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Research Paper:

Improved Genetic Algorithm for Train Platform Rescheduling Under Train Arrival Delays

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In this study, the train platform rescheduling problem (TPRP) at a high-speed railway station is analyzed. The adjustments of the train track assignment and train arrival/departure times under train arrival delays are addressed in the TPRP. The problem is formulated as a mixed-integer nonlinear programming model that minimizes the weighted sum of total train delays and rescheduling costs. An improved genetic algorithm (GA) is proposed, and the individual is represented as a platform track assignment and train departure priority, which is a mixed encoding scheme with integers and permutations. The individual is decoded into a feasible schedule comprising the platform track assignment and arrival/departure times of trains using a rule-based method for conflict resolution in the platform tracks and arrival/departure routes. The proposed GA is compared with state-of-the-art evolutionary algorithms. The experimental results confirm the superiority of the GA, which uses the mixed encoding and rule-based decoding, in terms of constraint handling and solution quality.

Keywords: high-speed railway, train platform rescheduling, conflict resolution, genetic algorithm, mixed encoding

1. Introduction

Arrival/departure routes and platform tracks in high-speed railway passenger stations are important to station transportation organizations as they directly affect the efficiency of station operations and the capacity of the station. When inevitable emergencies occur during train operations, such as infrastructure failure and undesirable weather, train operations may be disrupted, which is typically accompanied by delays [1]. Consequently, the original train platform schedule cannot satisfy the station operation requirements. Therefore, a rapid and efficient adjustment of the train platform schedule, including the platform track assignment and the arrival and departure times of the affected trains, should be performed. The safety of train operations should be ensured and regular operations should be recovered the soonest possible.

The problem of adjusting the train platform schedule is known in the literature as the train platform rescheduling problem (TPRP) [2]. Various studies have been conducted to solve the TPRP, which has been proven to be non-deterministic polynomial hard (NP-hard) [2]. In most studies, the problem is formulated as a mixed-integer linear programming (MILP) model [3–6] and a mixed-integer nonlinear programming (MINLP) model [7, 8]. Minimizing the total delay time of trains is typically set as the optimization objective. Other objectives include minimizing the total platform track assignment costs [5] and deviations from the original platform [2]. The CPLEX solver is typically used to solve the TPRP. However, when the scale of the problem increases, the computation time of the CPLEX solver increases significantly.

Metaheuristics are typically used to solve NP-hard problems [9]. Zhang et al. [5] proposed a genetic and simulated annealing hybrid algorithm to solve the re-optimization of train platforming cases involving train delays. Zhang et al. [7] proposed an improved discrete teaching and learning optimization algorithm to solve the above-mentioned problem. In most studies, only the train platform track assignment was used as the encoding for optimization. The arrival and departure times were adjusted through heuristics during conflict resolution and were not directly controlled by the algorithm.

The contributions of this study are summarized as follows. First, a TPRP with train delays is proposed and modeled as an MINLP problem. Second, an improved genetic algorithm (GA) is proposed using a novel mixed encoding method with integer and permutation encoding schemes for solution representation and a rule-based decoding method to obtain a new train platform schedule. The solution comprises two segments, one is the code of the assigned track, and the second is the code of departure priority. The constraints are addressed using an encoding/decoding strategy, and the solution space is significantly reduced. Crossover and mutation operators are developed for the mixed encoding scheme. Finally, experimental results show the efficiency and effectiveness of the proposed GA compared with state-of-the-art algorithms.

The remainder of this paper is organized as follows. The proposed model is presented in Section 2. Section 3 presents an improved GA for solving the TPRP. The performance of the proposed algorithm is evaluated in Section 4. Finally, the conclusions and future work are presented in Section 5.

2. Problem Formulation

This section introduces an MINLP model for formulating the TPRP with train arrival delays. This model minimizes the weighted sum of the total train delays and rescheduling costs.

2.1. Assumptions

Seven assumptions are introduced as follows:

(1) Only the arrival and departure of trains at the stations are considered. Trains passing through the station without stopping are not considered.

(2) The settings of the train station, train platform plan, and original train arrival and departure times are known.

(3) The number of platform tracks and routes satisfies the requirements for train arrivals and departures during regular operations.

(4) The upstream and downstream trains are operated separately on the sides of the platform tracks and on arrival and departure routes. Rescheduling is considered only on one side.

(5) Disruption at the station is not considered; for example, track blockage is not considered.

Table 1. Summary of notations.

