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An energy-efficient collaborative strategy of maintenance planning and production scheduling for serial-parallel systems under time-of-use tariffs

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HIGHLIGHTS

- An energy-efficient collaborative strategy for serial-parallel systems is developed.
- Relationships between maintenance, production, and impacts of TOU tariffs are explored.
- An energy-efficient two-stage maintenance (ETM) strategy is proposed.
- A machine-level dynamic multi-attribute maintenance planning is carried out.
- System-level electricity cost savings are realized by idle time insertion between production.

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ABSTRACT

The industrial sector is the largest consumer of total energy in the world, with the majority of its consumption in the form of electricity. Recently, to strengthen the capacity building of peak load regulation, many countries have implemented time-of-use (TOU) tariffs to encourage manufacturing enterprises to shift their electricity consumption from on-peak hours to mid-peak and off-peak hours. It brings the urgent requirement for energy-efficient operation and maintenance (O&M) schedules in manufacturing enterprises, among which the maintenance planning and production scheduling (MPPS) are both highly correlated to electricity consumption under this time-varying electricity charging modes. To tackle this key issue, a complex MPPS problem for serial-parallel manufacturing systems under TOU tariffs is studied in this paper. To solve the problem, an energy-efficient two-stage maintenance (ETM) strategy is developed to minimize the sum of the total electricity cost and tardiness cost. In the first stage, the preventive maintenance (PM) planning is presented to obtain the multi-attribute PM intervals for each machine, considering machine availability, maintenance cost, and the potential impact of planned PM actions on average electricity price. Based on the PM intervals, a mixed-integer programming model is proposed for a hybrid flow shop schedule with PM actions in the second stage. Finally, the results confirm the effectiveness of this ETM strategy in achieving electricity cost savings and ensuring system productivity, which can provide instructions for the operation of industrial enterprises.

1. Introduction

1.1. Background and motivation

Globally, the industrial sector is the largest energy consumer. Industrial energy consumption accounts for 40 % of the world's total energy consumption, especially in the form of electricity [1]. With growing concern about renewable energy reform and rising fuel prices, the utilization proportion of sustainable energy in the total electricity generation is increasing rapidly [2–4]. On the one hand, industrial electricity demand generally changes dramatically over time, over 10 % of peak power demand occurs within 1 % of hours in a year [5]. On the other hand, electricity cannot be efficiently stored so it has to be generated, transmitted, and consumed instantly. Based on the imbalance between demand and supply, countries around the world have adopted demand-side management approaches to encourage customers to adjust their electricity-consumption behaviors [6,7]. Among them, time-of-use (TOU) tariffs have been most widely promoted, which charge different electricity fees according to the average marginal cost of system

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Nomenclature

Abbreviations

MPPS	Maintenance planning and production scheduling
ETM	Energy-efficient two-stage maintenance strategy
PM	Preventive maintenance
MAR	Machine availability rate
MCR	Maintenance cost rate
AEP	Average electricity price
MLEGA	Multi-layer encoding genetic algorithm

Sets

$\mathscr{I}$	Set of jobs (index $i \in \mathscr{I} = \{1, 2, \cdots, I\}$)
$\mathscr{J}$	Set of processes (index $j \in \mathscr{J} = \{1, 2, \cdots, J\}$)
$\mathscr{K}$	Set of machines (index $k \in \mathscr{K} = \{1, 2, \cdots, K\}$)
$\mathscr{M}_k$	Set of PM periods of machine k (index $m \in \mathscr{M}_k = \{1, 2, \cdots, M_k\}$)

Input parameters

T	Length of the whole decision cycle
$\lambda_{km}(t)$	Hazard rate function of machine k in the m th PM cycle
a_k	Age reduction factor of machine k
b_k	Hazard rate increasing factor of machine k
$T_{PM,k}$	Length of PM action of machine k
$T_{CM,k}$	Length of CM action of machine k
$C_{PM,k}$	Cost of PM action of machine k
$C_{CM,k}$	Cost of CM action of machine k
$w_{1km}, w_{2km}, w_{3km}$	Weights of single-attribute PM model of machine k in the m th PM cycle
$tou(t)$	TOU tariff function
ep_k	Electricity power consumption rate of machine k
tp_{ij}	Required processing time of job i in process j
Td_i	Due date of job i
Cp_i	Tardiness cost per unit time of job i
pr_{ijk}	Processing rate of job i of machine k in process j

Auxiliary decision variables

$f_{ijk}(t)$	Processing state function of each job i in machine k in process j
TPC	Total production cost
TEC	Total electricity cost
TTC	Total tardiness cost

Decision variables

Seq_k^{PM}	PM interval sequence of each machine k, $Seq_k^{PM} = \{T^*_{O,k1}, T^*_{O,k2}, \cdots, T^*_{O,kM_k}\}$
x_{ijkm}	Binary variable: 1, if job i is processed on the mth PM cycle of machine k in process j, otherwise
t_{ij}	The start time of job i in process j

operations by time.

In this context, performing operation and maintenance (O&M) schedules becomes more interesting because it is likely to benefit from optimized enterprise activities under TOU tariffs [8]. As the major activities in manufacturing enterprises, maintenance and production interact with each other and are highly correlated to electricity consumption. Nowadays, manufacturing enterprises begin to realize effective electricity usage improvement by adapting the maintenance planning and production scheduling (MPPS) framework. Certainly, in the context of TOU tariffs, proper O&M schedules can shift production electricity consumption from peak (with higher prices) to mid-peak or off-peak periods (with lower prices) [9]. Electricity usage improvement can be obtained without tremendous investment in system structure changing [10]. It can also lead to significant electricity cost savings without unduly worsening traditional optimization targets such as the total maintenance cost or the makespan.

There are three difficulties in solving the MPPS problem under TOU tariffs. The first challenge comes from the contradict effects that maintenance and production cause [11]. These two activities both need to occupy the operation time of the machines. However, the former improves the reliability but inevitably reduces the productivity, while the latter does the opposite. The second challenge is the coupling between the machines. For a common serial-parallel system with a hybrid flow shop, the production scheme of one machine is determined not only by the attributes of jobs, such as the processing time and the due date but also by the production schemes of the machines in previous processes. The last challenge is the introduction of TOU tariffs, which brings a strong correlation between O&M costs and time, and further increases the complexity of decision-making. In this paper, the collaborative strategy of dynamic preventive maintenance (PM) and hybrid flow-shop production for serial-parallel systems under TOU tariffs is studied. In this strategy, two types of costs are comprehensively investigated, including both direct costs of production and maintenance and indirect costs related to electricity consumption, so as to increase economic benefits, save production costs, and improve the efficiency of electricity utilization.

1.2. Literature review

In recent years, there has been a growing number of studies on optimizing production scheduling to save energy costs under TOU tariffs [12–14]. Wang et al. [15] presented a mixed-integer linear program for the problem of minimizing total electricity cost on a two-machine permutation flow shop under TOU tariffs. Ho et al. [16] studied the joint optimization of makespan and electricity cost in the two-machine flow shop scheduling problem under electricity pricing to obtain an energy-cost-aware scheduling decision. And Cheng et al. [17] formulated the energy cost optimization problem of a two-machine Bernoulli serial line as the problem of optimally allocating the productivity over the time periods with different electricity rates. It can be concluded that the existing research on the production scheduling under TOU tariffs is mainly concerned with classical shop scheduling, such as the parallel machine system [12–14] and the flow shop system [15–17], and most of the research mainly takes the energy cost as the objective and established optimization methods to minimize the total cost of electricity.

With increasing requirements for both efficiency and flexibility in recent production processes, hybrid flow shops which represent a common manufacturing environment have been widely encountered [18]. A remarkable feature of a hybrid flow shop is that a set of jobs need to be processed in a series of production stages, and each stage consists of several parallel machines. As a result, the hybrid flow shop scheduling problem is more complex than the classical flow shop scheduling. The former needs to jointly optimize the parallel machine scheduling and the flow shop scheduling. Most of the existing research on the hybrid flow shop is to improve production efficiency by optimizing the makespan or the sum of the weighted tardiness and designing proper algorithms to solve it efficiently [18–21]. With growing concern about energy efficiency, some scholars also focused on the hybrid flow shop production scheduling problem under TOU tariffs [22–24]. Schulz et al. [25] integrated the three objectives of makespan, total energy costs, and peak power, and adopted a multi-phase iterative local search algorithm to find the three-dimensional Pareto front. And Shao et al. [26] studied a distributed heterogeneous hybrid flow shop scheduling problem under TOU tariffs and proposed an ant colony algorithm behaviour-based multi-objective evolutionary algorithm to solve the MILP model. Ho [27] considered Johnson's rule when solving the scheduling problem of a permutation flow shop to minimize the total electricity cost under TOU tariffs. Besides, Jiang [28] created a multi-objective evolutionary algorithm to solve the flexible job shop scheduling problem under TOU tariffs with minimizing both makespan and electricity cost objective. Park [29] also considered the downtime under TOU tariffs and modelled with the same objectives.

In the above studies, production scheduling optimization under TOU tariffs can achieve significant electricity cost savings. However, recent scheduling strategies on production scheduling under TOU tariffs usually focus on the improvement of the production plan to get the minimum total electricity cost, while lacking the consideration of maintenance planning. During long-term use of machines in different environments, their reliability, availability, and efficiency are reduced to a considerable extent and even lead to breakdowns, influencing the original production scheme [30,31]. Therefore, maintenance planning must be comprehensively considered. For example, Mokhtari [32] integrated total completion time, availability of the system, and total energy cost as the objective of flexible job shop scheduling model.

