

Integrated operation and maintenance optimization for high-speed train fleets considering passenger flow

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Highlights

- Operation and maintenance model for high-speed train fleet considering passenger flow is proposed.
- A new maintenance strategy for the model is developed.
- The characteristics of the model and the strategy are analyzed.
- The proposed strategy outperforms another strategy in many aspects.

Abstract

A joint optimization model of maintenance and operation of high-speed train fleets is established with the optimization objective of minimizing the total costs, considering dynamic passenger flow and maintenance resources. A new maintenance strategy CCPM (Coordinating Conflicts Preventive Maintenance) is proposed to optimize the problem. The effectiveness of the model and the strategy are verified by numerical examples. The comparison between the strategy in the paper and the existing approach proves that the new strategy is more effective and shows the importance of considering dynamic passenger flow. The model and the strategy provide decision support for the actual high-speed trains operation and maintenance program. This study also offers new ideas to the subsequent research on preventive maintenance of high-speed trains.

Keywords

preventive maintenance; high-speed train; fleet operation and maintenance; passenger flow.

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Abbreviations:

PM - Preventive Maintenance
CCPM - Coordinating Conflicts Preventive Maintenance
SAPM - Simulated Annealing Preventive Maintenance

Notations:

V_{train} - Set of the high-speed train fleet
 N_{train} - Train number of the high-speed train fleet
 N_{accept} - The number threshold of trains entering the workshop simultaneously
 N_{fix} - The number of PM for each train within the time horizon
 N_{de} - The number of trains which delay their PM actions
 N_{ad} - The maximal number of trains which advance their PM actions
 d - The duration of PM action
 t_{ad} - Advance coordination factor

s_m^t - Binary variables, $s_m^t = 1$ if train m starts to perform PM action, otherwise $s_m^t = 0$
 x_m^t - Binary variables, $x_m^t = 1$ if train m is under PM state, otherwise $x_m^t = 0$
 T - The length of time horizon
 T_i - The length of time interval i
 γ_i - The passenger flow of time interval i
 γ_0 - Basic passenger flow
 ε_i - The passenger flow factor of time interval i
 ρ_i - The operation rate threshold of time interval i
 ρ_0 - Basic operation rate threshold
 $\lambda_0(t)$ - Initial failure rate at t
 $\lambda(t)$ - Actual failure rate at t
 t_{begin} - The initial age
 t_{eq}^i - Equivalent age of time interval i
 t_s^i - The start point of the i th PM

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- t_e^i - The end point of the i th PM
- C^{total} - The total maintenance costs
- C^P - PM costs of the fleet
- C^c - Minimal repair costs of the fleet
- C^f - Operation penalty costs of the fleet
- C^s - Maintenance resource costs of the fleet
- c_m^p - PM costs of train m
- c_m^c - Minimal repair costs of train m
- $c^{fd}(t)$ - Operation penalty costs of the fleet at t
- $c^{sd}(t)$ - Maintenance resource costs of the fleet at t
- c^{up} - The unit PM cost
- c^{set} - The setup cost of PM
- c^{uc} - The unit minimal repair cost
- c^{uf} - The unit operation penalty cost
- c^{us} - The unit maintenance resource cost

1. Introduction

High-speed railways are growing by leaps and bounds. Especially in China, the total mileage of high-speed rail is over 38000 km in 2020. Preventive maintenance (PM) actions have been pervasively implemented in the industrial field [6, 27, 31]. In high-speed railways, PM can restore trains to a better condition, guarantee the safety of trains, and prolong residual lives of trains [14]. Currently, PM actions are carried out when the operating time or accumulated mileage of the train reaches a threshold. However, this approach ignores the impacts of operation loss and the limitation of maintenance resources. A certain number of high-speed trains constitute a fleet according to their operating information. As the passenger flow fluctuates in different time periods in a year [8], the number of trains performing maintenance simultaneously would be limited, or the fleet will suffer operation loss. Besides, the capacity of the workshop is limited, which should be taken into consideration when making maintenance decisions.

The research of integrating production and maintenance schedules has been studied mostly in three different ways [24, 25]. Some researchers develop PM schedules in the production system [1, 28], and some others take maintenance as a constraint to the production system [20, 26]. Few researchers optimize production schedules and maintenance schedules jointly [7, 11]. Cheung et al. [5] divide the maintenance into two steps: long-term and short-term scheduling to reduce the influence on production. Liu et al. [19] propose an optimization model integrating preventive maintenance and medium-term tactical production planning. The objective is to minimize the sum of production, maintenance and inventory, and the results prove the effectiveness of the model. Kuo and Chang [15] investigate the interaction of the optimal production schedule and the optimal PM plan. Naderi et al. [22] propose two approaches to solve job shop scheduling with sequence-dependent setup times and PM policies compared with original simulated annealing and genetic algorithms. Numerical analysis reveals the proposed algorithms perform better. Berrichi et al. [3] propose a bi-objective approach to solve the joint optimization problem, which optimizes two criteria simultaneously. Based on the study, they [2] further propose an algorithm based on ant colony optimization to solve the problem, and the numerical results show that the proposed algorithm outperforms conventional multi-objective algorithms. Najid et al. [23] model a linear mixed-integer program to tackle the integration problem. Hamed et al. [13] formulate a bi-

