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Optimal selective maintenance scheduling for series–parallel systems based on energy efficiency optimization

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HIGHLIGHTS

- An energy-oriented selective maintenance policy (ESMP) is developed.
- ESMP policy is applied to series–parallel multi-unit systems under sustainable manufacturing.
- Preventive maintenance and preventive replacement can be optimized comprehensively.
- Optimal maintenance schemes are obtained under limited maintenance resources.
- ESMP policy achieves a significant improvement of energy efficiency in batch production.

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ABSTRACT

With the industry sustainable development and increasing awareness of energy conservation, many manufacturing enterprises prefer to develop the operation and maintenance (O&M) with high production throughput and low energy consumption. In reality, many manufacturing systems are required to conduct a sequence of predefined missions with finite breaks between any two consecutive missions. To successfully complete the next mission production, maintenance actions are arranged and performed on machines during each scheduled break. In this paper, an energy-oriented selective maintenance policy (ESMP) for series–parallel systems is investigated. At each break, multiple maintenance actions with different impacts on machine degradation are available under limited maintenance resources. To obtain the throughput-and-energy based maintenance scheme, we first model the system energy efficiency based on system throughput and energy consumption. Then, we integer the energy efficiency modeling, production throughout analysis, and selective maintenance scheduling into an optimization model. And the model objective is to find the appropriate maintenance action for each machine at each break subject to cost and duration constraints. Numerical examples have been addressed to demonstrate the performance and adaptability of our proposed ESMP in long-term selective maintenance scheduling. Finally, a comparative analysis with traditional reliability-oriented policy shows the significant improvement of energy efficiency.

1. Introduction

All kinds of manufacturing enterprises in the world consume more than half of the energy, which is the main driver of the growth in energy demand [1,2]. As a fundamental issue in manufacturing enterprises, maintenance scheduling is essential to ensure machine reliability, production quality, and energy efficiency [3–5]. In this context, with the increasing awareness of energy conservation and emission reduction in the manufacturing industry, many manufacturing enterprises increasingly pursue operation and maintenance (O&M) with high production throughput and low energy consumption. On the one hand, the sustainable manufacturing paradigm has been proposed to meet the requirements of energy efficiency, as well as improve the competitiveness of enterprises in the face of economic globalization and green production [6,7]. On the other hand, numerous issues related to energy efficiency policies have been implemented by the governments to urge the industrial sectors to seek energy-saving potential. For example, time-of-

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Nomenclature

Sets

$\mathscr{M}$	Set of stations in the series–parallel system (index $i \in \mathscr{M} = \{1, 2, \cdots, M\}$)
$\mathscr{N}_i$	Set of machines in the station i (index $j \in \mathscr{N}_i = \{1, 2, \cdots, N_i\}$)
$\mathscr{U}$	Set of machining missions (index $u \in \mathscr{U} = \{1, 2, \cdots\}$)

Input parameters

M_{ij}	Machine j of the station i
T_{ij}^c	Duration of a CR action for machine M_{ij}
T_{ij}^p	Duration of a PM action for machine M_{ij}
T_{ij}^r	Duration of a PR action for machine M_{ij}
s_{ij}^1, s_{ij}^2	Capacity loss rate of machine M_{ij} under the operational state or failure state
$p_{ij}^1(t)$, $p_{ij}^2(t)$	Probability of machine M_{ij} under the operational state or failure state
C_{ij}^c	Cost for performing a CR action for machine M_{ij}
C_{ij}^p	Cost for performing a PM action for machine M_{ij}
C_{ij}^r	Cost for performing a PR action for machine M_{ij}
m_{ij}	Shape parameter of Weibull distribution for machine M_{ij}
η_{ij}	Scale parameter of Weibull distribution for machine M_{ij}
a_{ij}	Hazard rate increase factor for machine M_{ij}
b_{ij}	Age reduction factor for machine M_{ij}
P_{ij}^o	Power of operation for machine M_{ij}
P_{ij}^c	Power of a CR action for machine M_{ij}
P_{ij}^p	Power of a PM action for machine M_{ij}
P_{ij}^r	Power of a PR action for machine M_{ij}
ts_u	Start time of the u th mission
te_u	End time of the u th mission
T_u	Duration of the u th mission
TL^u	Mission-changing break between the u th mission and the $(u+1)$ th mission
CL^u	Maintenance cost limitation at the mission-changing break TL^u

Auxiliary decision variable

C^u	Total cost at the mission-changing break TL^u
T^u	Total maintenance duration in the mission-changing break TL^u
$\lambda_{ij}^u(t)$	Hazard rate function of machine M_{ij} in the u th mission
$q_{sys}^{lost}(t)$	Capacity loss rate of the series–parallel system at time t
E_{sys}^u	Total energy consumption in the u th mission
Q_{sys}^u	Total system throughput in the u th mission
EE_{sys}^u	Energy efficiency in the u th mission

Decision variable

x_{ij}^u	Binary variable: 1, if machine M_{ij} adapt a PM action at the mission-changing break TL^u, otherwise
y_{ij}^u	Binary variable: 1, if machine M_{ij} adapt a PR action at the mission-changing break TL^u, otherwise

use pricing, energy consumption allowance, and carbon tax regulation have been widely applied [8–10]. Therefore, these requirements and challenges motivate enterprises to develop energy-oriented maintenance policies that combine maintenance scheduling, energy control, and throughput improvement to achieve energy savings and systemic maintenance optimization [11].

In many industrial and military applications, especially in bath production, manufacturing systems are often required to execute a sequence of predefined missions during each batch order, and maintenance activities are performed during the break between two batch cycles [12]. Generally, enterprises often retain a limited pool of maintenance resources (i.e., maintenance duration, cost, and technician) to support maintenance activities for their multi-machine production systems. Therefore, to ensure production and control costs, enterprises typically prioritize the maintenance actions of machines and develop the optimal maintenance scheme based on limited maintenance resources [13]. There is a rich body of literature that is dedicated to studying selective maintenance policy (SMP) of production systems. And the purpose of these SMPs is to make a tradeoff between maintenance efficiency and consumption of all kinds of resources that restrict the execution of a complete set of desired maintenance actions. Some papers have focused on selective maintenance modeling with the consideration of system characteristics [14,15]. Typically, this line of work only considers perfect maintenance (failure replacement) and does not account for multiple maintenance actions. Others have studied the maintenance scheduling for the multi-unit system under different maintenance actions (i.e., minimal repair, preventive maintenance, and replacement) [16–18]. However, these mission-oriented studies mainly focus on the reliability-oriented selective maintenance policy (RSMP), where the maximization of system reliability is used as the objective function to guide systemic maintenance scheduling.

Our objective in this paper is to maintain a high level of energy efficiency and operating conditions for series–parallel systems while balancing limited maintenance resources with system performance. Therefore, the decision-maker is typically faced with an energy-oriented decision problem that arranges the optimal maintenance scheme during each mission-changing break. Specifically, we consider three types of actions for each machine: doing nothing (DN), preventive maintenance (PM), and preventive replacement (PR). However, the aforementioned RSMPs cannot be directly applied to solve this problem because they are not optimized from an energy perspective. In other words, the maintenance schemes obtained through RSMPs do not satisfy the requirement of sustainable manufacturing to ensure high production throughput and low energy consumption within the manufacturing enterprise. In this paper, we propose an energy-oriented selective maintenance policy (ESMP) that determines the appropriate actions (i.e., DN, PM, or PR) for each machine during each mission-changing break to achieve long-term O&M management.

With advances in technology, new energy consumption models and systemic maintenance policies have become technically and economically feasible. Moreover, there has been a trend to redefine some fundamental problems in manufacturing systems through the perspective of energy efficiency [19]. In reality, maintenance schemes optimized based on machine degradation and energy efficiency can significantly ensure system availability without deviating from the purpose of energy consumption. Chen et al. [20] explored the functional mapping relationship between reliability and processing energy consumption for machine-level maintenance scheduling optimization. Xu et al. [21] proposed a periodic maintenance policy for the deteriorating machine tools based on energy efficiency. Moreover, Xia et al. [22] presented an energy-oriented joint optimization of machine maintenance and tool replacement which extends the O&M management to the machine-tool system. It is worth noting that, most existing studies have mainly focused on energy model analysis of machines and opportunistic maintenance planning for series production systems. However, a real-life scenario faced by manufacturing enterprises usually has a more complex system construct and a more complex relationship between machine degradation and different levels of maintenance actions.