Recently, the joint optimization of maintenance planning and production scheduling (MPPS) under TOU tariffs are rather limited [33]. Notably, joint optimization of MPPS without the consideration of electricity tariffs has been studied thoroughly. The joint MPPS models of the current research take maintenance and production together as decision variables and put them in the same dimension for unified modeling, which can be further classified as an integrated decision model and a multi-stage decision model [31,34–36]. Firstly, for the integrated decision model, Cassady et al. [34] integrated PM and production schedule to get a minimization of total weighted tardiness. Liu et al. [35] considered the stochastic machine failures on production synchronization. Secondly, in order to improve the solution efficiency, multi-stage decision models have been proposed, which decompose the joint decision-making process into several semi-problems to reduce the computational complexity. Hajej et al. [36] put forward an integrated production, maintenance, and quality control strategy for a degradation production system, and firstly carried out the production scheduling and then performed the maintenance strategy.

With the increasing consideration on energy consumption, the energy-efficient MPPS has also been widely studied [37–39]. For example, Zhou [40] conducted a proactive opportunistic maintenance policy to maximize the effective throughput by unit energy consumption of a serial production system. However, the optimization models of these studies are to minimize the total cost by determining the sequence of assigned jobs and the optimal PM interval, without considering the time-varying tariffs background. For the MPPS under TOU tariffs, Sun [41] modeled the flow shop production scheduling with maintenance implementation and energy control, combined all objectives to cost minimization and used a particle swarm algorithm to find the best machine operation schemes. Cui [42] studied the flow shop MPPS problem with a two-layer math-heuristic algorithm, in which the maintenance's age thresholds are considered as the constraints of the joint optimization. To sum up, joint optimization of MPPS has been studied thoroughly, and the scheduling problems under TOU tariffs are also widely studied [4]. And the combination of MPPS under TOU tariffs is limited but is becoming a rising topic recently.

1.3. Novel contributions

Inspired by the concept of opportunistic maintenance, the ETM strategy is established to deal with the collaborative optimization of MPPS problem under TOU tariffs. The division of TOU periods is regarded as a new energy-saving opportunity, and the O&M schemes are arranged in consideration of machine availability, production tardiness, and electricity consumption. The coupling relationships between O&M and the impacts of TOU tariffs are further explored. The main contributions of this paper are as follows:

(1) The joint maintenance planning and production scheduling (MPPS) problem of hybrid flow shops under TOU tariffs is studied. Two couples of relationships including maintenance-production and machines in adjacent processes are considered thoroughly in the serial-parallel system.
(2) An energy-efficient two-stage maintenance (ETM) strategy is proposed to solve the MPPS problem in a timely and cost-effective manner. This two-stage hierarchical framework can effectively decrease the complexity of the decision-making process, and achieve electricity cost savings while ensuring system production.
(3) In the first stage, a dynamic multi-attribute preventive maintenance (PM) planning strategy is established for the combined objectives of machine availability rate (MAR), maintenance cost rate (MCR), and average electricity price (AEP) due to PM actions.
(4) In the second stage, a mixed-integer programming (MIP) model to minimize the total production cost is developed for hybrid flow shop scheduling under TOU tariffs. The final solution balances the trade-off between the total electricity cost and the total tardiness cost, while satisfying the PM plan constraints.

The rest of the paper is organized as follows. In Section 2, the problem and the methodology are described in detail. In Section 3, mathematical models of MPPS are separately formulated. Section 4 shows the detailed solution procedure of the two-stage maintenance and production scheduling. A case study is conducted and the computational results are further explained in Section 5. The conclusion and future research directions are presented in Section 6.

2. Problem description

This study focuses on energy-saving in the decision-making process of maintenance planning and production scheduling under TOU tariffs. For every day (24 h), the TOU tariff usually follows a standard, which normally includes three periods: on-peak periods, mid-peak periods, and off-peak periods. It can be seen in Table 1 as an example. And the corresponding TOU tariff function $tou(t)$ can be described in Fig. 1.

A complex serial-parallel production system is considered. The production structure is a hybrid flow shop with a set of machines $\mathscr{K} = \{1, 2, \cdots, K\}$ and a set of processes $\mathscr{J} = \{1, 2, \cdots, J\}$. It has at least two processes, and at least one process has more than one machine. For each process j, the available machine set is referred to as $\mathscr{K}_j = \{1, 2, \cdots, K_j\}$. And a set of jobs $\mathscr{I} = \{1, 2, \cdots, I\}$ is processed in the system. All jobs are available at time 0, and each job i has a specified processing time tp_{ij} in each process j and a different processing rate pr_{ijk} in each machine k. The processing sequence is fixed, from process 1 to the last. Each job can only be processed on one machine in each process, and can only be processed on one machine at a time. Meanwhile, each machine can only process one job at a time. And no interruptions or premotions are allowed during processing.

Besides, maintenance planning is also considered in the joint optimization of the MPPS problem. There are two types of maintenance actions: imperfect preventive maintenance (PM) and corrective maintenance (CM). PM is conducted when the scheduled time is reached,

Table 1
Time-of-use electricity charging standard for industrial customers.

TOU period	Price (¥/kWh)	Time periods (h)
On-peak	1.060	8:00–11:00, 13:00–15:00, 18:00–21:00
Mid-peak	0.693	6:00–8:00, 11:00–13:00, 15:00–18:00, 21:00–22:00
Off-peak	0.303	22:00–6:00

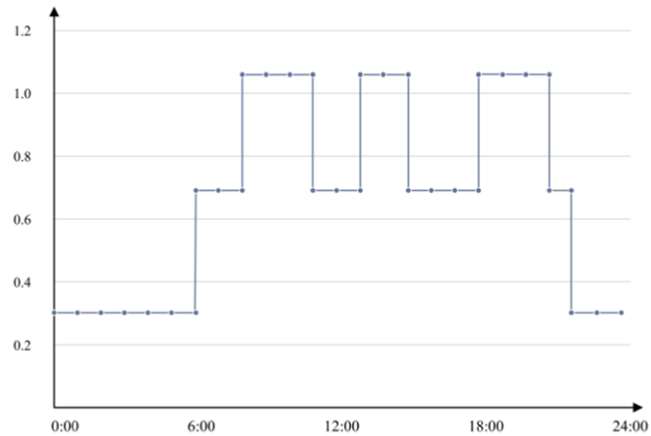

Fig. 1. Distribution of TOU tariff function under one day.

which recovers the machine to be younger but not as good as new. And if the machine fails during the PM interval, CM will be performed to recover the machine to the state before it failed. The scheduled PM time is calculated according to the degradations of individual machines, which are affected by the working environment, the age of service, etc. In that case, each machine has three states: on, off, and idle, with different electricity power consumption rates. The machine is off during PM and CM actions, and it is on when it is processing jobs. And it keeps idle for the rest of the time. The electricity power consumption rate is equal to 0 when machine k is off or idle, is greater than 0 when it is on, and is denoted as ep_k.

The collaborative optimization of the MPPS problem in actual industrial scenarios requires the correlation analysis of machine reliability and availability, focusing on the consistency of decision-making goals and constraints between maintenance planning and production scheduling. Besides, the production scheduling for a serial-parallel system is regarded as an NP-Hard problem, the introduction of TOU scenarios further increases the computational complexity, increasing the difficulty of joint decision-making. To decrease the complexity, an energy-efficient two-stage maintenance (ETM) strategy is developed to effectively solve the MPPS problem for a hybrid flow shop under TOU tariffs. And the main framework is shown in Fig. 2.

The collaborative optimization strategy can be described as follows. There are two stages to be considered. In stage 1, the degradation of each machine is obtained, and all machines are going to determine the PM scheme. Since the electricity price of peak periods can be much larger than that of off-peak periods, and there is no energy consumption when the machine is under PM, the PM duration can be taken as a great energy-saving opportunity. Thus, the PM schemes should be arranged at peak periods to avoid unnecessary energy waste. Therefore, when establishing the PM planning model, three aspects are considered: the machine availability rate, the maintenance cost rate, and the potential impacts on average electricity price at the production scheduling stage. A multi-objective dynamic PM strategy is established to output the PM sequence of each machine. Then, the PM scheme obtained from stage 1 is taken as the discontinuous time-available constraint to further carry out the production scheduling problem at stage 2. Idle time is considered to be added between the productions so that the energy consumption demand can be shifted from peak to off-peak periods. To efficiently solve this PM constrained production scheduling, a mixed integer programming (MIP) model of a hybrid flow shop under TOU tariffs is established, and a multi-layer encoding genetic algorithm is designed.

3. Mathematical formulations

In this section, the mathematical formulations of the ETM strategy are provided. In the first stage, a multi-attribute PM planning model under machine availability, maintenance cost, and electricity price targets is built for each machine. Then, the optimal PM intervals are regarded as an available time constraint for system-level production scheduling. Therefore, in the second stage, a MIP model with the objective of minimizing the total production cost is developed to solve the hybrid flow shops production scheduling under TOU tariffs. And the final production scheduling that satisfies the PM scheme constraints can be obtained by solving the optimization model.

3.1. Machine-level PM planning with multi-attribute objectives

In the maintenance planning stage, the multi-attribute model (MAM) uses an integrated multi-objective function to determine the PM intervals considering three objectives. Before the MAM model, three single-attribute model of MAR, MCR, and AEP of production are firstly

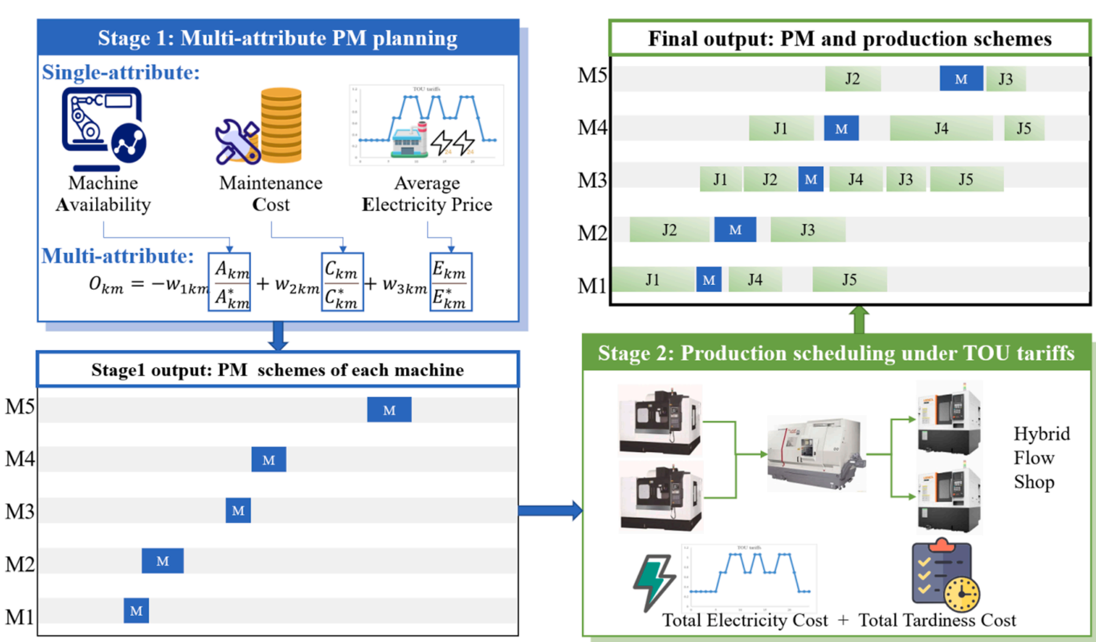

Fig. 2. Framework of energy-efficient two-stage maintenance strategy.

formulated.

