) = 1$ means PM actions of these machines ($M_1, M_2, M_3, M_4, M_5, M_6, M_8, M_{10}$) are originally scheduled to be performed during this new batch. Thus, ESW optimization is performed at t_{B2} :

For M_4 , $E_{A43} = 1331$ and $E_{D43} = 3256$ means both advanced PM and delayed PM can reduce energy. Since $E_{A43} < E_{D43}$, delayed PM will be chosen to save more energy (OS_3).

For M_8 , $E_{A83} = 6508$ and $E_{D83} = -7928$ means advanced PM can reduce energy while delayed PM cannot, thus advanced PM will be performed at t_{B2} (OS_2).

For M_1 , its PM action is originally scheduled at $t_{12} = 9778$ ($T_{O12}^* = 4578$ h). M_1 has already been performed a PM action at t_{B2} because of the last-cycle ESW decision. If advanced PM is performed again, the actual interval $T_{O12}^A = T_{O12}^* - (t_{12} - t_{B2}) = 0$ makes $E_{A13}^P = \text{Inf}$ and $E_{A13} = -\text{Inf}$. This averts two PM actions at the same changeover time.

In addition, Table 4 shows how to get the values of E_{Aj3} and E_{Dj3} in Table 3. Each energy saving of advanced PM or delayed PM has to be calculated based on its breakdown energy saving, PM energy saving, and CR energy saving. Then, ESW programming dynamically make the decision by comparing $E_{Aj(k+1)}$ and $E_{Dj(k+1)}$.

Furthermore, ESW programming at fourth changeover time is taken as an example to show in situ PM decisions. In Table 5, $E_{A25} = -9152$ and $E_{D25} = -11,038$ for M_2 , while $E_{A55} = -14,223$ and $E_{D55} = -699$ for M_5 . It implies neither advanced PM nor delayed PM of these two machines can reduce energy in this batch cycle; thus, in situ PM still at t_{ij} will be the choice.

5.3 Results of Preventive Maintenance Adjustments for Sequential Batch Productions. To handle the randomness in batch production, the ESW policy is designed for responding rapidly to sequential variable batches. Like the examples at second and fourth changeover time, ESW programming maximizes the energy saving of each machine in each cycle to obtain real-time PM adjustments. The energy saving analysis for sequential batch productions and system-layer opportunistic maintenance results are shown in Tables 6 and 7. In Table 6, the energy savings of advanced PM E_{Ajk} and delayed PM E_{Djk} are obtained. A positive value means the energy saving occurs, while a negative value implies the energy loss.

Table 5 ESW programming at fourth changeover time

M_j	t_{ij}	t_{B4}	T_{B5}	$\Phi(j, t_{B4})$	T_{Oij}^A	T_{Oij}^*	T_{Oij}^D	E_{Aj5}	E_{Dj5}	A-PM	I-PM	D-PM
M1	15,262	12,854	6000	1	2000	4408	8000	870	-8020	Y	-	-
M2	16,491			1	2000	5637	8000	-9152	-11,038	-	Y	-
M3	16,717			1	2000	5863	8000	-1829	1260	-	-	Y
M4	20,799			0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M5	16,604			1	2000	5750	8000	-14,223	-699	-	Y	-
M6	19,492			0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M7	17,421			1	12,800	17,367	18,800	4798	1946	Y	-	-
M8	16,280			1	2000	5426	8000	-4293	575	-	-	Y
M9	21,462			0	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
M10	15,182			1	2000	4328	8000	1807	838	Y	-	-

Table 6 Energy saving analysis for sequential batch productions

ESW (kW h)	B_k	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$
M1	E_{A1k}	-	-5889	-Inf	-	870	2008	-	6440	4015	6491
	E_{D1k}	-	5869	4716	-	-8020	-3125	-	1934	1441	1914
M2	E_{A2k}	-	-	12,531	10,164	-9152	-	12,530	-	11,455	13,396
	E_{D2k}	-	-	-36,209	-4402	-11,038	-	6059	-	-19,767	6775
M3	E_{A3k}	-	-	3303	3283	-1829	-	-	2649	-	2698
	E_{D3k}	-	-	-1756	2071	1260	-	-	3034	-	3191
M4	E_{A4k}	-	-	1331	-	-	-	4135	-	-	4283
	E_{D4k}	-	-	3256	-	-	-	2213	-	-	3138
M5	E_{A5k}	-	-	6088	6182	-14,233	-	1511	-	-6870	-
	E_{D5k}	-	-	-14,505	1997	-699	-	5713	-	5545	-
M6	E_{A6k}	-	-	486	-	-	3734	-	-	2224	-
	E_{D6k}	-	-	1934	-	-	3475	-	-	3187	-
M7	E_{A7k}	-	-	-	-	4798	-	-	-	-	3472
	E_{D7k}	-	-	-	-	1946	-	-	-	-	2361
M8	E_{A8k}	-	-	6508	6349	-4293	-	-	5231	-	5334
	E_{D8k}	-	-	-7928	2900	575	-	-	5582	-	5837
M9	E_{A9k}	-	-	-	11,588	-	-	11,309	-	-	-
	E_{D9k}	-	-	-	6406	-	-	9662	-	-	-
M10	E_{A10k}	-	1275	-Inf	-	1807	1518	-	2061	2016	2038
	E_{D10k}	-	1938	1798	-	838	1127	-	1494	1434	1459