objective optimization model integrating maintenance and production scheduling in a multi-factor production network. Two strategies are proposed to solve the problem and obtain the Pareto front. Linnéusson et al. [18] contribute a hybrid simulation-based optimization framework to balance economic requirements and maintenance constraints. Cheng et al. [4] propose a joint model of preventive maintenance, production and quality for a serial-parallel system. A simulation-based optimization approach combining genetic algorithm and Monte Carlo Simulation is presented to solve the problem. Maintenance threshold, quality threshold and the length of production run are optimized simultaneously in the model. Yang et al. [32] introduce a novel heuristic reinforcement learning method to solve the integrated problem.

In the transportation field, the problem of integrating the operation and maintenance schedule of trains is studied to improve the efficiency of railways [30]. Gu et al. [10] propose a model making decisions of arrival time at workshop considering the desired number of services and the capacity of workshop. Giacco et al. [9] propose a mixed-integer linear programming (MILP) formulation for integrating short-term maintenance schedule and railway rostering planning. Lai et al. [16] formulate a rolling stock assignment scheduling model considering maintenance and develop a hybrid heuristic approach to solve the problem. Luan et al. [21] address a problem of optimizing train routes, passing time at station as well as preventive maintenance tasks plan simultaneously. A Lagrangian relaxation solution is proposed to decompose the original problem into a sequence of single sub-problems. A standard label correcting algorithm is employed to solve each sub-problem, and numerical analysis evaluates the efficiency of the proposed approach. Zhang et al. [33] develop a microscopic optimization model integrating passenger timetabling and track maintenance scheduling. An iterative algorithm is proposed to compute near-optimal solutions. The algorithm decomposes the whole problem into sub-problems related to rolling stock scheduling. Zhong et al. [34] propose a problem of train scheduling with maintenance constraints. A two-stage heuristic approach is developed to solve the problem. In the first stage, it focuses on the candidate rolling stock schedule ignoring the maintenance restriction. In the second stage, maintenance requirements are considered, and the feasibility of the candidate schedule is checked.

Notably, the model of integrating train schedule and maintenance schedule is addressed in the current papers. However, the researchers mainly focus on the timetable of the trains and the short-term maintenance schedule. When developing the plan of long-term maintenance schedule, passenger flow is considered due to its influence on operation. The need for operation limits the number of trains being performed PM simultaneously. Wang et al. [29] study the maintenance adjustment strategy of the high-speed train under the influence of uneven passenger distribution and compared it with the maintenance scheme without considering this factor. Lin et al. [17] introduce a constraint for restricting the number of trains under maintenance because of the desire for passenger transport service. But their models are still based on the period maintenance strategy. This paper proposes a more flexible maintenance scheduling model for high-speed trains, which result in a large solution space. A strategy called Coordinating Conflicts Preventive Maintenance (CCPM) is developed to tackle the complex problem. The proposed strategy decomposes the original problem into sub-problems of single high-speed train which will be solved by interior method. Then the coordination is executed to integrate the results of a sequence sub-problems to obtain the final schedule.

The remainder of the paper is organized as follows. In Section 2, we formulate the high-speed train fleet model. Section 3 is devoted to CCPM strategy, which is applied to optimize the maintenance schedule. Numerical analysis is given in Section 4, whereas concluding remarks are presented in Section 5.

2. Model formulation

2.1. Problem description

We consider a high-speed train fleet set V_{train} which consists of N_{train} high-speed trains. A model is established for making preventive maintenance plans of the fleet. The objective is to minimize the total costs of operation and maintenance. In time horizon $[0, T]$, PM can only be performed in discrete time (minimum unit is day). The assumptions of the model are given as follows:

- The initial reliability of each high-speed train follows two-parameter Weibull distribution independently. Actual reliability is influenced by dynamic passenger flow [29].
- PM will restore the high-speed train to as-good-as-new state. Each PM action costs d days in which high-speed train cannot operate.
- Minimal repair is implemented when a failure happens without changing the failure rate of the high-speed train. The duration of minimal repair can be ignored.
- The operation rate threshold of the fleet changes as dynamic passenger flow fluctuates [17]. If the number of operating high-speed trains is lower than the operation requirement, a penalty cost will be added to the total costs.
- PM must be implemented in the workshop. If the number of trains entering the workshop simultaneously exceeds the capacity of the workshop [16], a maintenance resource cost will be added to the total costs.