Denote $\lambda_{km}(t)$ as the hazard rate function of machine k in the m th PM cycle. For the Single-MAR model, denote $T_{A,km}$ as the mean uptime. And then $\int_0^{T_{A,km}} \lambda_{km}(t)dt$ represents the expected frequency of failures in the PM cycle. The availability rate of machine k in the m th PM cycle can be defined as:

$$A_{km} = \frac{T_{A,km}}{T_{A,km} + T_{PM,k} + T_{CM,k}\int_0^{T_{A,km}} \lambda_{km}(t)dt} \tag{1}$$

where the numerator is the mean uptime, which refers to the PM interval used to arrange the following production scheduling in the whole PM cycle. And the denominator represents the total cycle length, which is mean uptime plus PM duration and mean CM duration. The optimal $T^*_{A,km}$ corresponding to maximum A^*_{km} can be obtained through $\left.\frac{d(A_{km})}{d(T_{A,km})}\right|_T = 0$.

For the Single-MCR model, consider the PM cost and the expected CM cost, suppose $T_{C,km}$ is the expected PM interval in the cost minimization model. The maintenance cost rate per unit time of machine k in the m th PM cycle is given by:

$$C_{km} = \frac{C_{PM,k} + C_{CM,k}\int_0^{T_{C,km}} \lambda_{km}(t)dt}{T_{C,km} + T_{PM,k} + T_{CM,k}\int_0^{T_{C,km}} \lambda_{km}(t)dt} \tag{2}$$

where the numerator equals to total maintenance costs of PM and CM, and the denominator represents the duration of the PM cycle. The optimal value of $T^*_{C,km}$ corresponding to minimum C^*_{km} can be obtained through $\left.\frac{d(C_{km})}{d(T_{C,km})}\right|_T = 0$.

For the Single-AEP model, there are two ways to evaluate the average electricity price of production, which result in different PM preferences. AEP-I focuses on the PM interval. The objective is to minimize the average electricity price during the PM interval directly. And AEP-D focuses on the PM duration, the objective of which is to maximize the average electricity price over the PM duration. Since the machine is down and consumes no electricity in PM durations, if the peak period is occupied by the PM action as much as possible, the production schedule can have as less probabilities as possible to be arranged in the peak period.

But no matter what definition of AEP is used, the evaluation of average electricity price needs to assume the same parameters. Therefore, $T_{E,km}$ is assumed to be the expected PM interval in the AEP calculation equations. When calculating the average electricity price, since the TOU tariff function can be regarded as time-related, it should be noticed that the upper and lower bound of the integral here are no longer $T_{E,km}$ and 0 as the calculation of MAR and MCR, rather, they vary by the iterative results of the previous MAM. Here, as shown in Fig. 3, $T_{SUM,km} = (m-1)T_{PM,k} + \sum_{q=1}^{m-1} T_{M,kq}$ represents the start time of the m th PM cycle, where $T_{M,kq}$ is the iteration result of the MAM model integrated MAR, MCR, and AEP. For each iteration, $T_{SUM,km}$ can be obtained through the previous calculation. And $T_{PCM,km} = T_{PM,k} + T_{CM,k}\int_0^{T_{E,km}} \lambda_{km}(t)dt$ is introduced to simplify the potential maintenance time in the current PM cycle.

For the Single-AEP-I model, the evaluation period of the mth cycle is the PM interval between the $(m-1)$ th and the m th PM action. And the average electricity price in the mth PM interval is defined as:

$$E^I_{km} = \frac{\int_{T_{SUM,km}}^{T_{SUM,km}+T_{E,km}+T_{CM,k}\int_0^{T_{E,km}}\lambda_{km}(t)dt} tou(t)dt}{T_{E,km} + T_{PCM,km}} \tag{3}$$

where $tou(t)$ is the time-dependent TOU tariff function. And the numerator denotes the expected total electricity price in this cycle, the denominator represents the total cycle duration in the AEP-I model.

And for the Single-AEP-D model, the evaluation period of the m th cycle is the time when the PM action is carried out. The average electricity price in the m th PM duration is defined as:

$$E^D_{km} = \frac{\int_{T_{SUM,km}+T_{E,km}+T_{CM,k}\int_0^{T_{E,km}}\lambda_{km}(t)dt}^{T_{SUM,km}+T_{E,km}+T_{PCM,km}} tou(t)dt}{T_{PM,k}} \tag{4}$$

where the numerator represents the total electricity price when machine k is under PM, and the denominator represents the length of PM action of machine k.

Then, the MAM model is developed to get the integrated objective of machine availability rate, maintenance cost rate, and average electricity price. Suppose w_{1km}, w_{2km}, and w_{3km} are the weights of these three objectives ($-1 \le w_{1km} \le 1, -1 \le w_{2km} \le 1, -1 \le w_{3km} \le 1, |w_{1km}| + |w_{2km}| + |w_{3km}| = 1$). Combine these three single-attribute models, the multi-objective function is defined as:

$$O_{km} = w_{1km}\frac{A_{km}}{A^*_{km}} + w_{2km}\frac{C_{km}}{C^*_{km}} + w_{3km}\frac{E_{km}}{E^*_{km}} \tag{5}$$

where the optimal A^*_{km}, C^*_{km}, and E^*_{km} are obtained from the single-attribute model. In this equation, decision makers can use either E^I_{km} or E^D_{km} to represent the E^*_{km} according to different preferences for different types of manufacturing systems. And then the optimal multi-attribute PM interval, denoted by $T_{O,km}$, is obtained by minimizing the overall objective function.

However, the optimal values of different single-attribute models may vary a lot, bringing great difficulties to the solution-finding of the multi-attribute model. Besides, the shape of the TOU tariff may also closely affect the optimal solution of these two AEP models. Based on the reasons above, MAR, MCR, AEP-I, and AEP-D curves in one cycle are drawn in Fig. 4 using the TOU tariff example of Fig. 1.

As can be seen in Fig. 4, the shapes of MAR and MCR are similar due to the similarity in their calculation functions. But these two AEP curves show a great difference. The introduction of TOU tariff brings periodic trends to these two curves. However, since the decision variable T is included in the denominator of AEP-I and not in that of AEP-D. The AEP-

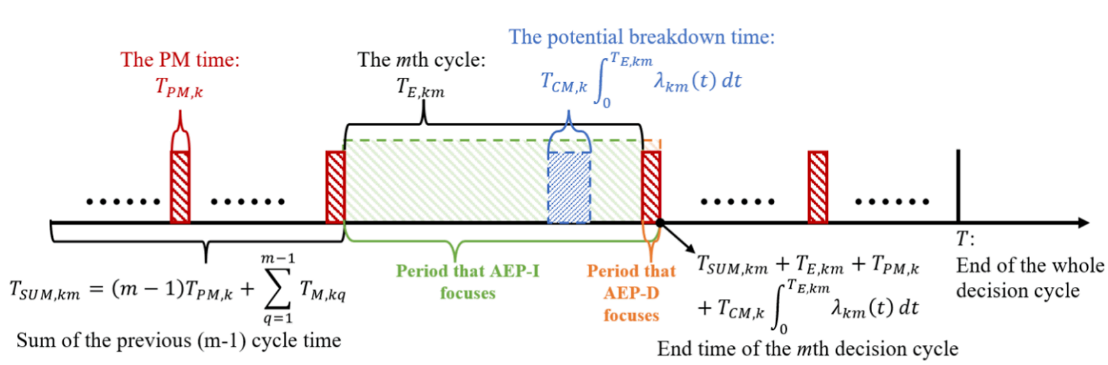

Fig. 3. Time denotation of the mth PM cycle of machine k.

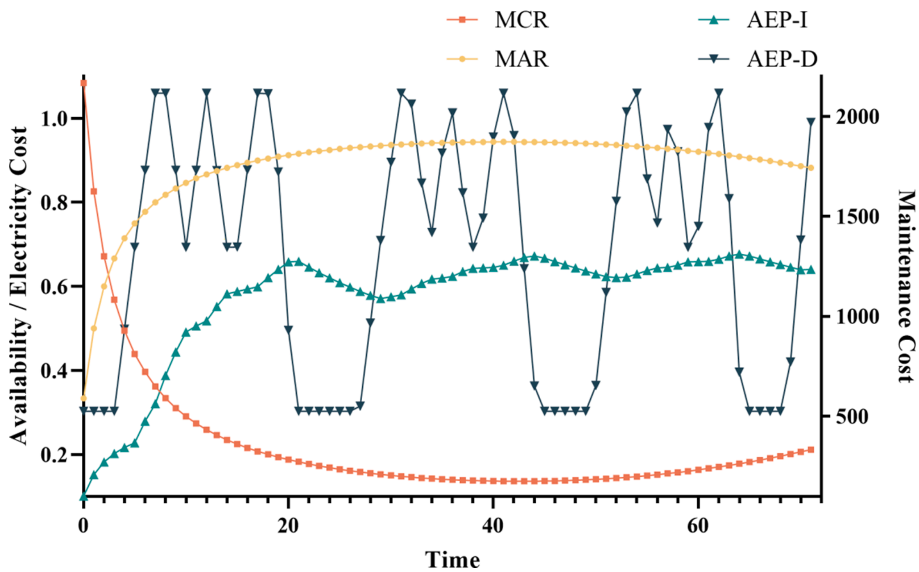

Fig. 4. Objective curves of MAR, MCR, and AEP models.