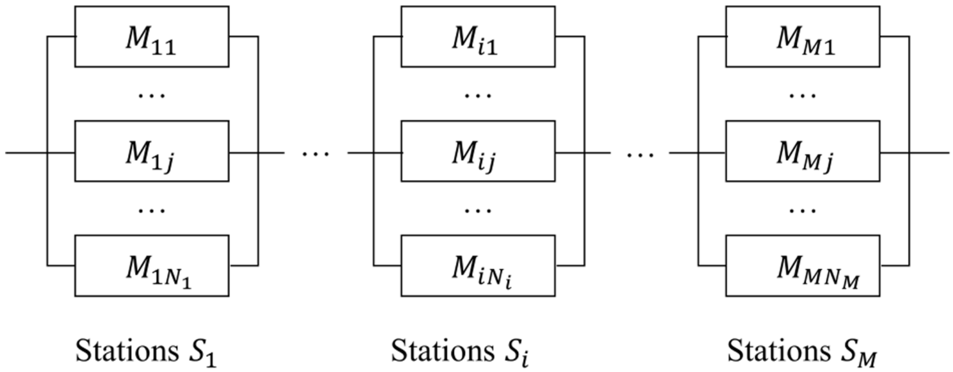

Fig. 1. Graphical model for the series–parallel system.

To the best of our knowledge, the selective maintenance policy of series–parallel systems based on energy efficiency optimization has not yet been appropriately addressed. Nevertheless, the above valuable studies rarely have incorporated energy efficiency into the SMP decision-making framework. Energy efficiency, as a fundamental index, is the ratio of throughput to energy consumption over the finite duration of the machining process [23]. In our proposed ESMP, we integrate the energy efficiency modeling, production throughout analysis, and selective maintenance scheduling into an optimization model to obtain the optimal maintenance scheme for series–parallel systems under limited resources. Therefore, the major contributions of this paper are summarized as follows:

1. We study the selective maintenance scheduling of series–parallel systems under the energy-saving transformation of manufacturing enterprises. To ensure high production throughput and low energy consumption of the next machining mission, we study a joint optimization problem to obtain the optimal maintenance scheme with limited resources at the current mission-changing break.
2. We propose an energy-oriented selective maintenance policy (ESMP) to formulate the research problem. We first model the total system throughput and energy consumption, so as to characterize the system energy efficiency. Then, we further consider the objective of maximizing the energy efficiency to optimize the appropriate maintenance actions of machines at each break.
3. To efficiently solve our proposed ESMP, the branch and band algorithm is customized. Moreover, based on the updating and rolling horizon, optimal maintenance schemes can be obtained sequentially by integrating real-time maintenance resource information and updated hazard rates of machines.
4. Different from traditional RSMPs, ESMP aims to pursue an energy-saving O&M process, so as to significantly improve the energy efficiency of series–parallel systems. From the perspective of maintenance schemes, ESMP provides lower total energy consumption, higher total throughput, and lower energy efficiency than RSMP across continuous missions.

The remainder of the paper is organized as follows. Section 2 describes the studied problem and the related assumptions. Section 3 introduces the mathematical formulation for energy efficiency. Section 4 illustrates the integrated selective maintenance model and customizes the branch and bound algorithm to solve this problem. Section 5 presents experimentation performed to illustrate the proposed policy. Finally, in Section 6, we conclude the article and discuss future research.

2. Problem statements

In modern industry, complex series–parallel systems are required to perform sequential machining missions. And there is a finite length intermission between two adjacent missions, which is called a mission-changing break. In this context, the manufacturing system is scheduled to execute the current mission, while maintenance actions are performed during the mission-changing break with limited maintenance resources to ensure the production of the next mission. In this paper, the mission-changing break is only for maintenance scheduling and does not involve system reconfiguration or tool replacement. Therefore, selective maintenance scheduling of series–parallel systems at each break is important to improve the energy efficiency of the subsequent mission. A graphical model of series–parallel systems is illustrated in Fig. 1. A complex system can be connected by multiple stations ($S_1,\cdots,S_i,\cdots,S_M$) in series, while station S_i is composed of multiple individual machines (M_{i1},

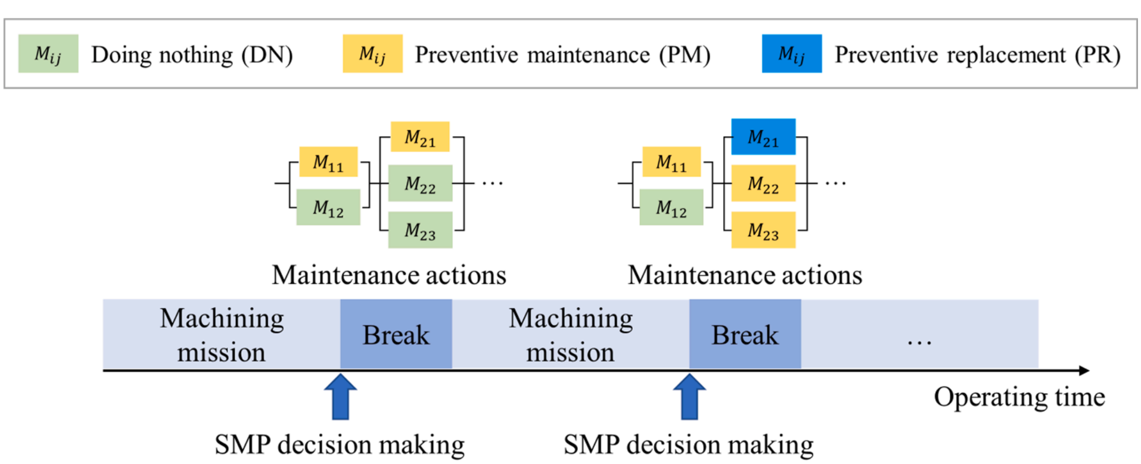

Fig. 2. Selective maintenance decision-making process.

$\cdots, M_{ij}, \cdots, M_{iN_i}$) connected in parallel.

For each machine of the series–parallel system, the failure rates of machines are independent of others. Maintenance actions are executed during the finite duration of mission-changing break TL_u to assure the continuity of missions and homogeneity of products. Because of the limitation of maintenance durations and costs, only a subset of maintenance actions can be performed to a subset of machines during each mission-changing break. In this paper, three types of maintenance actions can be performed on each machine during mission-changing breaks: doing nothing (DN), preventive maintenance (PM), and preventive replacement (PR). DN does not change the health condition of machines at all. PM can recover the machine to a better condition, but normally not as good as new. Whereas after a PR action, the machine is restored to brand new condition. Once a machine fails in the processing mission, corrective repair (CR) is executed to restore the machine and maintain the failure rate when the failure happens. Therefore, in order to calculate energy consumption $E(t)$ during each machining mission, we consider two types of energy consumption related to the machine condition: (1) operational and (2) corrective repair (CR).

Compared to traditional system-level maintenance scheduling, selective maintenance has special characteristics in terms of the selectivity of the machine being maintained, the constraints on maintenance resources, and the orientation to the objective function. The dynamic decision-making process includes the selection of the machine to be maintained and the corresponding maintenance actions, while different maintenance schemes will have different effects on the next machining mission. Therefore, during the mission-changing break TL_u between the u th and $(u+1)$ th mission, the decision-maker should allocate maintenance resources to promote the maximal energy efficiency. The decision-making process is illustrated in Fig. 2.

As mentioned above, this paper focuses on energy efficiency optimization while constructing the optimization model by considering both the total system throughput and the energy consumption over the $(u+1)$ th mission duration. The total system throughput is directly related to the structural dependency according to the bottleneck since the actual productivity of each station should be equivalent at any time. In our proposed ESMP, we firstly model the hazard rate updating of each machine after different maintenance actions. Then, the system-level energy efficiency metrics are constructed through the universal generating function (UGF). Based on the hazard rate and energy efficiency, we propose an optimization model with the maximization of energy efficiency as the objective function. Finally, the optimal selection and maintenance scheme under maintenance resource constraints are obtained by solving the optimization model. In detail, descriptions about capacity loss, machine failure, and energy consumption are as follows:

1. Assumed that machine M_{ij} processing speed per unit time is q_{ij}, and the processing speed of the series–parallel system is q_{sys}. When all the machine is at an operational state, the actual productivity of each station is equivalent with others according to the design of line-balance, that is $q_{\text{sys}} = \sum_{j=1}^{N_1} q_{1j} = \cdots = \sum_{j=1}^{N_M} q_{Nj}$. Obviously, the system loses all the capacity during the mission once all the machines in any station connected in parallel are failed.
2. During continuous production missions, random failures are inevitable and a major factor in production throughput degradation. Once a machine fails during the machining missions, the machines connected in the same station maintain regular productivity, while the machines of other stations are idle at times to keep the line balance. The impact of capacity loss caused by machine failure is allocated averagely. It is noted that proper maintenance schemes are important to reduce the risk of machine failures.
3. Electricity is regarded as the main form of energy consumption. For machine M_{ij} in the series–parallel system, the energy consumption can be derived when complementing the machining mission and the break between two adjacent missions. From all stages of machine processing, four types of energy consumption factors are considered. On the one hand, during the machining mission, the machines are in a binary state, i.e., it is either operational or failed. Therefore, the operational power is defined as P_{ij}^{o} and the power for the CR is defined as P_{ij}^{c}. On the other hand, during the break of two adjacent missions, the power of PM and PR are P_{ij}^{p} and P_{ij}^{r} respectively. We utilize the combination of different maintenance actions to improve the energy efficiency dynamically in the machining missions.