To make the maintenance plans for high-speed trains in time period $[0, T]$, we introduce the decision variable:

$$s_m^t = \begin{cases} 1 & \text{if train } m \text{ start to perform PM} \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where t is an integer, and $m \in V_{train}$. To better describe the model, we introduce another decision variable to represent the state of train:

$$x_m^t = \begin{cases} 1 & \text{if train } m \text{ is under PM state} \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

Equivalence between two decision variables is derived naturally:

$$x_m^t = \sum_{\tau=\max\{0, t-d+1\}}^t s_m^\tau, \quad (3)$$

where d is the duration of PM. A train cannot start to perform PM action when it is under PM state already. Thus, the train cannot start to perform PM actions twice in any interval which length is less than d ,

$$\text{that is, } \sum_{\tau=\max\{0, t-d+1\}}^t s_m^\tau \leq 1.$$

2.2. Reliability model

Initial reliability of train m follows two-parameter Weibull distribution $R_0(t) = \exp\left(-\left(\frac{t}{\alpha}\right)^\beta\right)$, and initial failure rate $\lambda_0(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha}\right)^{\beta-1}$.

The passenger flow fluctuates due to seasonal changes and holidays. Considering these factors, we separate the whole time horizon into θ time intervals:

$$[0, T] = [t_1, t_2] \cup [t_2, t_3] \cup \dots \cup [t_\theta, t_{\theta+1}], \quad (4)$$

where the length of time interval i is T_i , that is, $T_i = t_{i+1} - t_i$. The passenger flow of each time interval is different.

Wang et al. [29] propose that the passenger flow factor ε_i reflects the operating conditions under different passenger flow: $\varepsilon_i = \frac{\gamma_i}{\gamma_0}$, where γ_i represents the passenger flow of time interval i ; γ_0 represents the basic passenger flow. The operation rate threshold of the fleet ρ_i is assumed to be proportional to the passenger flow γ_i , that is, $\rho_i \propto \gamma_i$. Thus $\rho_i = \varepsilon_i \rho_0$, where ρ_0 represents the basic operation rate. Assuming $\rho_0 = 1$, the equation is derived naturally: $\rho_i = \varepsilon_i$.

The passenger flow factor represents the operating condition that would influence actual failure rate. According to [12], age transformation can express the change of the operating condition. Equivalent age of time interval i is calculated: $t_{eq}^i = \varepsilon_i T_i$.

If train m has not been executed PM yet at t , and t is within time interval n . The failure rate is derived:

$$\lambda(t) = \varepsilon_n \lambda_0 \left(\varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \sum_{i=1}^{n-1} t_{eq}^i + t_{begin} \right), \quad (5)$$

where t_{begin} is the initial age of train m . More factors are taken into consideration when train m has been executed PM at least once. PM would restore the train to as-good-as-new state, that is, $\lambda(t) = 0$. Assuming train m has been implemented PM k times, the end point of the last PM is t_e^k , which is within interval n' . The present time is t , which is within interval n . Then the failure rate is given:

$$\lambda(t) = \begin{cases} \varepsilon_n \lambda_0 \left(\varepsilon_n \left(t - t_e^k \right) \right) & n' = n \\ \varepsilon_n \lambda_0 \left(\varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \varepsilon_{n'} \left(\sum_{i=1}^{n'} T_i - t_e^k \right) \right) & n' = n-1 \\ \varepsilon_n \lambda_0 \left(\varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \varepsilon_{n'} \left(\sum_{i=1}^{n'} T_i - t_e^k \right) + \sum_{i=n'+1}^{n-1} t_{eq}^i \right) & n' \leq n-2 \end{cases}, \quad (6)$$

where three situations are considered. The present time and the end point of last PM are within the same interval; the two are within adjacent intervals; the two are at least one interval apart.

2.3 Maintenance costs

The total maintenance costs include PM costs, minimal repair costs, operation penalty costs, and maintenance resource costs.

PM costs consist of setup maintenance costs and variable costs depending on the number of PM. PM costs are given:

$$C^P = \sum_{t=0}^T \sum_{m \in V_{train}} x_m^t c^{up} + \sum_{t=0}^T \delta(t) c^{set}, \quad (7)$$

where c^{up} is the unit cost of PM. c^{set} is the setup cost. δ is indicator function:

$$\delta(t) = \begin{cases} 1, & \text{if } \sum_{m \in V_{train}} x_m^t \geq 1 \\ 0, & \text{otherwise} \end{cases}. \quad (8)$$