I curve shows an upward trend in one cycle, while the AEP-D curve remains almost in the same range. As for the extreme points of different curves, the extreme points of MAR and MCR are easy to be found according to the figure. But due to the periodic feature of TOU price function, the extreme points of AEP models are not single. Therefore, when optimizing the AEP objective, the local best point near the best of MAR and MCR is selected as the optimal solution of the AEP, so as to obtain a better multi-objective optimal solution.

To sum up, Eqs. (1)–(5) are used to calculate the PM interval of each machine. By calculating the PM intervals of all machines cycle by cycle, the PM scheme during the whole decision lifetime can be dynamically determined. And after obtaining all the PM schemes of machines, the PM action of each machine is carried out independently, and the hybrid flow shop scheduling is conducted based on that machine-independent PM schemes.

3.2. System-level production scheduling under TOU tariffs

After obtaining the PM schemes, it is necessary to reasonably arrange the production schemes to guarantee the on-time completion of production orders. To ensure the reliability of machines during the production, the PM planning obtained in stage 1 is regarded as the input here. And no production will be arranged when the machine is under PM. Therefore, the feasible time zone for the production scheduling of machine k, also denoted as the m th PM cycle of machine k, is defined as follows:

$$\text{Feasible zone} = \left[\sum\nolimits_{q=1}^{m-1} T^{*}_{O,kq} + (m-1)T_{PM,k}, \sum\nolimits_{q=1}^{m} T^{*}_{O,kq} + (m-1)T_{PM,k}\right), \forall k \in \mathscr{K} \tag{6}$$

where $\sum_{q=1}^{m-1} T^{*}_{O,kq} + (m-1)T_{PM,k}$ represents the start time of the m th PM cycle of machine k. And the production schedule can be arranged in any feasible zones.

And for the HFSP problem, a PM-constraints-based mixed integer model (MIP) is formulated. The indices and parameters are already defined in the nomenclature. Since the processing sequence of each job is the same and predetermined, the production scheme plan of each job should consist not only selection of machines but also the start time in each process. The decision variables of the MPPS model are categorized into two types: binary variables x_{ijkm} to represent the machine selection and corresponding PM cycle of job i in process j, and t_{ij} as the start time of job i in process j.

Using these denotations, the machine selection of job i in process j can be accessed as Eq. (8), as $x_{ijk} = 1$ when the machine k is selected. At the same time, since the two decision variables of machine choice and processing start time are determined, the completion time of jobs in each process can be obtained by Eq. (9). Before calculating the production cost, Eq. (10) is introduced as a time-dependent piecewise function to express the processing state of each job in the total decision cycle. When $t_{ij} \cdot x_{ijk} \le t < (t_{ij} + tp_{ij} \cdot pr_{ijk}) \cdot x_{ijk}$, $f_{ijk}(t) = 1$ to denote job i is under processing in that time period. Therefore, by summarizing all $f_{ijk}(t)$ function of jobs, the processing state function of each machine is further obtained according to Eq. (11). The electricity cost can be easily calculated through the expression of processing state function of machines. Then the performance of tardiness and electricity consumption are both measured through cost. The objective function (7) minimizes the total production cost *TPC*, which consists of two terms: total electricity cost *TEC* and total tardiness cost *TTC*. And the mathematical formulation for the problem is defined as follows:

$$\min TPC = \sum_{j=1} \sum_{k=1}^{K} \int_{t=0}^{T} \left[f_{jk}(t) \cdot ep_k \cdot tou(t)\right] dt + \sum_{i=1}^{I} \left(\max\{0, td_{iJ} - Td_i\} \cdot Cp_j\right) \tag{7}$$

$$\text{subject to} \quad x_{ijk} = \sum_{m=1}^{M_k} x_{ijkm} \ \forall i \in \mathscr{I}, \ j \in \mathscr{J}, \ k \in \mathscr{K} \tag{8}$$

$$td_{ij} = t_{ij} + \sum_{k=1}^{K} tp_{ij} \cdot pr_{ijk} \cdot x_{ijk} \ \forall i \in \mathscr{I}, \ j \in \mathscr{J} \tag{9}$$

$$f_{ijk}(t) = \begin{cases} 1 & t_{ij} \cdot x_{ijk} \le t < (t_{ij} + tp_{ij} \cdot pr_{ijk}) \cdot x_{ijk} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$f_{jk}(t) = \sum_{i=1}^{I} \left(f_{ijk}(t) \cdot x_{ijk}\right) \ \forall j \in \mathscr{J}, \ k \in \mathscr{K} \tag{11}$$

$$\sum_{k=1}^{K} x_{ijk} = 1 \forall i \in \mathscr{I}, j \in \mathscr{J} \tag{12}$$

$$\sum\nolimits_{i=1}^{I} f_{ijk}(t) \le 1 \forall j \in \mathscr{J}, k \in \mathscr{K} \tag{13}$$

$$t_{i(j+1)} \geq td_{ij} \forall i \in \mathscr{I}, j \in \mathscr{J} \tag{14}$$

$$t_{ij} \geq \left[\sum_{q=1}^{m-1} T^{*}_{O,kq} + (m-1)T_{PM,k}\right] \cdot x_{ijkm} \ \forall i \in \mathscr{I},\ j \in \mathscr{J},\ k \in \mathscr{K},\ m \in \mathscr{M}_k \tag{15}$$

$$td_{ij} \cdot x_{ijkm} \leq \sum_{q=1}^{m} T^{*}_{O,kq} + (m-1)T_{PM,k} \ \forall i \in \mathscr{I},\ j \in \mathscr{J},\ k \in \mathscr{K},\ m \in \mathscr{M}_k \tag{16}$$

$$x_{ijkm} \in \{0,1\} \forall i \in \mathscr{I}, j \in \mathscr{J}, k \in \mathscr{K}, m \in \mathscr{M}_k \tag{17}$$

$$t_{ij} \geq 0 \forall i \in \mathscr{I}, j \in \mathscr{J} \tag{18}$$

As the processing start time and machine selection are determined by decision variables, the constraints of this model are built considering 4 aspects. Firstly, constraint (12) ensures that each job can only be processed by one machine in each process. Constraint (13) makes sure that each job machine can only process at most one job at the same time. Meanwhile, constraint (14) guarantees that the processing start time of the job in the next process must be greater than the finish time in the previous process. Besides, constraints (15) and (16) are respectively constrained from the start time and the end time of the process, so as to ensure that the job is processed in the same PM cycle of machine k. Finally, Constraints (17) and (18) give the range of decision variables.

4. Solution approach

In this section, the solution approach of the ETM strategy is presented in detail, as shown in Fig. 5. As mentioned above, the joint decision-making procedure is divided into two main stages. In the first stage, information about machine reliability obtained from the original equipment manufacturers, long-term monitoring data, and historical experience is input. And for each machine, the dynamic multi-attribute PM planning is performed to output the PM interval sequences Seq_1^{PM}, Seq_2^{PM}, $\cdots$, Seq_K^{PM}. After obtaining all PM sequences, the system-level production scheduling based on PM schemes input is carried out in the second stage, and the MLEGA algorithm is executed to find the optimal production scheduling.

By doing so, the complexity of the collaborative optimization of MPPS is decreased while the interaction between maintenance and production is still well considered in the whole decision-making process. Therefore, the optimal results of MPPS can be obtained more easily.

4.1. Machine level: Dynamic MAM PM planning

In the PM planning problem, the dynamic MAM PM method is proposed. The PM cycle and the hazard rate of each machine are updated cycle by cycle to ensure a more accurate solution. MAR is considered to be one of the objectives related to efficiency. MCR and AEP are the other two objectives related to profits. The procedure of the dynamic MAM PM planning algorithm is proposed in Table 2.

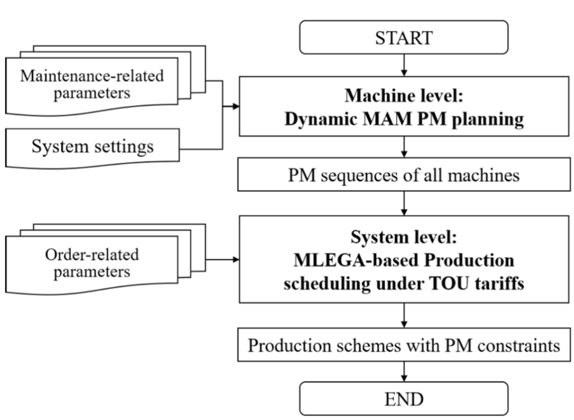

Fig. 5. Solution approach of the ETM strategy.

Table 2
Dynamic MAM PM planning algorithm.