3. Energy efficiency formulation for a series–parallel system

In the proposed ESMP, we consider the energy efficiency of a series–parallel system to achieve maintenance scheduling optimization under a limited pool of maintenance resources. Considering the constraints of maintenance time and maintenance cost for the series–parallel batch production process, the optimal maintenance scheme guided by energy efficiency is obtained. As a direct indicator to evaluate the efficiency of energy consumption, energy efficiency is widely used in manufacturing processes to assess the sustainability of production systems. Generally, energy efficiency $EE(t)$ is defined as the ratio of total system throughput $Q(t)$ to energy consumption $E(t)$ [23]. In other words, energy efficiency $EE(t)$ represents the system throughput under unit energy consumption. Thus, the energy efficiency of manufacturing systems is formulated as:

$$EE(t) = \frac{Q(t)}{E(t)} \tag{1}$$

where $EE(t)$ represents the energy efficiency at the time t, $Q(t)$ represents the total system throughput and $E(t)$ represents the energy consumption. To evaluate the energy efficiency for a series–parallel system over the predetermined machining mission, formulations for constructing the total system throughput $Q(t)$ and the energy consumption $E(t)$ over the duration of a machining mission are prerequisites.

Throughput is generally defined as the total production of a system over a given period [24]. Universal generating function, as a widely used approach, is proposed to estimate the capacity loss due to machine failures for series–parallel multi-state systems [25]. In this paper, we use UGF to evaluate the total capacity loss, so as to obtain the total system throughput within the machining mission. Due to the uncertain breakdown and various CR duration in a production mission, the estimation for the total throughput is a fairly complex problem. To obtain the total throughput in the duration of a mission, we can estimate the capacity loss rate of the manufacturing system, which is directly caused by the demand for CR actions. Once the capacity loss rate equals 1, it means that the whole system breaks down comprehensively in the duration of CR actions. The UGF is introduced to describe the relationship between machine failure and capacity loss since the UGF is an efficient method to solve the structure dependency problems. In general, the UGF is in a polynomial form, which presents the probability mass function (PMF) of the discrete random variable. For any machine M_{ij} in the series–parallel system with k states $(s_{ij}^1, s_{ij}^2, \cdots, s_{ij}^k)$, the PMF of UGF is written as:

$$u_{ij}(z,t) = \sum_{k=1}^{K} p_{ij}^{k}(t) \bullet z^{s_{ij}^{k}} \tag{2}$$

where k denotes the number of states of the machine M_{ij}. p_{ij}^{k} represents the probability that the machine M_{ij} is in the state k and the random variable takes the value s_{ij}^{k}. And z is the transformation operator. It is worth noting that the UGF considers all the states and the corresponding probability that the decision-making object is involved.

For a series–parallel system, each machine has two states: operational state ($k = 1$) and failure state ($k = 2$). And the probability of operational state ($k = 1$) and failure state ($k = 2$) are denoted by $p_{ij}^{1}(t)$ and $p_{ij}^{2}(t)$, respectively. Moreover, s_{ij}^{1} and s_{ij}^{2} represent the proportion of capacity loss to the system level caused by the machine in operational state ($k=1$) and failure state ($k=2$). Specifically, if the machine is in an operational state, the corresponding capacity loss rate $s_{ij}^{1}=0$. And if the machine is in a failure state, s_{ij}^{2} represents the ratio of machine capacity to the total system capacity, denoted by $s_{ij}^{2}=q_{ij}/q_{sys}$.

As for the development of UGF for the series–parallel system, composition operators $\otimes_{per}$ and $\otimes_{ser}$ are introduced to illustrate the structural dependency. Firstly, for each station in a series–parallel system, multiple machines are connected in parallel and the total capacity loss rate is the sum of loss caused by machine failures. Then, based on the UGF, the capacity loss function for station S_i composed by parallel machines is defined as:

$$u_i(z,t)=\otimes_{per}\{u_{ij}(z,t)\}=\sum_{2}^{k_{i1}=1}\sum_{2}^{k_{i2}=1}\cdots\sum_{2}^{k_{iN_i}=1}\left(\prod_{N_i}^{j=1}p_{ij}^{k_{ij}}(t).z^{\sum_{N_i}^{j=1}s_{ij}^{k_{ij}}}\right) \tag{3}$$

Moreover, in terms of multiple stations connected in series, the capacity loss rate changes with time and equals maximal capacity loss. Therefore, for a series–parallel multi-unit system, the capacity loss of each station $S_i(i\in\mathscr{M})$ can be calculated by the parallel composition operator $\otimes_{per}$ separately, and then the overall capacity loss of the system is calculated by the series composition operator$\otimes_{ser}$. Therefore, the total capacity loss of the series–parallel system is defined as:

$$\begin{aligned}u_{sys}(z,t)&=\otimes_{ser}\{u_i(z,t)\}\\&=\sum_{2}^{k_{11}=1}\sum_{2}^{k_{12}=1}\cdots\sum_{2}^{k_{MN_M}=1}\left(\prod_{M}^{i=1}\prod_{N_i}^{j=1}p_{ij}^{k_{ij}}(t).z^{max\left\{\sum_{M_1}^{j=1}s_{1j}^{k_{1j}},\dots,\sum_{M_N}^{j=1}s_{Mj}^{k_{1j}}\right\}}\right)\end{aligned} \tag{4}$$

Besides, the probability of a machine state depends on the condition of machine degradation, which can be employed by the machine hazard rate $\lambda_{ij}(t)$. Thus, the corresponding probabilities for the operational state and the failures state are $p_{ij}^{1}=1-\lambda_{ij}(t)$ and $p_{ij}^{2}=\lambda_{ij}(t)$ respectively. Moreover, the capacity loss rate of the machine can be described by the production rate in the series–parallel system, which are $s_{ij}^{1}=0$ and $s_{ij}^{2}=q_{ij}/q_{\mathrm{sys}}$ respectively. Thus, based on the total capacity loss $u_{\mathrm{sys}}(z,t)$ derived by the UGF, the capacity loss rate $q_{sys}^{lost}(t)$ can be written as:

$$\begin{aligned}q_{sys}^{lost}(t)=&\sum_{k_{11}=1}^{2}\\&\times\sum_{k_{12}=1}^{2}\cdots\sum_{k_{NN_M}=1}^{2}\left(\prod_{i=1}^{M}\prod_{j=1}^{M_i}p_{ij}^{k_{ij}}(t)\bullet\max\left\{\sum_{j=1}^{M_1}s_{1j}^{k_{1j}},\cdots,\sum_{j=1}^{M_N}s_{Mj}^{k_{1j}}\right\}\right)\end{aligned} \tag{5}$$

Based on the above calculations, we can obtain the total throughput Q_{sys}^{u} for the series–parallel system in the machining mission u, as shown in Eq. (6). Firstly, the number of system capacity losses is obtained by deriving the system capacity loss rate $q_{sys}^{lost}(t)$ from the start time ts_u to the end time te_u of the current mission u. Then, by multiplying the number of system capacity losses with the duration of a CR action T_{ij}^{c}, the equivalent total system downtime is obtained. Finally, by subtracting the total mission processing time T_u from the equivalent total system downtime, the actual processing mission duration of the system is obtained.

$$Q_{sys}^{u}=q_{sys}^{operation}\bullet\left(\mathrm{T_u}-\sum_{i=1}^{M}\sum_{j=1}^{N_i}\mathrm{T_{ij}^{c}}\bullet\int_{\mathrm{ts_u}}^{\mathrm{te_u}}\mathrm{q_{sys}^{lost}(t)dt}\right) \tag{6}$$

where $q_{sys}^{operation}$ is the processing speed of the series–parallel system that all the machine are in the operational state, ts_u is the beginning time of the u th mission, te_u is the end time of the u th mission, T_u is the duration of the u th mission, and T_{ij}^{c} is the duration of a CR action for machine M_{ij}. And the summation of T_{ij}^{c} represents the total duration to restore machines one after another by CR actions. Besides, the integrating of the capacity loss rate over the duration of the mission $\int_{ts_u}^{te_u}q_{sys}^{lost}(t)dt$ illustrates the numbers of the system's capacity failure. And $\sum_{i=1}^{M}\sum_{j=1}^{N_i}T_{ij}^{c}$ represents the total duration to restore the system from capacity failure by adapting CR actions one by one.