Minimal repair costs are calculated by the expected number of failures. If train m performs PM action n_m times, minimal repair costs of train m are given:

$$c_m^c = \begin{cases} c^{uc} \left(\int_0^{t_s^1} \lambda(t) dt + \int_{t_e^1}^T \lambda(t) dt \right) & n_m = 1 \\ c^{uc} \left(\int_0^{t_s^1} \lambda(t) dt + \sum_{i=1}^{n_m} \int_{t_e^{i-1}}^{t_s^i} \lambda(t) dt + \int_{t_e^{n_m}}^T \lambda(t) dt \right) & n_m \geq 2 \end{cases}, \quad (9)$$

where c^{uc} is the unit cost of minimal repair, t_s^i represents the start point of the i th PM, t_e^i represents the end point of the i th PM. The total minimal repair costs of the fleet are given:

$$C^c = \sum_{m \in V_{train}} c_m^c. \quad (10)$$

When the operation rate of the fleet is lower than the threshold of the interval, the fleet will spend great penalty costs. If the plan incurs no penalty costs, assuming t falls in interval n , the inequality is satisfied:

$$1 - \frac{\sum_{m \in V_{train}} x_m^t}{N_{train}} \geq \rho_n, \quad (11)$$

where $\frac{\sum_{m \in V_{train}} x_m^t}{N_{train}}$ is the maintenance rate. ρ_n is the operation rate threshold of interval n . The formulation is equivalent to $\sum_{m \in V_{train}} x_m^t \leq N_{train} (1 - \rho_n)$. Penalty costs are calculated by the extra number of trains that exceed the set constraints. The operation penalty costs of the fleet at t are given:

$$c^{fd}(t) = c^{uf} \max \left(0, \sum_{m \in V_{train}} x_m^t - N_{train} (1 - \rho_n) \right), \quad (12)$$

where c^{uf} is the unit penalty cost. The total operation penalty costs are given:

$$C^f = \sum_{t=0}^T c^{fd}(t). \quad (13)$$

Similarly, if the plan incurs no maintenance resource costs, assuming t falls in interval n , the inequality is satisfied:

$$\sum_{m \in V_{train}} s_m^t \leq N_{accept}, \quad (14)$$

where N_{accept} is the threshold number of trains entering the workshop simultaneously. Maintenance resource costs are calculated by extra number exceeding the threshold. Maintenance resource costs of the fleet at t are given:

$$c^{sd}(t) = c^{us} \max \left(0, \sum_{m \in V_{train}} s_m^t - N_{accept} \right), \quad (15)$$

where c^{us} is the unit maintenance resource cost. The total maintenance resource costs are given:

$$C^s = \sum_{t=0}^T c^{sd}(t). \quad (16)$$

2.4. Operation and maintenance model

Using the above equations and notations, we formulate the model as follows:

$$\min C^{total} = C^c + C^p + C^f + C^s \quad (17)$$

$$s.t. \sum_{t=0}^T s_m^t = N_{fix} \quad m \in V_{train} \quad (18)$$

$$x_m^t = \sum_{\tau=\max\{0, t-d+1\}}^t s_m^\tau \quad m \in V_{train} \quad t = 0, 1, \dots, T \quad (19)$$

$$x_m^t, s_m^t \in \{0, 1\} \quad m \in V_{train} \quad t = 0, 1, \dots, T. \quad (20)$$

In the model, the objective (17) is to minimize the total costs of fleet operation and maintenance. Constraint (18) guarantees that the number of PM for each train is N_{fix} in the time horizon. Constraint (19) reveals the equivalence of two decision variables. Constraint (20) ensures that the decision variables are binary.

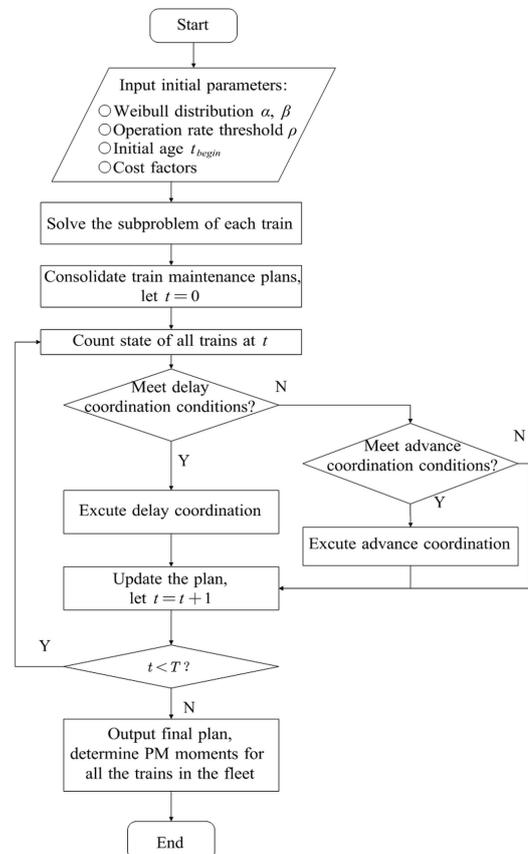


Fig. 1. Flow chart of Coordinating Conflicts Preventive Maintenance (CCPM)

3. Solution strategy

We build a mixed-integer programming model. The solution space is large due to a great number of decision variables and the complicated non-linear objective function. Conventional operation methods can hardly solve the problem efficiently. Therefore, considering the characteristics of the maintenance scheduling for high-speed train fleet, this paper proposes a maintenance strategy called Coordinating Conflicts Preventive Maintenance (CCPM). It can solve the problem flexibly and obtain a better solution.