Algorithm 1. Dynamic MAM PM Planning algorithm.
Input: Length of decision cycle T, number of machines K, reliability-related parameters ($\lambda_k(t)$, a_k, b_k), maintenance-related parameters ($T_{PM,k}$, $T_{CM,k}$, $C_{PM,k}$, $C_{CM,k}$), weights of single-attribute PM model (w_{1km}, w_{2km}, w_{3km}), and $tou(t)$.
Output: PM interval sequence of each machine $Seq_1^{PM}, Seq_2^{PM}, \cdots, Seq_K^{PM}$

```
for k = 1, 2, ⋯, K do
    Initialize m = 0, T_SUM,k0 = 0, M_k = 0.
    for m = 1, 2, ⋯, M (a very big number) do
        λ_k1(t) = λ_k(t).
        T*_A,km, T*_C,km, T*_E,km = 0, A*_km, C*_km, E*_km = 0; T*_O,km = 0.
        Apply Single-MAR model (maximize Eq. (1)), obtain and update T*_A,km, A*_km.
        Apply Single-MCR model (minimize Eq. (2)), obtain and update T*_C,km, C*_km.
        Apply Single-AEP model (minimize Eq. (3) or (4)), obtain and update T*_E,km, E*_km.
        Apply MAM model (minimize Eq. (5)), obtain T*_O,km.
        Update T_SUM,km = T_SUM,k(m-1) + T*_O,km.
        if T_SUM,km ≤ T then
            Save T*_O,km → Seq_k^PM.
            λ_k(m+1)(t) = b_k λ_km (t + a_k T*_O,km).
        else
            T*_O,km = T − T_SUM,k(m-1), M_k = m.
            Save T*_O,km → Seq_k^PM.
            break
        end if
    end for
end for
```

Through the dynamic MAM PM planning algorithm, the PM interval sequence of machine k in the whole cycle can be obtained as $Seq_k^{PM} = \{T^{*}_{O,k1}, T^{*}_{O,k2}, \cdots, T^{*}_{O,kM_k}\}$. The set of PM schemes of all machines can also be obtained as Seq_1^{PM}, Seq_2^{PM}, $\cdots$, Seq_K^{PM}.

4.2. System level: MLEGA-based production scheduling

Besides the NP-hard production scheduling problem, the introduction of maintenance and TOU tariffs further increases the computational complexity. To solve this key issue, a multi-layer encoding genetic algorithm (MLEGA) is proposed to solve the time-continuous HFSP with PM constraints.

4.2.1. MLEGA coding method

In the mathematical modeling of HFSP in Section 3.2, the decision variables are categorized into two parts: the binary variables x_{ijkm} to denote the selection of machine, and the float variables t_{ij} to represent the processing start time of jobs. In order to integrate these two types of variables, a multi-layer encoding rule is proposed in Fig. 6.

Each chromosome is divided into three layers, which represent the scheduling sequence, the machine selection, and the processing start time separately. To better ensure the feasibility of the chromosome, the generation of the third layer partly depends on the first and second layers. A total I start times are generated randomly and are assigned to each job according to the sequence of process 1 in the first layer. Meanwhile, the actual processing time can be calculated through both the required processing time of tp_{ij} and the machine selection in the second layer. Therefore, the feasible start time of the next process can be obtained by adding the start time of process 1, the actual processing time of process 1, and a random number to simulate the waiting time between each process.

Due to the interconnection between the third layer and the first two

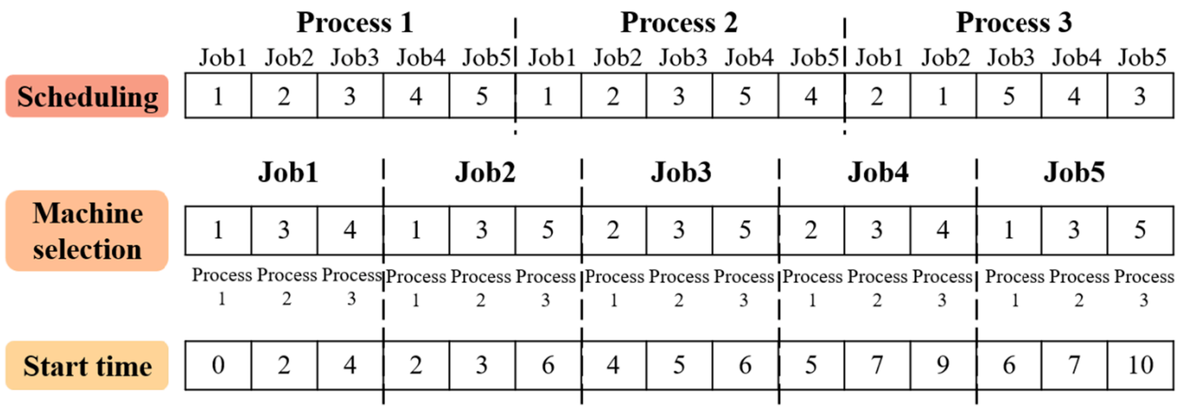

Fig. 6. Encoding rule of the MLEGA algorithm.

layers in the chromosome encoding process, the crossover in MLEGA is also carried out separately for each layer. The detailed crossover method of MLEGA is shown in Fig. 7. For the scheduling layer, Order Crossover (OX) method is used to deal with the production sequence in each process. And for the machine selection layer, the multi-point crossover method is used. And after generating the new generation of the first two layers. The crossover of the third layer is conducted, the start time of process 1 of the two-parent generations are extracted and reordered from smallest to largest first. Then the two-points crossover method is used for these two start time sequences, and a new generation of start times of process 1 is obtained. After that, the generating method mentioned in the encoding part is applied to regenerate the start time of other processes.

4.2.2. *MLEGA framework*

Based on the triple-layer encoding procedure, the MLEGA algorithm is described in Table 3, while the specific iterative steps are listed as follows:

Step 1: Input all the information and parameters of machines, jobs, and TOU tariffs. And then, as a procedure after PM planning, a PM-related penalty cost function of each machine is introduced. The PM-related penalty cost is set to be a very large positive number when the

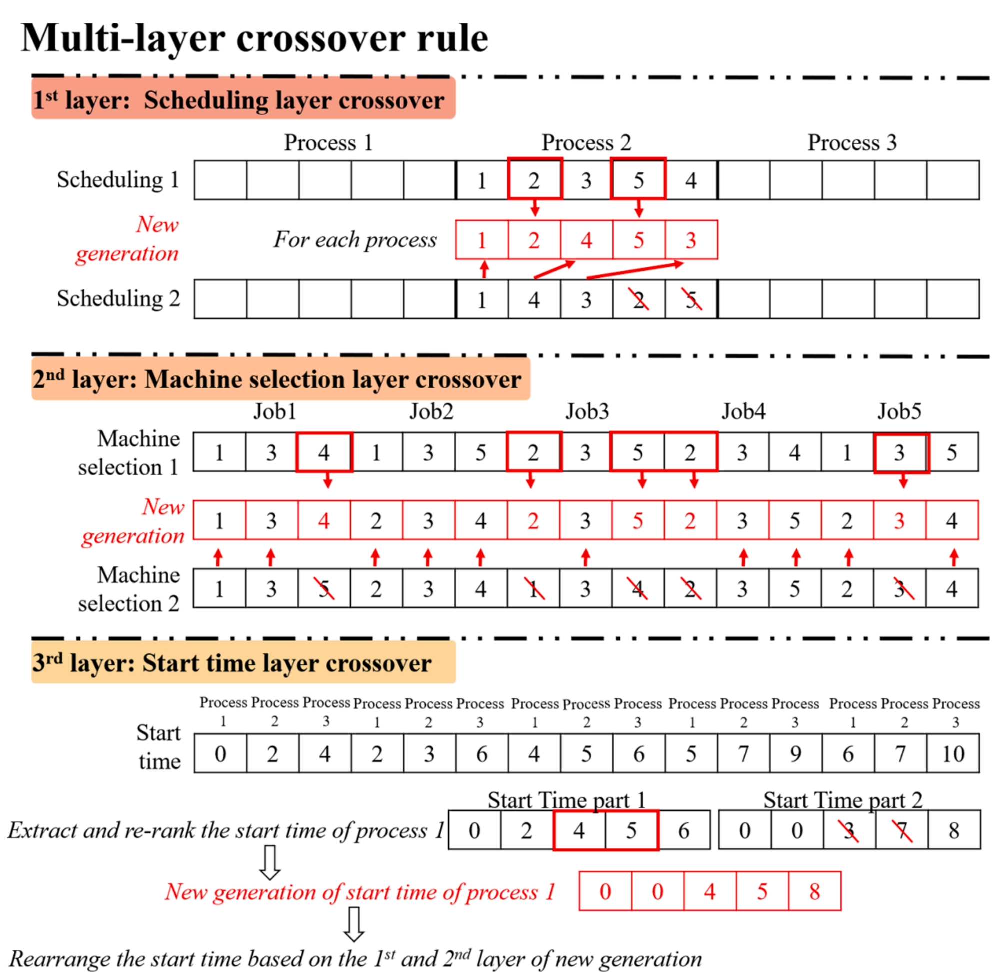

Fig. 7. Crossover rule of the MLEGA algorithm.

Table 3
Multi-layer encoding genetic (MLEGA) algorithm.

Algorithm 2. Multi-layer encoding genetic algorithm.
Input: GA related parameters (iteration number *Iter*, population size *Ps*, crossover rate *Cr*, mutation rate *Mr*, selection proportion *Se*), order related parameters (tp_{ij}, Td_i, Cp_i), machine related parameters (ep_k, pr_{ijk}), PM interval sequence ($Seq_1^{PM}, Seq_2^{PM}, \cdots, Seq_K^{PM}$), TOU tariffs function $tou(t)$.
Output: Optimal production scheduling
1. Initialize $iter = 1$.
2. Generate the first generation G_1 with the scale of *Ps* using the multi-layer encoding method.
3. **for** $iter = 1, 2, \cdots, Iter$ **do**
4. Calculate the **fitness** of each chromosome in the generation G_{iter}.
5. Record/Update the chromosome with the best fitness FIT_{best} as CHS_{best}.
6. Do **roulette wheel selection** with the proportion of *Se*, take the **selective** part as G_{select} and add them to G_{iter+1}.
7. Use G_{select}, do **crossover** with the possibility of *Cr*, add the generated chromosome to G_{iter+1}.
8. Use G_{select}, do **mutation** with the possibility of *Mr*, add the generated chromosome to G_{iter+1}.
9. Initialize a new chromosome randomly, add the generated chromosome to G_{iter+1}.
10. Repeat step7,8,9 until: (the scale of G_{iter+1}) $= Ps$.
11. **end for**
12. Output CHS_{best}, FIT_{best}.

machine is under PM, so as to ensure that the production plan does not overlap with the maintenance period.