On the basis of the total system throughput, the total energy consumption of the series–parallel system during each machining mission is further calculated to obtain an energy efficiency index. The energy consumption of each machine depends mainly on their working state, which includes (1) machine operation state (processes normal production) and (2) machine CR state (undergoes CR actions due to unexpected failures). Therefore, the power and duration parameters of each machine about operation state and CR state are collated separately to obtain the total energy consumption of the series–parallel system. The total energy consumption E_{sys}^{u} within mission u is formulated as:

$$E_{sys}^{u}=\sum_{i=1}^{M}\sum_{j=1}^{N_i}P_{ij}^{o}\bullet\left(\mathrm{T_u}-\mathrm{T_{ij}^{c}}\int_{\mathrm{ts_u}}^{\mathrm{te_u}}\lambda_{\mathrm{ij}}^{\mathrm{u}}(\mathrm{t})\mathrm{dt}\right)+\mathrm{P_{ij}^{c}}\bullet\mathrm{T_{ij}^{c}}\int_{\mathrm{ts_u}}^{\mathrm{te_u}}\lambda_{\mathrm{ij}}^{\mathrm{u}}(\mathrm{t})\mathrm{dt} \tag{7}$$

where P_{ij}^{o} is the power of operation for machine M_{ij} and P_{ij}^{c} is the power of a CR action for machine M_{ij}. T_u is the duration of the u th machining mission, T_{ij}^{c} is the duration of a CR action for machine M_{ij}, and $\int_{ts_u}^{te_u}\lambda_{ij}^{u}(t)dt$ represents the expected failure frequency of the u th machining mission. Accordingly, $\left(T_u-T_{ij}^{c}\bullet\int_{\mathrm{ts_u}}^{\mathrm{te_u}}\lambda_{\mathrm{ij}}^{\mathrm{u}}(\mathrm{t})\mathrm{dt}\right)$ represents the time interval when the machine is in operation state, and $T_{ij}^{c}\int_{ts_u}^{te_u}\lambda_{ij}^{u}(t)dt$ represents the time interval when the machine is in CR state. Meanwhile, it is true that different process parameters, cutting methods, or tool travel will correspond to different levels of machine health and energy consumption values. However, our proposed ESMP and energy consumption formulation E_{sys}^{u} can be expanded by updating the power of operation P_{ij}^{o} from a static fixed value to dynamic changeable value.

For a continuous machining mission u, energy efficiency can be obtained by formulating the ratio of total system throughput to total energy consumption, as defined in Eq. (1). Therefore, on the basis of the total system throughput Q_{sys}^{u} and total energy consumption E_{sys}^{u} obtained from Eq. (6) and Eq. (7), the energy efficiency EE_{sys}^{u} of the series–parallel system at mission u is formulated by:

$$EE_{sys}^{u}=\frac{Q_{sys}^{u}}{E_{sys}^{u}}=\frac{q_{sys}^{operation}\left(T_u-\sum_{i=1}^{M}\sum_{j=1}^{N_i}T_{ij}^{c}\int_{ts_u}^{te_u}q_{sys}^{lost}(t)dt\right)}{\sum_{i=1}^{M}\sum_{j=1}^{N_i}P_{ij}^{o}\bullet\left(T_u-T_{ij}^{c}\int_{ts_u}^{te_u}\lambda_{ij}^{u}(t)dt\right)+P_{ij}^{c}\bullet T_{ij}^{c}\int_{ts_u}^{te_u}\lambda_{ij}^{u}(t)dt} \tag{8}$$

By constructing the energy efficiency of series–parallel systems, the throughput per unit of energy consumption is modeled. Therefore, as the optimization objective of our proposed ESMP, energy efficiency can be considered integrally for the optimization of system throughput and energy consumption. Moreover, in the next section, the comprehensive consideration of resource constraints, energy efficiency optimization, and hazard rate evolutions corresponding to different maintenance actions is integrated into the maintenance decision-making process.

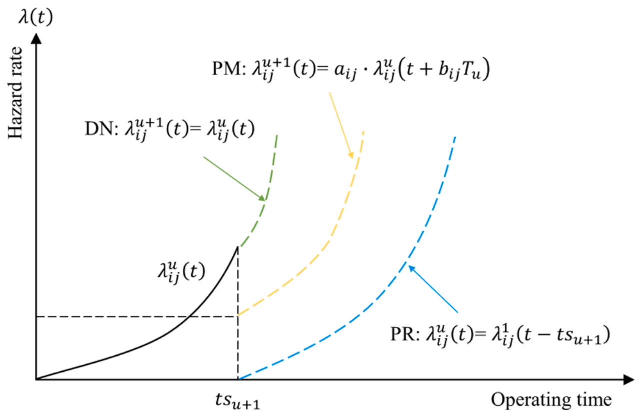

Fig. 3. Evolution of machine hazard rate.

4. Energy-oriented selective maintenance optimization

In this section, we first present the mathematical formulation for the proposed ESMP. In this model, we leverage limited maintenance resources and machine degradation assessment to derive the optimal decision-making for multiple maintenance operations to ensure the proper production of series–parallel systems. Then, a branch and bound algorithm is customized to solve the selective maintenance model accurately and efficiently.

4.1. The selective maintenance model based on energy efficiency optimization

To determine the most suitable maintenance action for machine M_{ij} under limited maintenance resources, we need to make decisions on the machine to be maintained and the corresponding maintenance actions (DN, PM or PR) to be taken, so as to maximize energy efficiency for the next machining mission period. For building the selective maintenance model, we consider two binary variables x_{ij}^{u} and y_{ij}^{u} to together define machine maintenance decisions. In retrospect, we consider three types of maintenance actions. Binary variable $x_{ij}^{u} = 1$ when machine M_{ij} is undergoing PM action at break TL^u. Binary variable $y_{ij}^{u} = 1$ when machine M_{ij} is experiencing PR action at break TL^u. In addition, when $x_{ij}^{u} = 0$ and $y_{ij}^{u} = 0$, machine M_{ij} does not perform PM or PR actions during the u th mission-changing break (execute DN action).

Moreover, the system health condition of completing the $(u+1)$ th mission is directly related to the decision-making during the break TL^u. Each machine is decided to be performed DN, PM or PR during the current u th break TL^u, then the hazard rate $\lambda_{ij}^{u+1}(t)$ and the expected failure frequency $\int_{ts_{u+1}}^{te_{u+1}} \lambda_{ij}^{u+1}(t)dt$ of the next $(u+1)$ th mission will be influenced. According to the formulation of total energy consumption E_{sys}^{u+1} as shown in Eq. (7), different hazard rates will directly lead to different energy consumption values. Meanwhile, the lower expected failure frequency also means stable output without wasting energy on unexpected CR actions. For the rest of this section, we introduce the maintenance resources constraints, hazard rate evolutions under different maintenance decisions, and the overall optimization model, respectively.

Firstly, we consider two kinds of resources constrains: a finite duration TL^u between two adjacent missions and a limited cost CL^u for maintenance in the mission-changing break. And the total cost C^u for maintenance actions in the mission-changing break TL^u is:

$$C^u = \sum_{i=1}^{M}\sum_{j=1}^{N} C_{ij}^{p} \bullet x_{ij}^{u} + \sum_{i=1}^{M}\sum_{j=1}^{N} C_{ij}^{r} \bullet y_{ij}^{u} \tag{9}$$

where C_{ij}^{p} is the cost for performing a PM action for machine M_{ij}, C_{ij}^{r} is the cost for performing a PR action for machine M_{ij}. The total duration T^u for the maintenance actions during the mission-changing break TL^u is given by [14]:

$$T^u = \sum_{i=1}^{M}\sum_{j=1}^{N} T_{ij}^{p} \bullet x_{ij}^{u} + \sum_{i=1}^{M}\sum_{j=1}^{N} T_{ij}^{r} \bullet y_{ij}^{u} \tag{10}$$

where T_{ij}^{p} and T_{ij}^{r} denote the duration of a PM action and a PR action for machine M_{ij}.

Secondly, the hazard rate $\lambda_{ij}^{u+1}(t)$ of machine M_{ij} for the next $(u+1)$ th mission will be influenced by different maintenance actions during the u th break TL^u. The hazard rate $\lambda_{ij}^{u+1}(t)$ would remain unchanged if DN action is taken on the machine M_{ij}. PR restores the hazard rate to the initial condition $\lambda_{ij}^{1}(t)$, while PM brings the serviced machine to a better condition but not as good as new. To formulate PM effects, internal and external factors are considered together to update the hazard rate after performing PM actions. The hazard rate after PM actions is given by:

$$\lambda_{ij}^{u+1}(t) = a_{ij}\lambda_{ij}^{u}(t + b_{ij}T_u) \tag{11}$$

where the a_{ij} is the hazard rate increase factor and b_{ij} is the age reduction factor for machine M_{ij} during the break TL^u between the mission u th and $(u+1)$ th. The evolution of hazard rate according to our considered actions (i.e., DN, PM, and PR) is illustrated in Fig. 3.