The process of CCPM is shown in Fig. 1. The detailed steps of the strategy are as follows:

Step 1: Input the parameters of the model and the initial age of the trains in the fleet.

Step 2: Decompose the main problem into subproblems of single high-speed train and solve the subproblems.

Step 3: Combine single train maintenance plans and build the initial fleet maintenance plan. Check the initial plan from $t = 0$.

Step 4: Check the states of all trains. The state of each train can be one of the three: $x_m^t = 0$; $x_m^t = 1$ $s_m^t = 0$; $x_m^t = 1$ $s_m^t = 1$. If the delay coordination condition is met, go to step 6; otherwise, go to step 5.

Step 5: If the advance coordination condition is met, go to step 7; otherwise, go to step 8.

Step 6: Choose the specific trains to delay their PM actions according to the preset rule. Go to step 8.

Step 7: Choose the specific trains to advance their PM actions according to the preset rule. Go to step 8.

Step 8: Update the fleet plan and $t = t + 1$. If $t > T$, go to step 9; otherwise, go to step 4.

Step 9: Output the final operation and maintenance plan.

Observing that operation penalty costs and maintenance resource costs link the trains together, we formulate subproblem with objective functions, including PM costs and minimal repair costs. The number of PM for train m in the total time horizon is N_{fix} . Assume the start points of PM are $t_s^1, t_s^2, \dots, t_s^{N_{fix}}$, and the end points are $t_e^1, t_e^2, \dots, t_e^{N_{fix}}$. Ignoring the setup costs, PM costs $c_m^p = c^{up} \cdot N_{fix}$. Minimal repair costs of train m are given:

$$c_m^c = c^{uc} \left(\int_0^{t_s^1} \lambda(t) dt + \sum_{i=1}^{N_{fix}} \int_{t_e^{i-1}}^{t_s^{i+1}} \lambda(t) dt + \int_{t_e^{N_{fix}}}^T \lambda(t) dt \right). \quad (21)$$

The subproblem of train m is as follows:

$$\min c_m^c + c_m^p \quad (22)$$

$$s.t. t_s^1 < t_e^1 < \dots < t_s^{N_{fix}} < t_e^{N_{fix}} \quad (23)$$

$$t_e^i - t_s^i + 1 = d \quad i = 1, 2, \dots, N_{fix} \quad (24)$$

$$t_s^i, t_e^i \in \{0, 1, \dots, T\} \quad i = 1, 2, \dots, N_{fix}. \quad (25)$$

Considering that the objective function is non-linear, the interior point method is applied to solve the subproblem. Combining maintenance decisions of all trains, we step into the loop to condition judgment from the beginning of the time horizon.

If the operation rate or maintenance resource at t exceeds the thresholds, that is, $\sum_{m \in V_{train}} x_m^t > N_{train}(1 - \rho_n)$ or $\sum_{m \in V_{train}} s_m^t > N_{accept}$, the delay coordination will be executed.

The number of trains to delay their PM is given:

$$N_{de} = \min \left\{ \sum_{m \in V_{train}} x_m^t - N_{train}(1 - \rho_n), \sum_{m \in V_{train}} s_m^t - N_{accept} \right\}. \quad (26)$$

Exceeding the thresholds means that several trains start to perform PM at t . Assume the trains which $s_m^t = 1$ constitute set V_{de} . We need to select N_{de} trains in V_{de} to delay their PM actions.

Similar to calculating the failure rate, if train m has not been executed PM yet at t , and t is within time interval n . Equivalent age is given:

$$A_{eq}(t) = \varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \sum_{i=1}^{n-1} t_{eq}^i + t_{begin}. \quad (27)$$

If train m has been implemented PM k times, we assume end point of last PM is t_e^k , which is within interval n' . The present time is t , which is within interval n . The equivalent age is given:

$$A_{eq}(t) = \begin{cases} \varepsilon_n (t - t_e^k) & n' = n \\ \varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \varepsilon_{n'} \left(\sum_{i=1}^{n'} T_i - t_e^k \right) & n' = n - 1 \\ \varepsilon_n \left(t - \sum_{i=1}^{n-1} T_i \right) + \varepsilon_{n'} \left(\sum_{i=1}^{n'} T_i - t_e^k \right) + \sum_{i=n'+1}^{n-1} t_{eq}^i & n' \leq n - 2 \end{cases} \quad (28)$$

Sorted by the equivalent age from smallest, the top N_{de} trains in V_{de} delay their PM actions to the next day. Then the process steps into the next loop to the judgment.