Step 2: The first generation of chromosome is generated according to the encoding rule mentioned in Section 4.2.1. The population size of each generation is pre-set.

Step 3: Each chromosome in the generation is then decoded to calculate the fitness. The fitness function is defined as the reciprocal of the sum of *TPC* and *TMC* (total PM penalty cost). The *TPC* can be easily obtained according to the decoding information and the input parameters. And the *TMC* is calculated by integrating the product of the processing state function and the PM-related penalty cost function of each machine. For each generation, record the chromosome with the best fitness FIT_{best} as CHS_{best}.

Step 4: According to the fitness, the roulette wheel selection method is adopted to select a certain proportion of individuals as parents. Then crossover and mutate the parents with a pre-set probability to generate more new chromosomes. At the same time, in order not to fall into a local optimization, some randomly generated individuals are appropriately added to the new generation.

Step 5: Iterate step 3 and 4 until the required number of iterations is reached, and finally output the current optimal chromosome and decode it to the optimal solution.

5. Case study

In this section, the PM planning results of dynamic MAM and single-attribute optimization are presented first. And then the production scheduling optimization is carried out with different PM scheduling inputs to demonstrate the validity of the energy-conscious two-stage optimization strategy.

5.1. Data description

The ETM strategy is carried out on a hybrid flow shop with 3 processes for a cigarette packaging system, which consists of 2 cigarette-making machines, 1 packaging machine, and 2 sealing machines. There are 2 machines in processes 1 and 3, and only one machine in process 2. All related parameters are collected by the professional engineers in the cooperative enterprise. And the TOU tariffs follow the standard of TOU pricing in Shanghai 2019, as shown in Table 1 and Fig. 1. Data about the process of this system have been collected by the engineers with cooperative enterprise. For the investigated PM planning, the hazard rate of each machine is obtained through simulating with the historical data collected within 2 months. And it follows a Weibull distribution in real production scenarios:

$$\lambda(t) = \frac{u_k}{\eta_k}\left(\frac{t}{\eta_k}\right)^{u_k - 1} \tag{19}$$

where u_k represents the shape parameter and η_k represents the scale parameter. Hazard rates of machines increase due to the aging of machine key components. And since the components after PM are usually not as good as new, the value of hazard rate at that time is decreased but not to be zero. Simultaneously, the PM action not only decreases the hazard rate to some degree, but also increases the slope of the hazard rate function. Therefore, the relationship between the hazard rate of machine k before and after PM (the m th and $(m+1)$ th cycle) is defined as:

$$\lambda_{k(m+1)}(t) = b_k \lambda_{km}(t + a_k T_{km}) \tag{20}$$

where T_{km} is the length of the m th PM interval of machine k, which refers to $T_{O,km}$ in the MAM model. And b_k ($b_k > 1$) is the hazard rate increasing factor of machine k, a_k ($0 < a_k < 1$) is the age reduction factor of machine k. These two factors and other reliability information can be collected based on the information provided by OEMs and the historical data of daily maintenance experience [43]. And all the parameters are shown in Table 4.

Meanwhile, order-related parameters such as the processing time in each process tp_{ij}, the due date Td_i, the delay penalty cost Cp_i, and production-related parameters such as processing rate of jobs in each machine pr_{ijk} are also collected by the production engineers and are shown in Table 5.

5.2. Computational **results**

5.2.1. Comparison of the MAM PM scheduling

To validate the proposed dynamic MAM PM scheduling strategy, the parameters mentioned above is used to carry out the PM scheduling with both the MAM strategy and three single-attribute maintenance strategies. A total decision length is set to be $T_{all} = 72h$. And in order to further analyze the characteristics of different PM strategies, the MAR, MCR, and AEP curves of the first PM cycle are visualized to present the changes in different PM objectives over time, which is shown in Fig. 8.

From Fig. 8, the following observations can be obtained:

(1) From the trend of objective curves, the MAR curve is concave, while the MCR curve is convex. The two curves are basically only related to the degradation and maintenance parameters of machines themselves.
(2) The overall trends of the AEP-I and AEP-D curves are more affected by the TOU price rather than the maintenance parameters of machines. These two curves show periodic characteristics, while the cycle gradually shortens with the increase of time. The AEP-I curve also rises periodically and tends to reach the upper

Table 4
Maintenance parameters of all machines.

	Process 1		Process 2	Process 3	
	M_1	M_2	M_3	M_4	M_5
u	5.1	3.8	4.2	4.1	3.8
η	65	50	70	60	45
a	0.055	0.016	0.018	0.038	0.025
b	1.035	1.037	1.042	1.041	1.035
$T_{PM,k}$(h)	2	4	2.4	2	3
$T_{CM,k}$(h)	6.6	7.5	6.8	6.8	8
$C_{PM,k}$(¥)	6500	8800	6000	9600	7400
$C_{CM,k}$(¥)	18,000	22,000	57,000	28,000	30,000

Table 5
Order and production related parameters.

Batch	Processing time in each process(h)	Due date(h)	Tardiness penalty cost(¥)	Processing rates				
				M_1	M_2	M_3	M_4	M_5
1	(5.03, 3.93, 4.74)	45.77	59.61	0.87	0.84	0.89	1.00	1.26
2	(7.76, 3.47, 4.71)	66.57	48.07	1.06	1.66	1.29	1.11	0.81
3	(5.27, 4.67, 7.37)	76.34	37.68	1.96	1.56	0.87	0.99	0.72
4	(7.71, 7.95, 6.00)	47.23	35.93	1.97	0.91	1.62	0.87	0.80
5	(2.67, 6.41, 4.40)	84.26	56.21	0.69	1.23	0.82	0.87	0.98

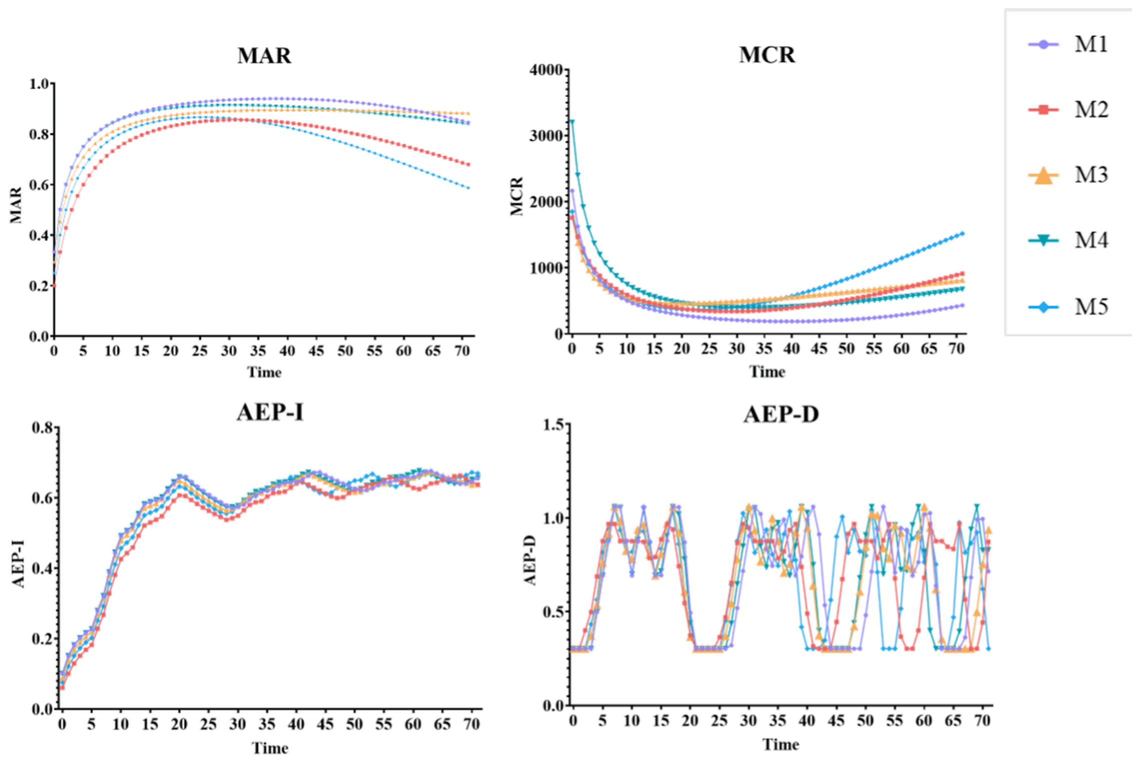

Fig. 8. Different objective curves of all machines.

bound gradually. And the shape and range of the AEP-D curve are similar to the TOU curve.

The optimal values under different PM strategies for the same machine also vary a lot. Therefore, different single-attribute PM strategies are carried out cycle by cycle and the corresponding optimal PM sequences Seq_k^{PM} for each machine k are listed in Table 6.

To further compare the performance of different PM strategies, more MAM PM strategies with different weight groups are added in Fig. 9. MAM-X# unifies the name of different MAM strategies, where $X \in \{I, D\}$ represents what AEP strategy is chosen, and $\# \in \{1, 2, 3\}$ denotes the groups of weights for different single-attribute objectives. If X = I, then AEP-I strategy is used in the MAM model and $w_{3km} \geq 0$, otherwise $w_{3km} \leq 0$. And when # = 1, the weights group is $(w_{1km}, w_{2km}, |w_{3km}| = -0.3, 0.3, 0.4)$; when # = 2, the weights group is $(w_{1km}, w_{2km}, |w_{3km}| = -0.3, 0.4, 0.3)$; and when # = 3, the weights group is $(w_{1km}, w_{2km}, |w_{3km}| = -0.4, 0.3, 0.3)$. The descriptive statistics analysis of performance on MAR, MCR, and AEP among all PM strategies are presented in Table 7.