Combining with the binary variables x_{ij}^{u} and y_{ij}^{u} for maintenance decision-making, the update of hazed rates after maintenance actions performed at the break TL^u can be obtained iteratively:

$$\lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right) = \begin{cases} \dfrac{m_{ij}}{\eta_{ij}}\left(\dfrac{t}{\eta_{ij}}\right)^{m_{ij}-1} & u=0 \\ a_{ij}\lambda_{ij}^{u}(t+b_{ij}T_u)x_{ij}^{u} + \lambda_{ij}^{1}(t-ts_{u+1})y_{ij}^{u} + \lambda_{ij}^{u}(t)\left(1-x_{ij}^{u}-y_{ij}^{u}\right) & u>0 \end{cases} \tag{12}$$

Further, the total capacity and energy consumption in the $(u+1)$ th mission can be obtained based on the decision-making subsets. Thus, the energy efficiency EE_{sys}^{u+1} of the series–parallel system for the $(u+1)$ th mission is updated referring to the Eq. (8) as:

$$EE_{sys}^{u+1} = \frac{q_{sys}^{operation}\left(T_{u+1} - T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}} q_{sys}^{lost}(t)dt\right)}{\sum_{i=1}^{M}\sum_{j=1}^{N_i} P_{ij}^{m} \bullet \left(T_{u+1} - T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}} \lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right)dt\right) + P_{ij}^{c} \bullet T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}} \lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right)dt} \tag{13}$$

With the objective function given in the Eq. (13), the nonlinear programming formulation aimed to obtain the optimal maintenance scheme for maximizing the energy efficiency in the $(u+1)$ th mission is given as:

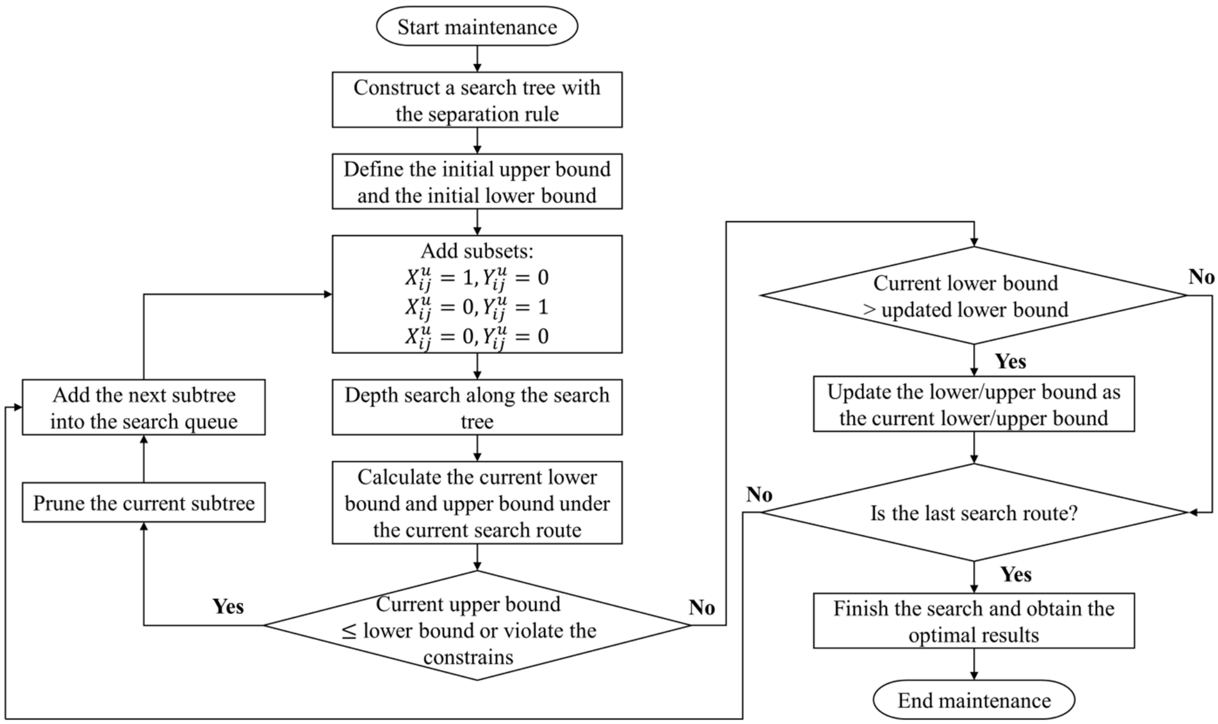

Fig. 4. Flowchart of branch and bound algorithm to solve the ESMP.

$$\max EE_{sys}^{u+1} = \frac{q_{sys}^{operation}\left(T_{u+1} - T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}} q_{sys}^{lost}(t)dt\right)}{\sum_{i=1}^{M}\sum_{j=1}^{N_i} P_{ij}^{o}\bullet\left(T_{u+1} - T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}}\lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right)dt\right) + P_{ij}^{c}\bullet T_{ij}^{c}\int_{ts_{u+1}}^{te_{u+1}}\lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right)dt} \tag{14}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N_i} T_{ij}^{p}\bullet x_{ij}^{u} + \sum_{i=1}^{M}\sum_{j=1}^{N} T_{ij}^{r}\bullet y_{ij}^{u} \le TL^{u} \tag{15}$$

$$\sum_{i=1}^{M}\sum_{j=1}^{N_i} C_{ij}^{p}\bullet x_{ij}^{u} + \sum_{i=1}^{M}\sum_{j=1}^{N} C_{ij}^{r}\bullet y_{ij}^{u} \le CL^{u} \tag{16}$$

$$\lambda_{ij}^{u+1}\left(t, x_{ij}^{u}, y_{ij}^{u}\right) = \begin{cases} \dfrac{m_{ij}}{\eta_{ij}}\left(\dfrac{t}{\eta_{ij}}\right)^{m_{ij}-1} & u=0 \\ a_{ij}\lambda_{ij}^{u}\left(t+b_{ij}T_{u}\right)x_{ij}^{u} + \lambda_{ij}^{1}\left(t-ts_{u+1}\right)y_{ij}^{u} + \lambda_{ij}^{u}(t)\left(1-x_{ij}^{u}-y_{ij}^{u}\right) & u>0 \end{cases} \tag{17}$$

$$x_{ij}^{u} + y_{ij}^{u} \le 1 \tag{18}$$

$$x_{ij}^{u}, y_{ij}^{u} \in \{0, 1\} \tag{19}$$

The formulations mentioned above give the optimization objective and constraints for the ESMP proposed in this paper. Maximizing the energy efficiency in the next mission T_{u+1} is regarded as the objective function given by (14). Constraints (15) and Constraints (16) restrict the total maintenance duration in the mission-changing break TL^u is shorter than the duration of the mission-changing break and the maintenance cost is less maintenance cost CL^u. Constraints (17) give the update of the hazard rate in the mission to support the estimation of energy efficiency. Constraints (18) restrict that one machine takes at most one kind of maintenance action at the mission-changing break. Constraints (19) define the domain of the decision variables.

4.2. Branch and bound algorithm design

Selective maintenance planning for a series–parallel system that considers the optimization of energy efficiency is a complex and non-linear problem. In this context, heuristic and exact algorithms have been designed to solve selective maintenance problems [26]. On the one hand, the goal of heuristic algorithms is to quickly provide a feasible solution. And the commonly used heuristic algorithms include genetic algorithm and tabu search. On the other hand, the exact approach such as branch and bound procedure is to find the optimal solution and assess its optimality. Recently, some scholars have tried to study the cooperative (or hybrid) optimization approach between metaheuristics and exact algorithms to solve large-scale problems [27]. However, in order to obtain the exact result while highlighting the energy efficiency of the ESMP without being affected by its solution algorithm, we develop the branch and bound algorithm to solve the energy-oriented selective maintenance optimization model.

The branch and bound algorithm is an arborescent proceeding and takes advantage of the pruning procedure to narrow the solution space. The key steps are defining the separation rule, evaluation function, and exploration strategy. Among them, the separation rule is applied to create the subset of solutions, the evaluation function is designed to evaluate the subsets of solutions and the exploration strategy is to direct the research in the tree structure.

Firstly, the separation rule is used to create the subsets of solutions. Machine M_{ij} in the mission-changing break TL^u can choose to conduct one of the maintenance actions including PR, PM, and DN. It means each machine has three subsets to select, which are $\left(x_{ij}^{u} = 1, y_{ij}^{u} = 0\right)$, $\left(x_{ij}^{u} =\right.$

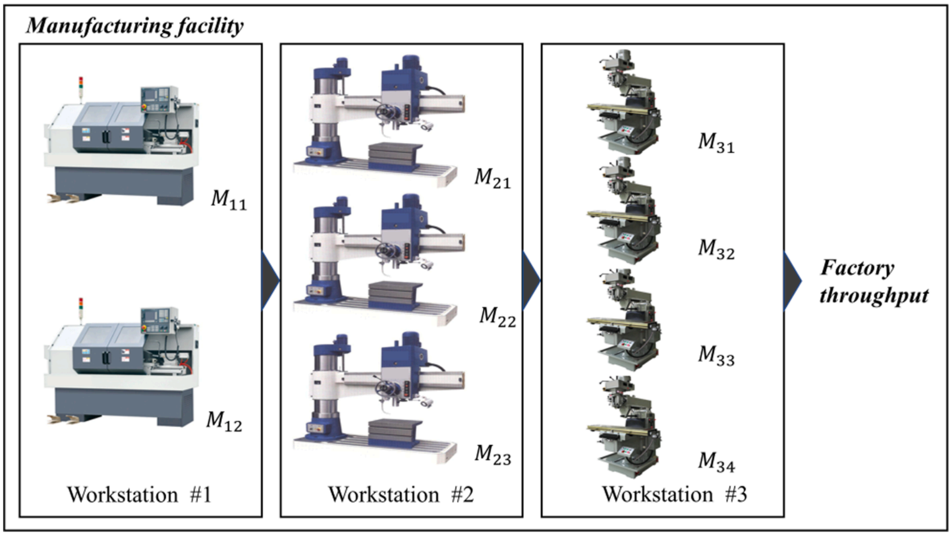

Fig. 5. Machine layout of the engine craft production system.