If the operation rate and maintenance resource at t do not exceed the threshold, the maximal number of advance trains is given:

$$N_{ad} = \min \left\{ N_{train}(1 - \rho_n) - \sum_{m \in V_{train}} x_m^t, N_{accept} - \sum_{m \in V_{train}} s_m^t \right\}. \quad (29)$$

Defining advance coordination factor t_{ad} , we search the trains which will start to perform PM actions from t to $t + t_{ad}$. If no train meets the condition, we step into the next loop; otherwise, the trains constitute a set V_{ad} . The maximal number is N_{ad} , which means the search will stop when the size of V_{ad} reaches N_{ad} . Finally, the trains in V_{ad} advance their PM actions to t (present time), and the process steps into the next loop.

The delay coordination and the advance coordination are further illustrated with simple examples ($N_{train} = 5$) in Fig. 2a and Fig. 2b. In the figures, PM processes are depicted with blue bars. The green lines and the yellow lines represent PM start points and PM end points respectively. The maintenance rate and the operation rate are also shown to better understand the whole process. We assume $N_{accept} = 5$, so maintenance resource constraint is not considered in the example. Assume the operation rate threshold is 40% in the interval. Accordingly, the maximal number of trains under PM simultaneously is $N_{train}(1 - \rho_n)$, that is, 3.

In Fig. 2a, we focus on delay coordination. When t comes to 5S, four trains are under PM simultaneously, which means that the operation rate is lower than the threshold. Train 5 starts to perform PM so it becomes the train to delay PM actions. When t comes to 2S, Train 2 and Train 5 start to perform PM. The operation constraint is violated. So Train 2 and Train 5 delay PM actions together. When t comes to 1E, $N_{de} = 1$ according to (26). We choose one from Train 2 and Train 5 to delay PM actions. In this example, the equivalent age of Train 2 is smaller than that of Train 5. So Train 2 delay PM action to 4E. The operation rate would not violate operation constraint after 4E.

In Fig. 2b, we focus on advance coordination. When t comes to 1S, number of trains to advance PM actions is 2. We search the interval

$[t, t + t_{ad}]$. Train 2 and Train 5 meet the requirement. They would advance PM actions, and PM start point is 1S. The procedure in actual practice is much more complicated than the example. Maintenance resource needs to be considered, and the operation rate is dynamic. The proposed strategy can solve the problem efficiently, and the results are analysed in the next section.

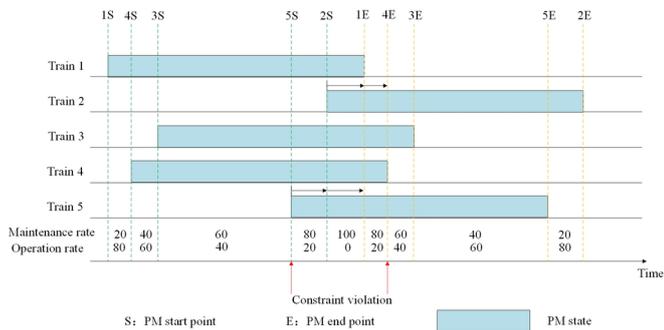


Fig. 2a. Example for delay coordination

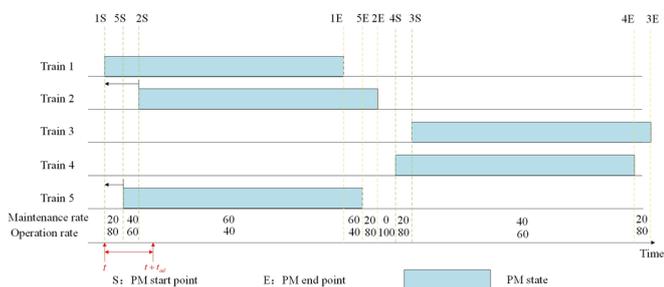


Fig. 2b. Example for advance coordination

4. Numerical analysis

This study considers a high-speed train fleet consisting of N_{train} trains. For the sake of computing convenience, the time horizon is set as $[0, 369]$. The time horizon can mainly cover a year, which accords with the practice situation of maintenance planning. The following parameters are set based on the study [29]. The initial reliability of trains follows the Weibull contribution where $\alpha = 120$, $\beta = 3$. The duration of PM $d = 5$. The initial age of each train is a random number in $[0, 200]$. We set $c^{up} = 400$, $c^{set} = 400$, $c^{uc} = 1000$, $c^{uf} = 1000$, $c^{us} = 1200$, $N_{fix} = 3$, $N_{accept} = 5$. The operation rate thresholds are listed in Table 1, referring to the research [17]. In the table, the operation rate thresholds of Spring Festival travel, summer holiday and spring-summer peak are especially high. This is because the number of passengers surges in these time periods. More trains are required to work to ensure normal operation.