Table 7 System-layer results of energy-oriented opportunistic PM adjustments

	OS_1	OS_2	OS_3	OS_4	I-PM	I-PM	OS_5	OS_6	OS_7	OS_8	OS_9	OS_{10}
k	$k=1$	$k=2$	$k=3$	$k=4$	-	-	$k=5$	$k=6$	$k=7$	$k=8$	$k=9$	$k=10$
t_{Bk}	1500	5200	10,824	12,854	16,491	16,628	18,912	19,930	22,460	24,778	28,202	30,226
T_{Pkmax}	0	24	30	18	24	16	18	30	18	24	24	N/A
M1	-	PM	PM	PM	-	-	PM	-	PM	PM	PM	N/A
M2	-	PM	PM	-	PM	-	-	PM	-	PM	PM	N/A
M3	-	PM	PM	-	-	-	PM	-	-	PM	-	PM
M4	-	-	PM	-	-	-	-	PM	-	-	PM	N/A
M5	-	PM	PM	-	-	PM	-	-	PM	-	PM	N/A
M6	-	-	PM	-	-	-	PM	-	-	-	PM	N/A
M7	-	-	-	PM	-	-	-	-	-	-	PM	N/A
M8	-	PM	PM	-	-	-	PM	-	-	PM	-	PM
M9	-	-	PM	-	-	-	-	PM	-	-	-	N/A
M10	-	PM	PM	PM	-	-	PM	-	PM	PM	PM	N/A

Furthermore, according to the decision function $\Psi(j, t_{Bk})$, system-layer results of PM adjustments are shown in Table 7. It is worth noting that 45 PM actions are originally scheduled to be carried out during these ten batch cycles. By using our ESW policy, 43 PM actions have been adjusted to changeover moments. This scheme means that frequent system breakdown has been

avoided; thus, the system throughput has been ensured by no-interruption batch production.

5.4 Effectiveness of Energy-Oriented Opportunistic Maintenance Methodology. To prove the effectiveness of this MAM-ESW methodology, we investigate the system-layer

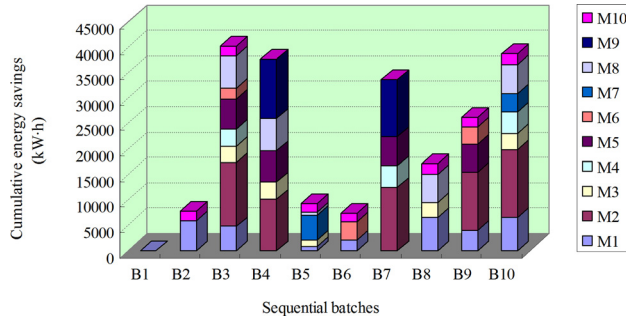


Fig. 5 System-layer cumulative energy savings in batch cycles

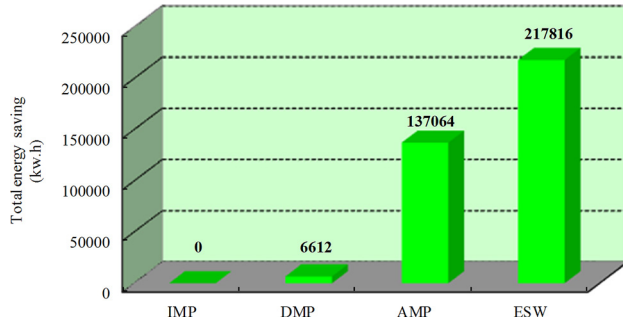


Fig. 6 TES comparison with classical policies

cumulative energy savings in sequential batch cycles. Three other classical maintenance policies are employed to make a comparison, where ESW programming achieves significant energy reduction for sustainable manufacturing.

In Fig. 5, the system-layer cumulative energy savings achieved in sequential batch cycles are presented. Notably, ESW programming of diverse machining lines with different energy data, production data, and maintenance data leads to various cumulative energy savings. However, the mechanism of ESW policy for dynamically maximizing the energy saving of each machine in each batch cycle to obtain the real-time optimization (advanced PM, delayed PM or in situ PM) can ensure its energy-efficient performance.

In sum, the aim of the MAM-ESW methodology is to achieve a significant energy reduction. Three classical maintenance policies are compared to validate the proposed ESW policy in Fig. 6: (1) Individual maintenance policy performs PM actions just at the original machine-layer PM times, which is defined as the baseline of the total energy saving (TES); (2) Delayed maintenance policy is promoted by PM energy saving for delaying all the PM actions to the next set OS_{k+1} , while TES = 6612 kW h is achieved in this case; and (3) Advanced maintenance policy is promoted by CR energy saving for advancing all the PM actions to the current set OS_k , while TES = 137,064 kW h can be achieved.