Table 1
Energy, production rate and maintenance parameters of machines in CASE 1.

M_{ij}	T^p_{ij}	T^r_{ij}	T^c_{ij}	s^2_{ij}	C^p_{ij}	C^r_{ij}	m_{ij}	η_{ij}	a_{ij}	b_{ij}	P^o_{ij}	P^c_{ij}
M_{11}	34	64	45	0.6	200	560	2.1	8010	1.012	0.0485	12	79
M_{12}	35	62	25	0.4	280	460	2.3	8920	1.010	0.0497	18	60
M_{21}	31	55	30	0.3	290	690	3.2	7672	1.014	0.0480	16	70
M_{22}	32	61	41	0.4	300	550	2.2	7430	1.015	0.0490	15	65
M_{23}	30	60	28	0.3	320	690	3.6	7723	1.025	0.0466	13	55
M_{31}	25	58	32	0.1	210	520	2.8	7730	1.024	0.0431	10	75
M_{32}	36	66	20	0.2	250	630	3.0	8646	1.012	0.0495	11	68
M_{33}	29	57	18	0.3	280	680	2.5	7953	1.017	0.0410	14	72
M_{34}	25	65	23	0.4	270	610	2.7	8631	1.011	0.0480	21	40

$0, y^u_{ij} = 1\big)$ and $\big(x^u_{ij} = 0, y^u_{ij} = 0\big)$. The evaluation for the subset of solutions is defined as the follows to obtain the upper and lower bounds: The estimation for the upper bound is obtained by relaxation of the maintenance duration and cost constraints, which means the machines that haven't been selected so far are regarded as taking the PR action to restore machines to the optimum health condition. While the estimation for the lower bound requires strict constraints, thus the remaining machines are regarded as adapting DN actions during the mission-changing break.

Secondly, in terms of search strategy, the common search strategies are breadth-first search (BFS) and depth-first search (DFS). In the BFS, the search process is performed from front to back in order of machine number. Individual machines are searched and energy-efficiency values are calculated in the order of maintenance effects (i.e., in the order of PR, PM, and DN actions). In the DFS, nodes are traversed along with the depth of the tree, and branches are searched as deeply as possible. Compared with DFS, BFS has higher space complexity, but it is more likely to find the optimal solution faster than DFS. Therefore, BFS is used in the solution process.

And in the pruning strategy, the upper and lower bounds under the current search need to be found, which are used to prune the search tree. The upper bound is generally the previous optimal solution, and the lower bound is the unconstrained optimal solution in the current search path. For machines that are not searched temporarily, the lower bound is evaluated by relaxing the constraint limit of the maintenance resources, this is, these machines obtain the lower bound if they all take the PR action and the upper bound if they all take the DN action.

Combining the branching strategy, search strategy and pruning strategy, the solution process of the energy-oriented selective maintenance model is mainly as follows. First, a set of initial feasible solutions is obtained, and the energy efficiency value corresponding to the set of feasible solutions is taken as the initial upper bound. Next, a trinomial search tree is constructed, and the upper and lower bounds are solved separately for the current search path respectively. If the lower bound of the search path is lower than the current upper bound, the search path is pruned. And if the upper bound of the search path is better than the current upper bound, the current upper bound is updated to the upper bound of the search path. When all the sub-goal values are lower than the current upper bound, the search ends and the current optimal value is obtained. Fig. 4 illustrates the whole solution process.

Table 2
Parameters about the time of mission and maintenance constraints.

u	ts_{u+1}(h)	te_{u+1}(h)	TL^u(hours)	CL^u($)
1	4140	8140	140	2000
2	8290	12,290	180	2300
3	12,450	16,450	205	3000
4	16,620	20,620	225	2500
5	20,800	24,800	240	2400

5. Numerical examples and discussion

In this section, to illustrate the validity of ESMP methodology, a production system of engine craft is taken as an example. Manufacturing facilities are subdivided into multiple workstations that operate together to produce. These workstations can be composed of a single machine, or a group of machines, which typically have different capabilities in terms of which products they can process. Fig. 5 presents the example for facility topology, which consists of 9 individual machines, including

Table 3
Maintenance schemes for the series–parallel system of CASE 1 under ESMP.

M_{ij}	The break between missions					The numbers of PM times	The numbers of PR times
	T_1	T_2	T_3	T_4	T_5		
M_{11}	PM	PM	PM	PM	PM	5	0
M_{12}	DN	DN	PM	PM	DN	2	0
M_{21}	PM	PR	DN	DN	PM	2	1
M_{22}	PM	PM	PM	PM	PM	5	0
M_{23}	PM	PM	PM	PM	PM	5	0
M_{31}	DN	DN	DN	PM	PM	2	0
M_{32}	DN	DN	PM	PM	PM	3	0
M_{33}	DN	PM	PM	PM	PM	4	0
M_{34}	DN	DN	DN	DN	DN	0	0
Total	**--**	**--**	**--**	**--**	**--**	**28**	**1**

Table 4
Throughput, energy consumption, energy efficiency, and total cost results of CASE 1.

T_u	Throughput (pieces)	Energy consumption (kW•h)	Energy efficiency (pieces/kW•h)
T_1	217,719	522,618	0.4166
T_2	209,256	531,645	0.3936
T_3	199,673	530,078	0.3767
T_4	185,070	530,649	0.3488
T_5	163,989	530,776	0.3087

machining centers, drilling machines, and grinding machines.

Based on energy and maintenance parameters, the detailed maintenance decision-making process for applying the ESMP is presented in Section 5.1. Then maintenance effects are discussed to show how the proposed ESMP adapts parameter changes to obtain optimal maintenance schemes in Section 5.2. Finally, we benchmark the ESMP with the traditional RSMP to highlight its effectiveness in Section 5.3. Moreover, to express easily, the parameters of Table 1 and the corresponding maintenance results are defined as CASE 1. And parameters after updating the hazard rate increase factor and age reduction factor shown in Table 5 are defined as CASE 2.

5.1. Decision-making process of energy-oriented selective maintenance policy

In this paper, the hazard rate of machines follows the Weibull distribution, which has been widely used to fit repairable machines in mechanical engineering. The hazard rate of the machine M_{ij} is shown as:

$$\lambda_{ij}(t) = \frac{m_{ij}}{\eta_{ij}}\left(\frac{t}{\eta_{ij}}\right)^{m_{ij}-1} \tag{21}$$

where m_{ij} and η_{ij} are the shape and scale parameters respectively.

To apply the ESMP, the energy and reliability parameters are collected by reliability engineers and shown in Table 1. Among them, the estimation method about the parameters of Weibull distribution can refer to the reliability tests. Besides, the power values of different maintenance actions are collected from reliability engineers, since it will be their duty to evaluate the energy consumption of each machine within the plant. The productivity of the system can be estimated from the historical data in the operational state, which is 60 parts per hour.

Five consecutive production missions are considered to obtain the sequential output of the maintenance scheme. Under the framework of ESMP, the maintenance actions are performed in the break interval of successive missions. Furtherly, the finite duration for the maintenance actions (PM or PR) in the break intervals of missions, cost limitations, the start time, and the corresponding end time of each mission are shown in Table 2. Taking the first mission as an example, the start time of next mission ts_2 is at 4140 h and the end time te_2 is at 8140 h. When finishing the first mission, the second mission starts after 140 h. The duration of break intervals between missions can be utilized to perform PR or PM actions with $2000 maintenance cost.

With the preparation of the basic data set and the design of the branch and bound algorithm, we obtain the maintenance scheme in each break interval of missions as shown in Table 3. Taking the maintenance scheme of M_{12} as an example, M_{12} performs PM for 2 times in the mission-changing break of mission T_3 and mission T_4 respectively. While no maintenance action is adapted in other mission-changing breaks. It is worth noting that M_{11} and M_{22} perform PM at each mission-changing break while M_{34} doesn't perform any maintenance action. In addition, it is worth noting that due to the largest share of capacity occupied by M_{11} ($s_{11}^2 = 0.6$), PM action is performed on M_{11} at the end of each mission.