From Fig. 9 and Table 7, it is obvious that Single-MAR strategy achieves the optimal availability (max, 0.8910), while the best maintenance cost is obtained by MAM-I3 strategy. And the Single-AEP-D strategies achieve the optimal electricity cost during PM (max, 1.042). Besides, different weight groups may also lead to totally different and even contrast results as can be proved from the objective curves in Fig. 8. Meanwhile, it can be seen that for different PM strategies, the MAR, MCR, and AEP-I have only a little variation. While the data of AEP-D is very discrete, which is greatly affected by different PM strategies. It can be interpreted in the form of Eqs. (1)–(4). In the calculation of MAR, MCR, and AEP-I, the decision variable t is included in the denominator, which weakens the volatility of data brought from the variation of time t, thus the curve of MAR, MCR, and AEP-I is relatively smooth. However, the AEP-D equation takes the fixed $T_{PM,k}$ as the denominator, and it is much smaller than the decision variable t, which makes the Single-AEP-D strategy easier to fluctuate, and results in a higher coefficient of

Table 6
PM sequences output of different strategies.

	Single-MAR	Single-MCR	Single-AEP-I	Single-AEP-D
M_1	{39.00, 31.00}	{40.46, 29.94}	{27.91, 28.94, 11.15}	{42.00, 28.00}
M_2	{32.32, 31.38, 0.31}	{29.61, 28.73, 5.65}	{25.43, 31.16, 7.41}	{38.75, 29.25}
M_3	{41.59, 28.01}	{21.09, 20.15, 19.68, 3.89}	{26.62, 21.83, 18.75}	{40.00, 29.60}
M_4	{31.67, 30.24, 6.09}	{33.50, 32.00, 2.50}	{27.36, 28.69, 11.95}	{40.00, 30.00}
M_5	{26.51, 25.61, 13.87}	{23.39, 22.58, 20.04}	{26.00, 31.48, 8.51}	{37.85, 31.15}

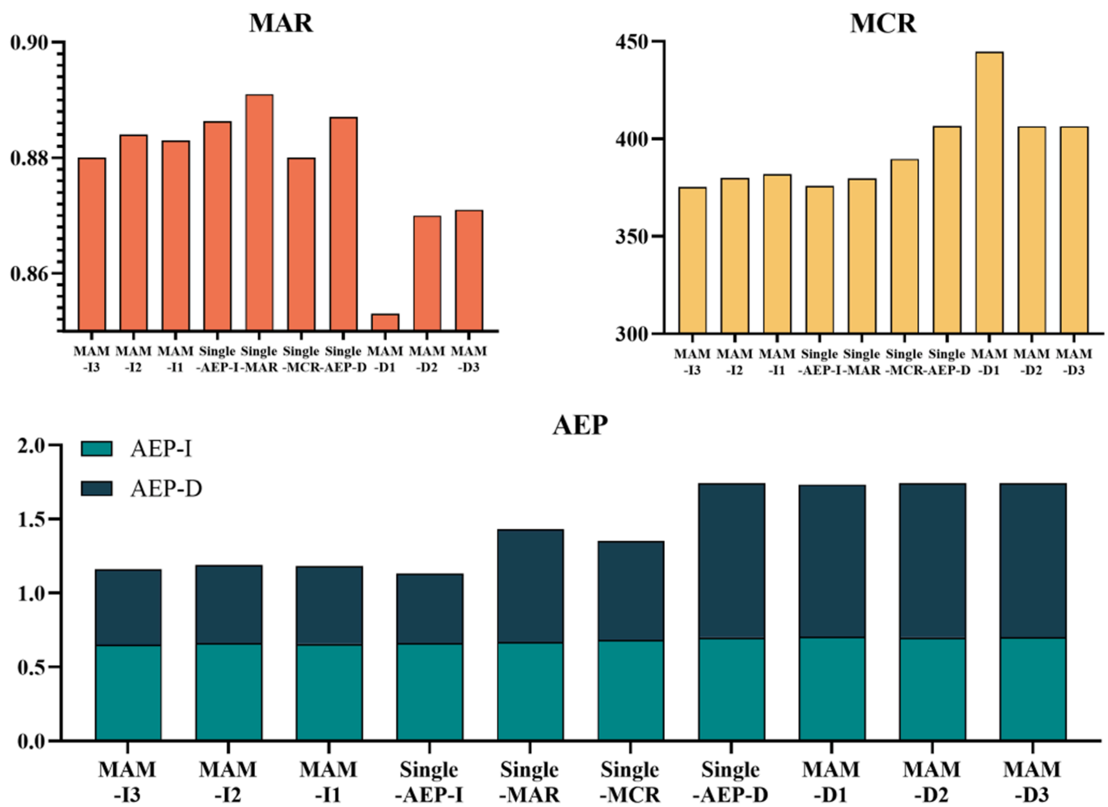

Fig. 9. Performance comparison of different PM strategies.

Table 7
Descriptive statistics analysis of performance under different PM strategies.

	MAR	MCR	AEP-I (¥/h)	AEP-D (¥/h)
Minimum	0.8530	375.3	0.6510	0.4709
Maximum	0.8910	444.7	0.7060	1.042
Range	0.03800	69.35	0.05500	0.5708
Mean	0.8785	394.7	0.6787	0.7617
Standard Deviation	0.01118	21.79	0.02146	0.2518
Standard Error of Mean	0.003535	6.891	0.006785	0.07963
Coefficient of variation	1.272%	5.521%	3.161%	33.06%

variation of AEP-D. Therefore, among all PM strategies, more attentions should be paid on the following production performance of the Single-AEP-D model.

5.2.2. *Production scheduling output and analysis*

In the production scheduling stage, the PM output plan obtained in stage 1 of each machine needs to be taken as the input. Therefore, in order to compare different results of the maintenance models and prove the effectiveness of our model. Different schemes are used for comparative exploration. There are 4 PM strategies, Single-MAR, Single-MCR, Single-AEP-I, and Single-AEP-D models, used as inputs in the following production scheduling stage. And the performance of each strategy is evaluated in 4 dimensions: (1) *TEC*: total electricity cost; (2) *TTC*: total tardiness cost; (3) makespan: the total length of the production schedule; (4) average proportion of production in each TOU period. For each machine, the proportions of production in each TOU period for machine k are calculated by:

$$\begin{cases} OFF\% = \dfrac{\int_0^{T_{all}} \left\{ f_{jk}(t) \cdot \left[1 - \max\left(\left\lceil (tou(t) - 0.303)^2 \right\rceil, 0 \right) \right] \right\}}{\int_0^{T_{all}} f_{jk}(t)\, dt} \\ MID\% = \dfrac{\int_0^{T_{all}} \left\{ f_{jk}(t) \cdot \left[1 - \max\left(\left\lceil (tou(t) - 0.693)^2 \right\rceil, 0 \right) \right] \right\}}{\int_0^{T_{all}} f_{jk}(t)\, dt} \\ ON\% = \dfrac{\int_0^{T_{all}} \left\{ f_{jk}(t) \cdot \left[1 - \max\left(\left\lceil (tou(t) - 1.060)^2 \right\rceil, 0 \right) \right] \right\}}{\int_0^{T_{all}} f_{jk}(t)\, dt} \end{cases} \tag{21}$$

Firstly, *TPC* is taken as the optimization objective of production scheduling with different PM strategies, and the production scheduling problem is solved. After that, the performance of each scheme under different PM strategies is calculated to verify the effectiveness of AEP model in the PM scheduling stage. The output and performance are shown in Fig. 10. It can be seen from the results that:

(1) Comparing the results of Single-MAR, Single-MCR strategies with Single-AEP-I and Single-AEP-D strategies, these two AEP strategies result in a much lower TEC, and also significantly increase the average proportion of production in the off-peak periods. Also, the PM sequences under Sing-MAR and Single-MCR are relatively more discrete than that of two Single-AEP strategies.
(2) Comparing the Single-AEP-I and Single-AEP-D strategies, although they both consider the average electricity price for the production stage, different modes of electricity usage are achieved due to their different emphases. Since AEP-D seeks a higher price during PM actions, it prefers to arrange more PM actions in peak periods, and the *ON*% (calculated by Eq. (21)) is significantly lower than that in the Single-AEP-I strategy. While the

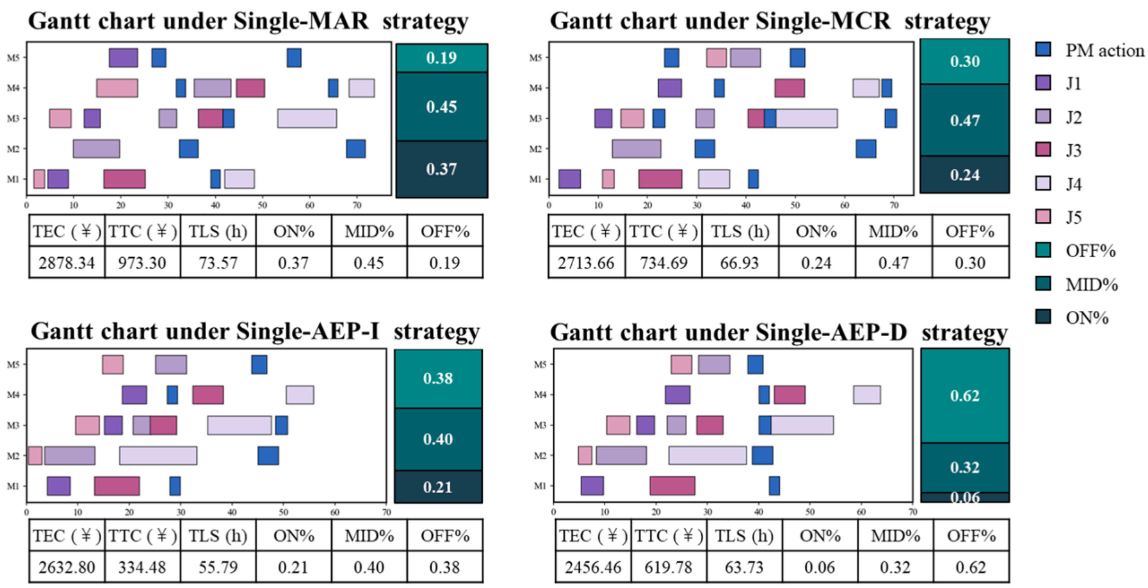

Fig. 10. Production performance comparison of PM strategies.

proportions in different periods under the Single-AEP-I strategy are relatively balanced and can also achieve a relatively lower TEC.