Symbol	Description
	Indices
i	index of platform track, $i \in I$
l,k	index of train, $l,k \in L$
	Parameters
I	set of platform tracks
L	set of trains
T_l^a	arrival time of train l in the original schedule
T_l^d	departure time of train l in the original schedule
T_S	safety interval time between two consecutive arrival trains that occupy the same platform track
h^a	minimal headway between two consecutive arrival trains
h^d	minimal headway between two consecutive departure trains
w	weight value for rescheduling cost
$X_{l,i}$	platform track assignment of train l in the original schedule, which is 1 if train l occupies platform track i and 0 otherwise
d_l	arrival delay for train l
τ_l^a	estimated arrival time of train l
$q_{l,k}^a$	actual order for train arrival, which is 1 if train l arrives before train k and 0 otherwise
M	a large positive number
	Decision variables
$x_{l,i}$	actual platform track assignment of train l, which is 1 if train l occupies platform track i and 0 otherwise
t_l^a	actual arrival time of train l
t_l^d	actual departure time of train l
$q_{l,k}^d$	actual order for train departure, which is 1 if train l departs before train k and 0 otherwise

(6) Some trains are in sections with known delay times.

(7) The trains arrive from one direction, which implies that the occupation order of the routes and platform tracks (train arrival order) is determined based on the estimated arrival time.

2.2. Parameters and Decision Variables

The notations used for the proposed model are shown in **Table 1**.

2.3. Objective Function

The objective function in this model is the weighted sum of the two components. The first component, Z_1, is the sum of the total train arrival and departure delays. The second component, Z_2, is the rescheduling cost of the train platform schedule, which includes the total number of train arrival/departure time adjustments and train platform track adjustments. Here, $\mathrm{sgn}(\cdot)$ returns 1 when the rescheduled arrival/departure time is later than the original arrival/departure time and returns 0 when the arrival/departure time remains the same. $\sum_{i \in I} 0.5|X_{l,i} - x_{l,i}|$ equals 1 when the train platform track is adjusted and 0 otherwise.

$$Z_1 = \sum_{l \in L}(t_l^a - T_l^a) + \sum_{l \in L}\left(t_l^d - T_l^d\right), \quad \ldots \ldots \quad (1)$$

$$Z_2 = \sum_{l \in L}\operatorname{sgn}(t_l^a - T_l^a) + \sum_{l \in L}\operatorname{sgn}\left(t_l^d - T_l^d\right) + \sum_{l \in L}\sum_{i \in I} 0.5|X_{l,i} - x_{l,i}|. \quad \ldots \quad (2)$$

2.4. Constraints

The constraints for train operations at the station are described as follows:

$$\sum_{i \in I} x_{l,i} = 1, \quad \forall l \in L, \quad \ldots \quad (3)$$

$$t_k^a - t_l^d \geq T_S q_{l,k}^a - M(3 - x_{l,i} - x_{k,i} - q_{l,k}^a), \quad \forall l,k \in L, l \neq k, i \in I, \quad \ldots \quad (4)$$

$$t_k^a - t_l^a \geq h^a q_{l,k}^a - M(1 - q_{l,k}^a), \quad \forall l,k \in L, l \neq k, \quad (5)$$

$$t_k^d - t_l^d \geq h^d q_{l,k}^d - M\left(1 - q_{l,k}^d\right), \quad \forall l,k \in L, l \neq k, \quad (6)$$

$$q_{l,k}^d + q_{k,l}^d = 1, \quad \forall l,k \in L, l \neq k, \quad \ldots \quad (7)$$

$$t_l^d - t_l^a \geq T_l^d - T_l^a, \quad \forall l \in L, \quad \ldots \quad (8)$$

$$\tau_l^a = T_l^a + d_l, \quad \forall l \in L, \quad \ldots \quad (9)$$

$$t_l^a \geq \tau_l^a, \quad \forall l \in L, \quad \ldots \quad (10)$$

$$t_l^d \geq T_l^d, \quad \forall l \in L, \quad \ldots \quad (11)$$

$$t_l^a, t_l^d \geq 0, \quad \forall l \in L, \quad \ldots \quad (12)$$

$$x_{l,i} \in \{0,1\}, \quad \forall l \in L, i \in I, \quad \ldots \quad (13)$$

$$q_{l,k}^d \in \{0,1\}, \quad \forall l,k \in L, l \neq k, \quad \ldots \quad (14)$$

where Eq. (3) ensures that only one platform track is assigned to train l. Eq. (4) guarantees a safe interval time between two consecutive trains that occupy the same platform track. Eqs. (5) and (6) guarantee that the arrival and departure headways for any two trains satisfy the station requirements, which avoids conflicts in the arrival and departure routes. Eq. (7) represents the departure order constraint of the two trains at station. Eq. (8) ensures that the dwell time at the train station is greater than or equal to the original dwell time. Eq. (9) represents the estimated arrival times. Eqs. (10) and (11) ensure that the actual arrival and departure times are not less than the estimated arrival and original departure times, respectively. Eqs. (12)–(14) restrict the decision variables to real and binary numbers.