Furtherly, the exact results in Table 4 including throughput, energy consumption, and energy efficiency during each machining mission are obtained. Along with the execution of the machining mission, the energy efficiency is decreasing because of the reduction of the throughput and the increase of energy consumption.

5.2. The impact of maintenance effect on maintenance schemes

According to the optimal maintenance schemes shown in Table 3, an intuitive result can be observed that more than 4 machines are selected

Table 5
Parameters for ESMP after updating hazard rate parameters in CASE 2.

M_{ij}	T_{ij}^p	T_{ij}^r	T_{ij}^c	s_{ij}^2	C_{ij}^p	C_{ij}^r	m_{ij}	η_{ij}	a_{ij}	b_{ij}	P_{ij}^o	P_{ij}^c
M_{11}	34	64	45	0.6	200	560	2.1	8010	**1.12**	**0.485**	12	79
M_{12}	35	62	25	0.4	280	460	2.3	8920	**1.10**	**0.497**	18	60
M_{21}	31	55	30	0.3	290	690	3.2	7672	**1.14**	**0.480**	16	70
M_{22}	32	61	41	0.4	300	550	2.2	7430	**1.15**	**0.490**	15	65
M_{23}	30	60	28	0.3	320	690	3.6	7723	**1.25**	**0.466**	13	55
M_{31}	25	58	32	0.1	210	520	2.8	7730	**1.24**	**0.431**	10	75
M_{32}	36	66	20	0.2	250	630	3.0	8646	**1.12**	**0.495**	11	68
M_{33}	29	57	18	0.3	280	680	2.5	7953	**1.17**	**0.410**	14	72
M_{34}	25	65	23	0.4	270	610	2.7	8631	**1.11**	**0.480**	21	40

Table 6
Maintenance schemes of CASE 2 after updating hazard rate parameters.

M_{ij}	The break between missions					The numbers of PM times	The numbers of PR times
	T_1	T_2	T_3	T_4	T_5		
M_{11}	PR	DN	PR	DN	DN	0	2
M_{12}	DN	DN	DN	PR	PR	0	2
M_{21}	DN	PR	DN	PR	DN	0	2
M_{22}	DN	PR	DN	PR	PM	1	2
M_{23}	PR	DN	PR	DN	PR	0	3
M_{31}	DN	DN	DN	PM	PR	1	1
M_{32}	DN	DN	PR	DN	DN	0	1
M_{33}	DN	PR	DN	DN	DN	0	1
M_{34}	DN	DN	DN	DN	DN	0	0
Total	--	--	--	--	--	**2**	**14**

Table 7
Maintenance results of CASE 2 under updating parameters.

T_u	Throughput (pieces)	Energy consumption (kW•h)	Energy efficiency (pieces/ kW•h)
T_1	209,962	529,238	0.3967
T_2	195,727	533,993	0.3665
T_3	183,764	538,206	0.3414
T_4	179,278	535,477	0.3338
T_5	167,533	532,238	0.3148

for PM action in all five breaks, while the number of PR actions is only 1. This is because the maintenance effect of PM actions is close to that of PR actions. In the failure rate iteration of PM actions, the hazard rate increase factor a_{ij} and the age reduction factor b_{ij} are taken as low values, so that the restore ability of PM actions is quite close to the repair-as-new level. With the same maintenance duration and maintenance cost for PM action, the PM action won't always be selected once the restoring effect declines, since the PM actions are not as worthy as previous. Therefore, under the constraints of maintenance resources, our proposed ESMP prefers to select PM actions for machines from an energy-effectiveness perspective.

The restore ability of PM actions is analyzed to validate our proposed maintenance policy. To further analyze the PM effect that effectively influences the results of systemic maintenance schemes, we adjust the values of the hazard increasing factors and age reduction factors for each machine. As shown in Table 5, we increase the values of parameters a_{ij} and b_{ij}, while the other parameters maintain unchanged.

With the updating of parameters, the maintenance schemes in each break are shown in Table 6. Compared with the results shown in Table 3, with the increase of a_{ij} and b_{ij}, the number of PM actions decreases and the number of PR actions increases obviously. Taking the maintenance scheme of M_{22} as an example, PR actions are performed at the second and the fourth mission-changing breaks respectively while the PM action is performed at the fifth mission-changing break.

Similarly, throughput, energy consumption, energy efficiency, and total cost during each machining process after updating hazard rate parameters are given in Table 7. By comparing with the results shown in Table 4, in every machining mission, the throughput decreases while the energy consumption increases. As a result, the energy efficiency of the series–parallel system decreases with the more rapid deterioration of machines.

Moreover, by further comparing the maintenance schemes under two different maintenance effects, the detailed number of maintenance actions (including DN, PM, and PR) for the studied system can be obtained. By gathering the results of Table 3 and Table 6, the structures of maintenance schemes under two maintenance effects are shown in Fig. 6. Maintenance planning is required for 9 machines at each break, therefore, the total number of maintenance actions shown in each column is 9. It can be noticed that under the constraint of limited

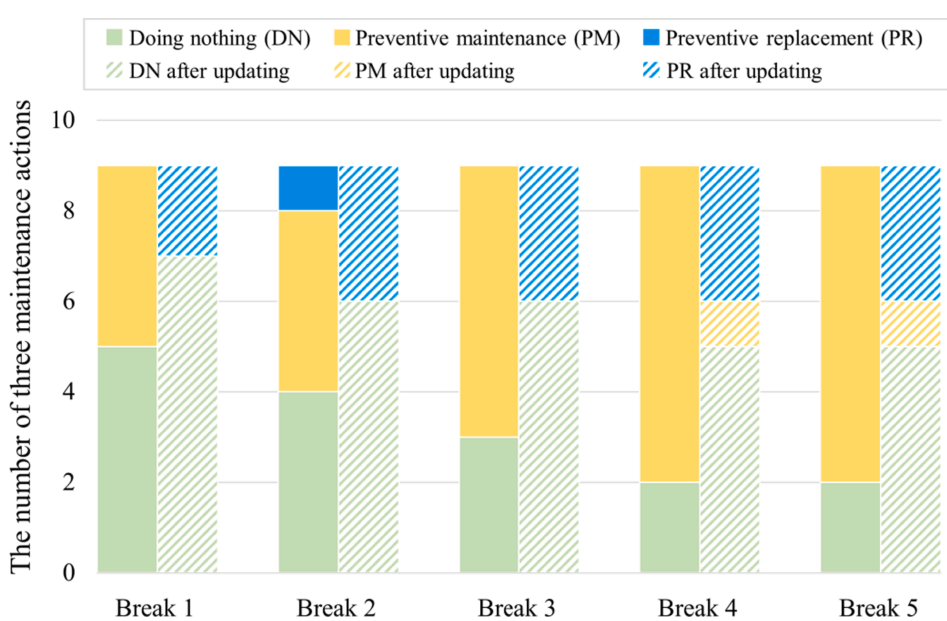

Fig. 6. The number of different maintenance actions under two maintenance effects.

Table 8
Maintenance schemes of CASE 1 under RSMP.

M_{ij}	The break between missions					The numbers of PM times	The numbers of PR times
	T_1	T_2	T_3	T_4	T_5		
M_{11}	PM	DN	DN	DN	DN	4	0
M_{12}	DN	PR	PM	PM	PR	2	2
M_{21}	DN	PM	PM	PM	PM	4	0
M_{22}	DN	DN	DN	DN	DN	0	0
M_{23}	PM	PM	PM	PR	PM	4	1
M_{31}	DN	PM	PM	DN	PM	3	0
M_{32}	DN	DN	PM	PM	DN	2	0
M_{33}	DN	PM	DN	PM	PR	2	1
M_{34}	DN	DN	DN	DN	DN	0	0
Total	--	--	--	--	--	**21**	**4**

Table 9
Results comparison of ESMP and RSMP under CASE 1.

T_u	ESMP			RSMP			Increasing rate
	Throughput	Energy consumption	Energy efficiency	Throughput	Energy consumption	Energy efficiency	
T_1	217,719	522,618	0.4166	208,123	528,247	0.3940	5.7%
T_2	209,256	531,645	0.3936	200,011	529,067	0.3780	4.1%
T_3	199,673	530,078	0.3767	191,879	530,188	0.3619	4.1%
T_4	185,070	530,649	0.3488	170,233	534,192	0.3187	9.4%
T_5	163,989	530,776	0.3087	158,290	538,105	0.2942	4.9%

Table 10
Maintenance schemes of CASE 2 under RSMP.

M_{ij}	The break intervals between missions					The numbers of PM times	The numbers of PR times
	T_1	T_2	T_3	T_4	T_5		
M_{11}	DN	PR	DN	PR	DN	0	2
M_{12}	PR	DN	PR	DN	PR	0	3
M_{21}	DN	PR	DN	PR	DN	0	2
M_{22}	DN	DN	DN	DN	DN	0	0
M_{23}	PR	DN	PR	DN	PR	0	3
M_{31}	DN	PR	DN	PM	DN	1	1
M_{32}	DN	DN	PR	DN	PR	0	2
M_{33}	DN	DN	DN	PR	PM	1	1
M_{34}	DN	DN	DN	DN	DN	0	0
Total	--	--	--	--	--	**2**	**14**

Table 11
Results comparison of ESMP and RSMP under CASE 2.