(3) Among all PM strategies, the Single-AEP-D strategy obtains the best TEC result, which can also prove the conclusion mentioned in session 5.2.1.

Then, the output of Single-AEP-D strategy is taken as the input to all contrast experiments with different production objectives to verify the effectiveness of the system-level production scheduling model. Since the makespan is usually an important performance when evaluating a production scheme in real production scenarios, three optimization objectives are adopted: (1) *TPC*: total production cost, referred to as *TEC* + *TTC*; (2)*TLS*: total length of the schedule, also known as makespan; (3) *TTC*: total tardiness cost. The performance comparison is presented in Fig. 11.

From the comparison of the production performance, it is obvious that the *TLS* and the *TTC* are positively correlated. When the *TLS* is reduced, the total tardiness cost is also minimized due to the optimization of the *TLS*. But at the same time, the excessive pursuit of the *TTC* and *TLS* brings more production time in the peak periods, resulting in a much higher *TEC* value increase than the reduction of *TTC*. In contrast, the *TPC* objective function used in the ETM strategy emphasizes a comprehensive balance between *TEC* and *TTC*, and is willing to give up some *TTC* to achieve higher proportions of production in the mid-peak and off-peak periods. Therefore, a significant reduction of *TEC* can be achieved, and effective energy savings are realized.

Based on the results shown in Fig. 10 and Fig. 11, the electricity consumption cost for different periods under different MPPS strategies can be compared in Fig. 12 and Table 8.

It can be seen from the above figure that the ETM strategy with single-AEP-D as maintenance objective and *TPC* as production objective outperforms among all strategies in the *TEC*, *TEC*, and percentage of On-peak and Off-peak periods. It reaches both the optimal *TEC* and *TPC*, and

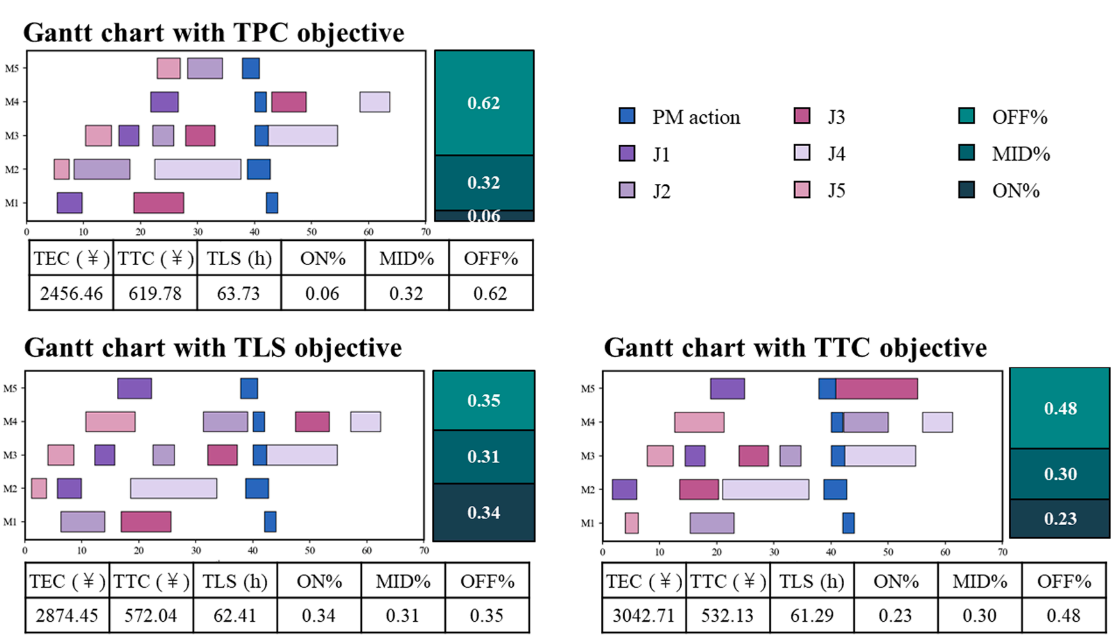

Fig. 11. Performance comparison of production strategies under Single-AEP-D PM strategy.

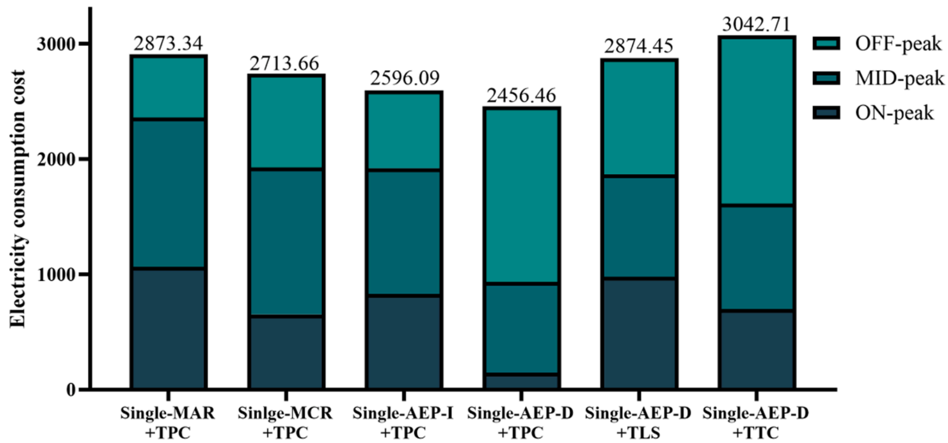

Fig. 12. Electricity consumption cost under different MPPS strategies.

Table 8
Result analysis under different MPPS strategies.

	TEC	ON %	MID %	OFF %	TTC	TLS	TPC
Single-MAR + TPC	2878.34	0.37	0.45	0.19	973.30	73.57	3851.64
Single-MCR + TPC	2713.66	0.24	0.47	0.30	734.69	66.93	3448.35
Single-AEP-I + TPC	2596.09	0.32	0.42	0.26	761.84	77.95	3357.93
Single-AEP-D + TPC	2456.46	0.06	0.32	0.62	619.78	63.73	3076.24
Single-AEP-D + TLS	2874.45	0.34	0.31	0.35	572.04	62.41	3446.49
Single-AEP-D + TTC	3042.71	0.23	0.30	0.48	532.13	61.29	3574.84

the minimum ON% among all plans is achieved to 6%. At the same time, considering that the PM planning in nowadays real industrial scenario mainly concentrates more on the availability of machines, ignore the impact of PM schemes in the context of TOU, and the production planning puts tardiness cost as the first consideration, two strategies close to the current MPPS goals are selected for comparison the prove the effectiveness of the ETM strategy. Among all strategies mentioned above, the Single-AEP-D + TPC (denoted as BASE) strategy best represents the ETM strategy's focus on the TOU impact and electricity cost saving, and the Single-MAR + TPC (denoted as M) and Single-AEP-D + TTC (denoted as P) strategies are selected to represent the real industrial preference on MPPS separately.

Compared with the M strategy, the performance of BASE strategy dominates in all aspects with *TLS*, *TTC*, *TEC* and *TPC* all surpassed, the improvement percentage reaches 13.38%, 36.32%, 14.66%, and 20.13% respectively. At the same time, compared with the solution of P strategy, although the *TTC* of BASE strategy increases by 8.35%, the increase of *TLS* is only 2.12%, and at the same time, through *TEC* optimization, 14.54% of *TEC* is saved, and 10.74 % of the *TTC* saving is achieved.

To sum up, the proposed ETM strategy achieves energy savings in two main aspects. Firstly, the average electricity price is considered in advance in the maintenance decision-making process. Secondly, the comprehensive consideration of the total electricity cost *TEC* and the total tardiness cost *TTC* in the production stage also reaches a balance between energy saving and productivity. They bring electricity balance from different angles, which all have positive impacts on the improvement of the system energy utilization efficiency and the balance of energy consumption. Through the application of the ETM strategy, manufacturing enterprises can achieve electricity cost savings by little adjustment to the O&M scheduling, which can avoid a higher investment in the changing of production structure and the updating of machines.

6. Conclusion and future work

This paper studies the MPPS problem for serial-parallel manufacturing systems under TOU tariffs and proposes an efficient ETM strategy. In the first stage, the multi-attribute PM planning strategy is proposed which integrates machine availability rate, maintenance cost rate, and the average electricity price impact of production. Under this TOU circumstance, on-peak periods are taken as an energy-saving opportunity to arrange PM actions. And in the second stage, the production scheduling also takes the total electricity cost as one of the objectives. Idle time is properly inserted into the production scheme to make further savings on the electricity consumption cost. And an MLEGA algorithm is developed to solve the production scheduling problem. To further explain the effectiveness of the proposed ETM strategy, a case study and the analysis are carried out. The results show that the proposed strategy can improve the energy-saving level in two dimensions. At the maintenance stage, the advanced consideration of the PM action impact on the production scheduling can arrange more PM actions in the on-peak periods, bringing more opportunities to carry out production in the periods with lower prices. At the production stage, the joint optimization of total electricity cost and total tardiness cost can also obtain electricity cost savings by arranging more idle time between job production.

For future work, the problem could be further explored in the following directions. Algorithms with more effective optimization strategies could be explored. More complicated objectives and constraints could be considered, such as the random arrival time of jobs, the carbon emission of production, and so on.

CRediT authorship contribution statement

Xiangxin An: Methodology, Software, Writing – original draft. **Guojin Si:** Validation, Investigation. **Tangbin Xia:** Conceptualization, Supervision. **Dong Wang:** Data curation, Visualization. **Ershun Pan:** Resources, Formal analysis. **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.

Data availability

Data will be made available on request.

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