2.5. Proposed Model

The TPRP model was formulated to minimize the weighted sum of the total train arrival/departure delays and the rescheduling costs of the train platform schedule under several constraints.

$$\min\ Z = Z_1 + wZ_2 \text{ s.t. Constraints (3)–(14)}, \quad . \quad (15)$$

where w is the weight to control the rescheduling costs.

2.6. Model Reformulation

Owing to the nonlinear terms ($\operatorname{sgn}(\cdot)$ and $|\cdot|$) in Eq. (2), a linearization method is developed. Three auxiliary variables are introduced, i.e., $\mathbf{r}_1 = [r_1^l]_{|L|\times 1}$, $\mathbf{r}_2 = [r_2^l]_{|L|\times 1}$, and $\mathbf{r}_3 = [r_3^{li}]_{|L|\times|I|}$, which are defined as follows:

$$\begin{cases} r_1^l = \operatorname{sgn}(t_l^a - T_l^a) \\ r_2^l = \operatorname{sgn}\left(t_l^d - T_l^d\right) \\ r_3^{li} = |X_{l,i} - x_{l,i}| \end{cases}, \quad \ldots \quad (16)$$

Substituting Eq. (16) into Eq. (2) yields a reformulated MILP model. Thus, Eq. (2) is reformulated as follows:

$$Z_3 = \sum_{l \in L} r_1^l + \sum_{l \in L} r_2^l + \sum_{l \in L}\sum_{i \in I} 0.5 r_3^{li}. \quad \ldots \quad (17)$$

Meanwhile, the TPRP model can be reformulated as follows:

$$\min\ Z = Z_1 + wZ_3 \quad \ldots \quad (18)$$

$$\text{s.t.}\quad Mr_1^l \geq t_l^a - T_l^a, \quad \forall l \in L, \quad \ldots \quad (19)$$

$$Mr_2^l \geq t_l^d - T_l^d, \quad \forall l \in L, \quad \ldots \quad (20)$$

$$r_1^l \leq t_l^a - T_l^a, \quad \forall l \in L, \quad \ldots \quad (21)$$

$$r_2^l \leq t_l^d - T_l^d, \quad \forall l \in L, \quad \ldots \quad (22)$$

$$r_3^{li} \geq X_{l,i} - x_{l,i}, \quad \forall l \in L, i \in I, \quad \ldots \quad (23)$$

$$r_3^{li} \geq x_{l,i} - X_{l,i}, \quad \forall l \in L, i \in I, \quad \ldots \quad (24)$$

$$r_1^l, r_2^l \in \{0,1\}, \quad \forall l \in L, \quad \ldots \quad (25)$$

$$r_3^{li} \in \{0,1\}, \quad \forall l \in L, i \in I, \quad \ldots \quad (26)$$

$$\text{Constraints (3)–(14)}, \quad \ldots \quad (27)$$

where Eqs. (19)–(26) ensure that the reformulated model is equivalent to the original model. The reformulated model is an MILP model belonging to the class of NP-hard problems.

3. Proposed Method

In this section, we propose an improved GA to solve the TPRP. First, encoding and decoding are introduced to transform the original MILP problem into an integer- and permutation-based combinatorial optimization problem without constraints. The population of the GA is updated using crossover and mutation operators. The GA process is presented in **Algorithm 1**.

3.1. Encoding and Decoding

To solve the TPRP, most studies used the integer-value-encoding scheme to represent the platform track assignment. When delays occur, the affected trains are likely to change their platform track, which may cause conflict with other trains. We propose a novel encoding scheme for the TPRP, which is a mixed encoding scheme with integer values and permutation-value encodings. The integer-value encoding is similar to that of previous studies, which indicates the platform track assignment. The value range is $[1, |I|]$. The length of the first segment

Algorithm 1 The improved genetic algorithm for TPRP.