Whether the TES value of advanced maintenance policy is higher than that of delayed maintenance policy or not depends on the actual energy data, production data, and maintenance data of the machining line. However, by comparing the energy savings at each changeover time, ESW policy can certainly achieve the highest TES value by choosing the PM adjustments with $\text{Max}\{E_{Ajk}, E_{Djk}\}$ cycle by cycle. Thus, our ESW policy has achieved TES = 217,816 kW h, comparing with the performance of this system without using the optimization methods. In addition, this opportunistic maintenance policy can avoid the traditional scheduling complexity $O(2^{(J-1)})$. Because traditional opportunistic maintenance policies calculate all possible machine combinations at each decision-making time. Thus, ESW programming can deal with more complicated manufacturing systems, even when

the machine number J increases. Energy-oriented PM optimizations can be dynamically outputted for future sustainable manufacturing.

6 Conclusions

Most research studies on opportunistic maintenance focus on system-layer PM optimization without considering energy savings. For sustainable manufacturing, this paper proposes an energy-oriented maintenance framework to handle a machining line in batch production. The machine-layer MAM method integrates the energy attribute to dynamically schedule PM intervals. Furthermore, the system-layer ESW policy integrates energy consumption interactivities, batch production characteristics, and system-layer maintenance opportunities. The energy savings achieved by this MAM-ESW methodology have been demonstrated through an engine crankshaft line. Results indicate that the total energy saving achieved by ESW programming is much higher than classical opportunistic maintenance policies.

The mechanism of ESW policy ensures the significant energy reduction of manufacturing lines. This research provides an energy-oriented reliability management method to promote the application of sustainable manufacturing. Besides, real-time choice of PM adjustments can help managers to take timely and effective actions to keep the whole system in its good condition. Furthermore, the conception of opportunistic maintenance has been expanded by utilizing systems' changeover times and machines' standby power values. In the future work, we will improve the industrial implementation of this newly proposed ESW policy in the worldwide. Although systematic energy-oriented maintenance schedules can help to maximize the energy savings, we could also take real-time energy efficiency deterioration into consideration. How to model the potential relationship of energy efficiency deterioration and machine service age will be investigated in future studies, especially for the bottleneck machine with large work load and high energy consumption. Besides, it should be noticed that the power rating as shown on nameplates may not be representative of actual power consumption. Extensive measurement has to be carried out on all machines to apply the proposed framework in field setting.

Funding Data

- National Natural Science Foundation of China (Grant Nos. 51505288, 51475289, and 51705321).
- Programme of Introducing Talents of Discipline to Universities (Grant No. B06012).
- Foundation for Innovative Research Groups of National Natural Science Foundation of China (Grant No. 51421092).
- Fraunhofer Association-Shanghai Jiao Tong University Project Center for Smart Manufacturing (Grant Nos. ZN2017020101 and ZN2017020102).

Nomenclature

Parameters Description

- C_{Pij} = cost of a PM action (\$)
- C_{Rij} = cost of a CR action (\$)
- i = index of PM cycles in the machine-layer scheduling, $i \in \{1, 2, \dots, I\}$
- j = index of the machine M_j , $j \in \{1, 2, \dots, J\}$
- k = index of the batch production B_k , $k \in \{1, 2, \dots, K\}$
- P_{Pij} = actual power of a PM action (kW)
- P_{Rij} = actual power of a CR action (kW)
- P_{Sj} = standby power of M_j during changeover duration (kW)
- P_{Wj} = working power of M_j during batch production (kW)
- T_{Bk} = time duration of the batch production B_k (h)
- T_{Pij} = time duration of a PM action (h)

T_{Pkmax} = maximum duration for PM actions combined in OS_k (h)
 T_{Rij} = time duration of a CR action (h)

Functions

A_{ij} = availability of the i th PM cycle
 C_{ij} = cost rate of the i th PM cycle (\$/h)
 $E_{Aj(k+1)}$ = energy saving of advanced PM for M_j in B_{k+1} (kW h)
 $E_{Dj(k+1)}$ = energy saving of delayed PM for M_j in B_{k+1} (kW h)
 O_{ij} = machine-layer object of the i th PM cycle
 W_{ij} = energy rate of the i th PM cycle (kW)
 $\lambda_{ij}(t)$ = hazard rate function prior to the i th PM action

Decision Variables

OS_k = PM optimization set after B_k
 t_{Bk} = the changeover time after B_k for the system-layer optimization
 t_{ij} = the time of the i th PM from the machine-layer scheduling
 $T_{\Delta ij}$ = PM interval of the availability model (h)
 T_{Cij} = PM interval of the cost model (h)
 T_{Oij} = PM interval of the machine-layer MAM model (h)
 T_{Wij} = PM interval of the energy model (h)
 $\Psi(j, t_{Bk})$ = maintenance decision for M_j at t_{Bk}

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