Table 1. Online rate thresholds for different periods

Time period	Spring Festival travel	Spring-summer peak	Summer holiday	Normal period
Interval	[52,92]	[93,223]	[224,284]	Other
ρ	96.9%	92.9%	93.9%	87.9%

Lin et.al [17] propose a simulated annealing based strategy to solve the maintenance problem of high-speed trains. The strategy defines a vector to represent one solution. Starting with an initial solution, the strategy generates a new one and evaluate the new solution is either accepted or rejected. The evaluation is based on the specific acceptance rule. After several loops, the strategy explores the solution space and obtains a feasible suboptimal. This strategy (simulated annealing based preventive maintenance, hereinafter called SAPM) is applied to compare with the strategy proposed in this paper (CCPM).

Table 2. Comparison of O&M costs of different strategies

Train number		60	80	100	120	140
CCPM	C^{total}	404966	566977	683346	839701	987634
	C^P	92000	116400	142800	165600	191600
	C^c	312966	450577	540546	668901	786834
	C^f	0	0	0	4000	8000
	C^s	0	0	0	1200	1200
SAPM	C^{total}	456424	637327	762757	988841	1176737
	C^P	128400	168400	201600	234800	265600
	C^c	302224	437927	527157	713641	868537
	C^f	21000	25000	28000	32000	33000
	C^s	4800	6000	6000	8400	9600

Table 3. Comparison of the costs of the simplified problem by different strategies

Train number		60	80	100	120	140
CCPM	C^{total}	252336	335221	417223	500558	583905
	C^P	75600	98400	122400	146800	172000
	C^c	176736	236821	294823	353758	411905
SAPM	C^{total}	262896	347888	427421	512266	591951
	C^P	94000	124000	156800	182000	209600
	C^c	168896	223888	270621	330266	382351

The comparison of cost results is shown in Table 2. In the table, four types of costs and the total costs of two strategies are shown. The size of the fleet changes from 60 to 140, which is close to the practical situation. As can be seen from the table, the costs of the two strategies both increase as the number of trains grows. The total costs of CCPM are much lower than that of SAPM, no matter how the size of the fleet changes. Besides, the gap between the two strategies increases as the number of trains. When $N_{train} = 60$, the absolute gap of the total costs of two strategies is 51458. But when $N_{train} = 140$, the gap is 189103.

When the number of trains is limited, CCPM results in no operation penalty costs and no maintenance resource costs. Even when $N_{train} = 140$, the operation penalty costs and the maintenance resource costs of CCPM are 8000 and 1200 respectively. But the two costs of SAPM are up to 33000 and 9600. Therefore, CCPM considers the influence of the operation rate and maintenance resources. The strategy proposed in this paper can save maintenance costs and contribute to economic benefits.

The calculation time of the two methods is shown in Fig. 3. The calculation time of CCPM is shorter than SAPM, and CCPM becomes stable within 150s as the number of trains increases. SAPM increases linearly as the number of trains, especially up to 608s when $N_{train} = 140$. CCPM can be applied to large-scale examples compared to SAPM. This is because as the number of trains increases, the size of the solution vector in SAPM grows quickly. It takes much time to generate a new solution when the size is considerable.

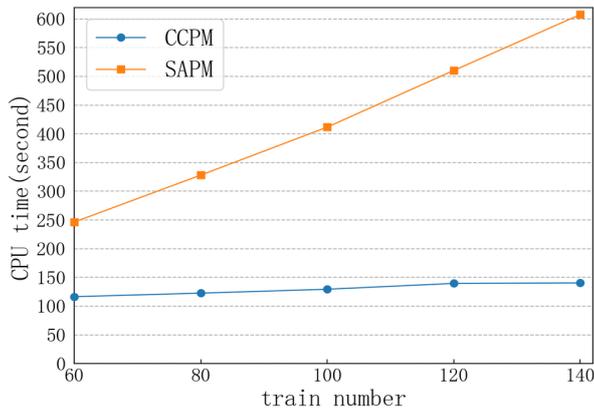


Fig. 3. Comparison of the running time of the strategies

Table 4. Sensitive study on maintenance costs of different strategies

Parameters		CCPM					SAPM				
		C^{total}	C^P	C^c	C^f	C^s	C^{total}	C^P	C^c	C^f	C^s
d=5	$c^{uf} = 1000$ $c^{us} = 1200$	683346	142800	540546	0	0	762757	201600	527157	28000	6000
	$c^{uf} = 2000$ $c^{us} = 2400$	694448	151600	542848	0	0	791712	204000	529312	44000	14400
d=10	$c^{uf} = 1000$ $c^{us} = 1200$	1415065	146800	1199065	44000	25200	1630644	206400	1246244	142000	36000
	$c^{uf} = 2000$ $c^{us} = 2400$	1545239	152800	1254039	88000	50400	1832132	212400	1308532	232000	79200