Input: Population size N_p.
Output: Final population P.

```
Generate the initial population P with N_p individuals randomly
while terminate condition is not satisfied do
    Select parent individuals through roulette wheel selection.
    Update P through single-point crossover and modified order crossover.
    Update P through single-point mutation and swap mutation.
    Merge the new populations with the original ones and obtain the best individuals based on the population size.
end while
return
```

of an individual is equal to the number of trains $|L|$. Permutation-value encoding is performed to determine the priority of the trains. When a conflict occurs in determining the departure time of trains, the departure time of the train with lower priority is adjusted for conflict resolution. The value range is $[1,|L|]$. The length of the second segment of an individual is equal to the number of trains $|L|$.

The key issue in decoding is the method to minimize the change in the train arrival/departure time to avoid delays and minimize the increase in the number of additional adjustments. For an individual with a platform track assignment and train departure priority, three types of conflicts exist between trains at the station, as shown in **Fig. 1**.

1) **Conflicts when trains occupy the same platform track:** This refers to Eq. (4). The actual order of train arrivals is determined by the estimated arrival time. The arrival and departure times of the subsequent train are adjusted based on the safety interval time constraint in Eq. (4) (see **Fig. 1(a)**).

2) **Conflicts in the arrival routes:** This refers to Eq. (5). Similar to the former conflict, because the order of the arriving trains is determined, the arrival and departure times of subsequent trains are adjusted based on the arrival headway constraint in Eq. (5) (see **Fig. 1(b)**).

3) **Conflicts in the departure routes:** This refers to Eq. (6). The actual order of departure of the affected trains is based on the train departure priority. The departure times of the affected trains with a lower priority are adjusted based on the departure headway constraint in Eq. (6) (see **Fig. 1(c)**).

Based on the rules above for conflict resolution, the constraints in the TPRP model can be addressed effectively and the model can be converted into an unconstrained one. The feasibility of the solution under mixed coding is guaranteed, and the efficiency in solving the original constrained optimization problem is significantly improved.

3.2. Population Initialization

The initial population was randomly generated. The platform track assignment was an integer randomly generated within the range $[1,|I|]$. The train departure priority was a randomly generated permutation within the range $[1,|L|]$.

3.3. Selection Operator

The operator used for selection was a roulette wheel, which is typically used in GA. Individuals were selected based on their fitness values. Because we were addressing a minimization problem, the probabilities of the individuals were set based on the exponential of the negative fitness values.

3.4. Crossover Operator

Based on the encoding characteristics, two crossover operators were adopted based on the crossover rate p_c [10].

1) Single-point crossover was adopted for integer-value encoding. This operator selects two parents and randomly selects a point for crossover. Two offspring are obtained by combining the parents at a crossover point.

2) A modified-order crossover (MOC) was adopted for permutation-value encoding. The MOC operator randomly selects a crossover point to divide both parent individuals p_1 and p_2 to obtain left and right strings of the same length. The order of the right string p_1 is used to change the order of the positions in p_2 and vice versa.

3.5. Mutation Operator

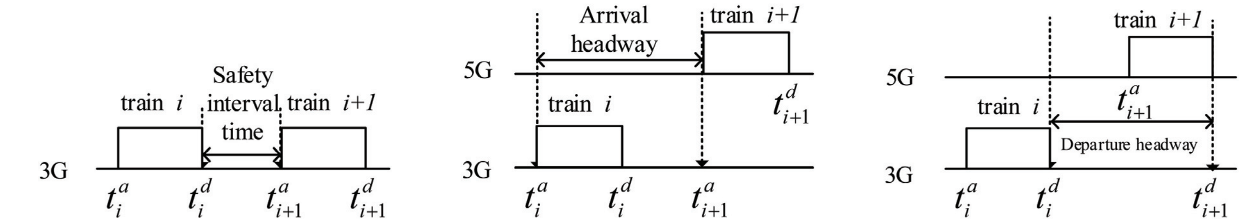
Based on the encoding characteristics, two mutation operators were adopted based on the mutation rate p_m.

1) Single-point mutation was adopted for integer-value encoding. The position of an individual was randomly selected and replaced to obtain a new integer.

2) Swap mutation was adopted for permutation-value encoding. Two positions for each individual were randomly selected and swapped to obtain a new permutation.