T_u	ESMP			RSMP			Increasing rate
	Throughput	Energy consumption	Energy efficiency	Throughput	Energy consumption	Energy efficiency	
T_1	209,962	529,238	0.3967	200,084	530,396	0.3772	5.2%
T_2	195,727	533,993	0.3665	181,012	531,753	0.3404	7.7%
T_3	183,764	538,206	0.3414	174,163	536,499	0.3246	5.2%
T_4	179,278	535,477	0.3348	161,103	536,079	0.3005	11.4%
T_5	167,533	532,238	0.3148	148,598	543,157	0.2736	15.1%

maintenance resources, with the increase of hazard rate parameters, ESMP prefers to select the PR action with a higher cost to ensure the normal operation of machines in the next mission. Therefore, our proposed ESMP can adapt different maintenance effects to obtain the optimal maintenance schemes with maximal energy efficiency.

5.3. Policy comparison

To illustrate the energy-effectiveness of our proposed methodology, we benchmark our ESMP with the traditional RSMP which takes the maximal reliability in the next mission as the optimization objective. For RSMP, we derive the failure distributions by using the same Weibull distribution $\lambda_{ij}(t)$. Combining with the hazard rate function, the reliability of machine M_{ij} is given by:

$$R_{ij}(t) = \exp\left[-\int_0^t \lambda_{ij}(t)dt\right] \tag{22}$$

The system reliability is the product of the reliability of multiple machines in a series system, while the reliability of a parallel system is equal to the minimal reliability of the machines. The reliability of a series–parallel system can be calculated by obtaining the reliability of parallel stations first and then obtaining the values of stations'

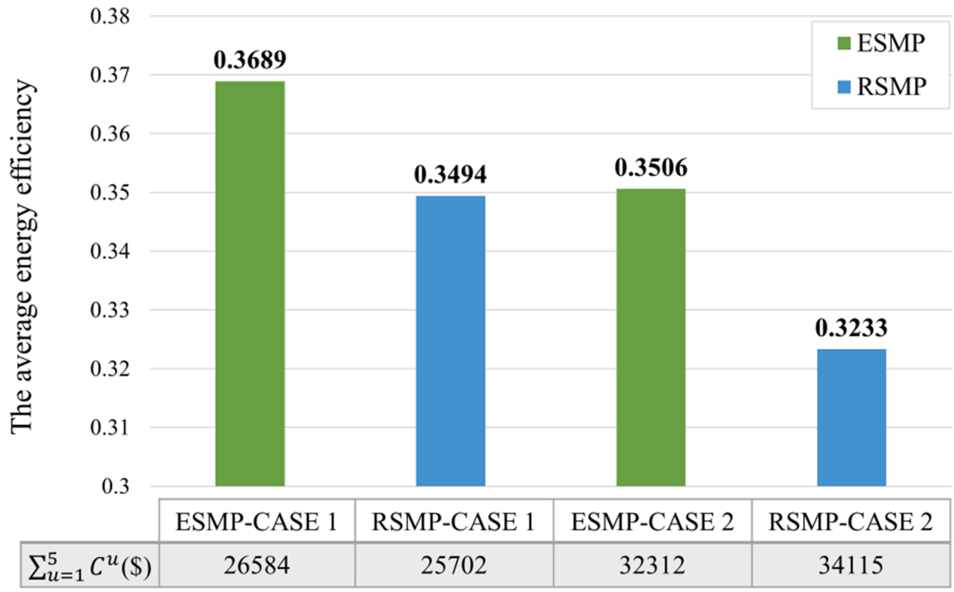

Fig. 7. Results comparison under two maintenance policies.

reliability. Therefore, the reliability function of the series–parallel system can be calculated as:

$$R_{sys}t = \prod_{l}^{i=1} \cdots \prod_{l}^{i=1} min\{R_{i1}, R_{i2}, \ldots, R_{iN}\} \tag{23}$$

The objective of traditional RSMP is to obtain the reliability-optimal maintenance scheme for each at each break under limited duration and cost resources. Therefore, the objective function of RSMP is to maximize the system reliability given in Eq. (23) and the constraints are the same as the ESMP given in Eqs. (15)–(19). To fully highlight the effectiveness of the proposed ESMP, we utilize the same parameters in Section 5.1 and Section 5.2 to show the performance of the traditional RSMP in selective maintenance scheduling. The optimal maintenance scheme of CASE 1 under the RSMP is shown in Table 8. Moreover, the comparison of the energy efficiency and the increasing rates of energy efficiency between RSMP and ESMP are given in Table 9. Compared with the scheme results of CASE 1 under ESMP which are listed in Tables 3 and 4, the maintenance scheme under RSMP takes more PR actions. In terms of the comparison about energy efficiency, the energy efficiency under ESMP is higher than the RSMP in all the durations of the machining process. Thus, the ESMP is more efficient than RSMP in terms of energy efficiency. In other words, with the same maintenance resource allocation, the maintenance scheme obtained by ESMP has a better performance with high production throughput and low energy consumption.

Moreover, CASE 2 is utilized to further illustrate the validation of ESMP. The optimal maintenance schemes of the series–parallel system under RSMP methodology are given in Table 10. Referring to Table 10, the PR action is performed 14 times while the PM action is performed 2 times. Furtherly, the value of energy efficiency and the energy efficiency increasing rate of ESMP over RSMP are shown in Table 11. In CASE 2, the values of energy efficiency show a downward trend for every machining mission under RSMP. In addition, the energy efficiency increasing rates of ESMP over RSMP are higher than the results in CASE 1. Compared with the energy efficiency under RSMP, the values of energy efficiency under ESMP increase. The positive increasing rate means more throughput with the equivalent input of energy consumption or equivalent throughput with less input of energy consumption. High energy efficiency is the goal for the maintenance effect under the ESMP methodology.

Based on the above two comparative studies and the corresponding maintenance schemes, the average energy efficiency $\overline{EE}$ under different maintenance policies is shown in Fig. 7. The advantages of our proposed ESMP in dealing with the maintenance scheduling problem under limited maintenance resources can be summarized as follows: (1) compared with the traditional RSMP, ESMP aims to pursue energy-saving operation and maintenance process, so as to significantly improve the energy efficiency of manufacturing systems. Meanwhile, from the perspective of maintenance decision-making results, the ESMP is better in terms of both production throughput and energy consumption. Due to the cumulative effect, as the production tasks of the series–parallel system proceeds, the difference in throughput and energy consumption of ESMP compared to RSMP becomes larger. (2) our proposed ESMP adapts the changeable PM effects to optimize the systematic maintenance scheme. Specifically, under the constraints of limited maintenance resources, ESMP provides lower total energy consumption, higher total throughput, and lower energy efficiency than the RSMP across multiple continuous missions.

6. Conclusion

In this paper, we provide a unified policy for selective maintenance scheduling in series–parallel systems by effectively integrating energy efficiency optimization into an adaptive maintenance model. Differ from the traditional reliability-oriented maintenance policy, our proposed energy-oriented selective maintenance policy (ESMP) aims to increase production capacity and reduce the corresponding energy consumption. At each production break, under the constraints of limited maintenance resources, the machine to be maintained and the corresponding maintenance actions (DN, PM, or PR) are selected to maximize the energy efficiency of the next machining mission period. Specifically, the UGF is applied to formulate the throughput of a series–parallel structure, and then energy efficiency is further constructed by considering the total energy consumption in a given duration of the machining mission. Furthermore, maintenance resource constraints, the evolution health condition of machines, and the energy efficiency optimization objective are integrated into the ESMP. A branch and bound algorithm is designed to obtain optimal maintenance schemes sequentially.

We construct comprehensive numerical examples to show the performance and energy-effectiveness of our policy and present a comparative example to show proposed ESMP achieves an improvement in energy efficiency. Therefore, the mechanism of ESMP ensures to achieve the significant energy efficiency lifting of manufacturing systems. On the one hand, the ESMP fill the gap of energy-saving maintenance policy for series–parallel systems since the current study focuses on the series manufacturing line. On the other hand, this research provides an energy-oriented management method to promote the application of sustainable manufacturing. Besides, the updating of hazard rates after maintenance can reflect the real health condition and support the decision making on the choice of maintenance actions. Additionally, extending the selective maintenance modeling for multiple systems while considering the geographical dependence between systems and optimizing maintenance resource allocation for multiple subsequent missions will be adapted in our future work.

CRediT authorship contribution statement

Tangbin Xia: Conceptualization, Methodology, Software, Supervision. **Guojin Si:** Data curation, Writing – original draft. **Guo Shi:** Visualization, Investigation. **Kaigan Zhang:** Software, Validation. **Lifeng Xi:** Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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