Without considering the operation penalty and the maintenance resource, the problem would degrade to a pure maintenance decision problem of train fleet, where the objective function $C^{total} = C^P + C^c$. The two strategies are applied to solve the simplified problem, and the results are shown in Table 3. As can be seen in the table, the costs of the two methods differ very little. The total costs of CCPM and SAPM are 583905 and 591951 respectively when $N_{train} = 140$, where the relative gap is 1.4%. SAPM and CCPM can both be applied to solve the normal maintenance problem. But in terms of the complicated problem proposed in this paper, CCPM performs much better than SAPM.

Operation rate is a significant variable in the model. The operation rate curves of the two methods are shown in Fig. 4. In the figure, the operation rate of SAPM is below the threshold at some time. Utilizing the principle of threshold change, CCPM results in a proper operation rate that exceeds the threshold and decreases the operation loss. The analysis shows that CCPM can consider the reliability of trains and the demand of fleet operation. SAPM is too random when making

fleet maintenance plans, which leads to high maintenance costs.

The influence of maintenance duration and operation cost factor is studied, and the results are listed in Table 4 ($N_{train} = 100$). When the maintenance duration increases, operation penalty costs and maintenance resource costs will increase sharply. When the operation cost factor increases, the total costs of the two strategies increase.

5. Conclusions

In this paper, a new operation and maintenance optimization model for high-speed train fleets is developed. The objective of the model is to minimize the total costs. Passenger flow and maintenance resources are considered due to the operation requirements, which would limit PM plans. A new maintenance strategy CCPM for high-speed train fleets is proposed to cope with the large solution space efficiently. It decomposes the original problem into several sub-problems and integrates the results with delay and advanced coordination.

A comprehensive case study is carried out to demonstrate the proposed strategy. The numerical results indicate that the proposed strategy outperforms one current strategy (SAPM) in total costs and computing time as the size of the fleet changes. The new strategy follows the principle of fluctuation of the operation rate, which results in the reduction of operation costs. Therefore, the proposed strategy provides efficient decision supports for the high-speed train fleet under different operating requirements.

It is noted that the high-speed train is regarded as a whole system in developing reliability in this research. Our future study is to extend the proposed strategy and solve preventive maintenance optimization for the high-speed train with complex components.

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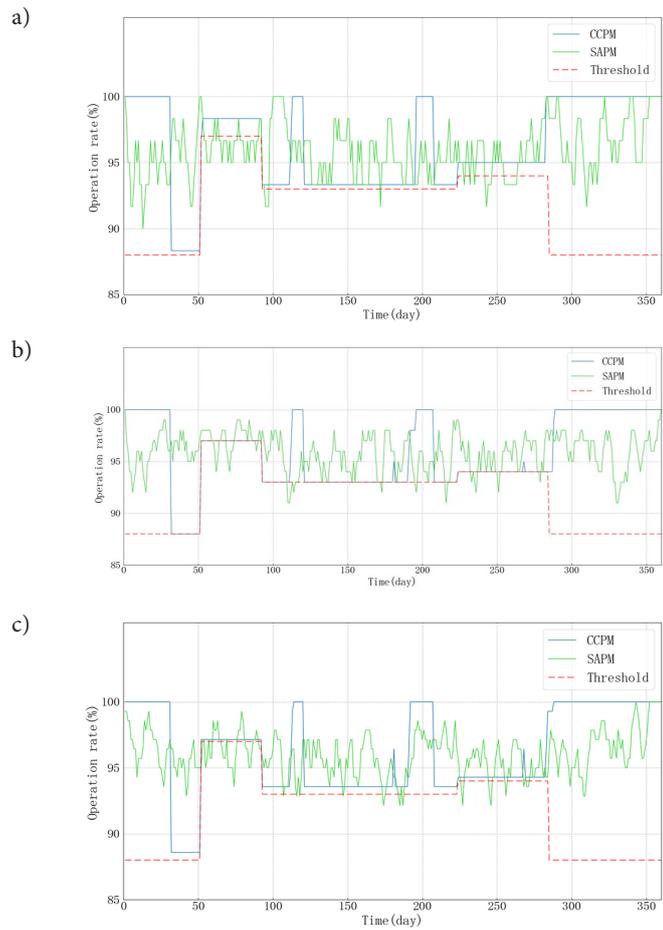


Fig. 4. Comparison of the operation rate of the strategies and threshold: a) $N_{train} = 60$ b) $N_{train} = 100$ c) $N_{train} = 140$

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