3.6. Computational Complexity

The proposed GA includes encoding and decoding, population initialization, as well as selection, crossover, and mutation operators. Let N_p be the population size and $|L|$ be the number of trains. The computational complexity of the fitness evaluation is $O(|L|^2)$, the computational complexity of the population initialization is



(a) Conflicts when trains occupy the same platform track

(b) Conflicts in the arrival routes

(c) Conflicts in the departure routes

Fig. 1. Conflicts between trains at the station.

Table 2. Parameters settings for test instances.

Parameters	Values	Parameters	Values
$\lvert I\rvert$	5, 6	h^d	4 min
$\lvert L\rvert$	45, 50, 55, 60, 70, 79	w	1, 10
T_S	3 min	M	2,000
h^a	4 min		

$O(N_p * |L|)$, the computational complexity of the selection operator is $O(N_p)$, the computational complexity of the crossover operator is $O(N_p * |L|)$, and the mutation operator is $O(N_p * |L|)$. Therefore, the total computational complexity of the proposed GA is $O(N_p * |L|^3)$.

4. Computational Experiments

This section discusses the performance of the proposed GA. First, test instances were generated. Subsequently, the problem was solved using the proposed GA and other algorithms for comparison, including exact solutions using CPLEX. All the experiments were conducted on a personal computer with an Intel Core i7-9700T CPU @2.00 GHz and 16 GB of internal memory. Exact solutions for the TPRPs were implemented in MATLAB R2020b using YALMIP as the modeling language and CPLEX 12.10, with default parameter settings [11]. Other algorithms used for solving TPRPs were implemented using MATLAB R2020b.

4.1. Test Instances

We first developed test instances owing to the nonexistence of benchmark instances with train arrival delays for the TPRP in the literature. The trains propagated downstream at a high-speed railway station from 12:00 to 22:00. The arrival delay of train l (d_l) was an integer randomly generated within $[1, 10]$ min. The remaining parameters are listed in **Table 2**. Twelve test instances were generated based on the combination of $|L|$ and w.

4.2. Algorithms for Comparison

To evaluate the performance of the proposed GA, we used the following three algorithms: the self-adaptive differential evolution (SaDE) algorithm [12], comprehensive learning particle swarm optimizer (CLPSO) [13], and GA. The crossover and mutation operators were not the same as those in the proposed GA. They were real-coded GAs with arithmetic crossovers [14] and Gaussian mutations [15]. All three algorithms performed search in a continuous space. The integer value for the platform track assignment was obtained via rounding, and the permutation value for the train departure priority was obtained using a random key algorithm [1].

4.3. Parameter Settings

The parameters for the proposed GA were set through empirical testing. The population size N_p was set to 1,000. The crossover rate p_c was set to 0.8 for $w = 1$ and 0.9 for $w = 10$. The selection probability of the crossover operator was set to 0.95 for the single-point crossover and 0.05 for the MOC operator. The mutation rate p_m was set to 0.5. The selection probability of the mutation operator is set to 0.95 for the single-point mutation operator and 0.05 for the swap mutation operator. For the real-coded GA, the population size N_p was set to 200. The crossover rate p_c and mutation rate p_m were set to 0.9 and 0.05, respectively. For the SaDE, a population size $N_p = 50$ was set, as in the original study [12]. For the CLPSO, a population size $N_p = 40$ and the acceleration constant $c = 1.49445$ were set, as in the original study [13]. The number of independent trials for each algorithm for each instance was set to 20. The maximum number of fitness evaluations for all algorithms was set to 2×10^5.

4.4. Results and Analysis

We compared the performance of the proposed GA with those of the three algorithms and CPLEX. **Table 3** lists the results of 20 independent trials for each algorithm, with the mean values and standard deviations. CPLEX was executed only once. The best metaheuristic results are indicated in bold. As shown in **Table 3**, the proposed GA outperformed the other three metaheuristics in most instances. The best values yielded by the proposed GA for all instances were the same as the optimal values yielded by CPLEX. For the other three metaheuristics, the CLPSO outperformed the proposed GA on instances 8, 10, and 11. The performances of the SaDE and real-coded GA were worse than those of the proposed GA and CLPSO because the SaDE and real-coded GA

Table 3. Comparison results of objective value of different algorithms.

Instance	$\|I\|/\|L\|/w$	SaDE	CLPSO	Real-coded GA	The proposed GA	CPLEX
1	5/45/1	673.25±1.83	670.00±2.51	700.45±8.34	**663.95±2.16**	661.00
2	5/50/1	767.65±2.89	759.20±2.65	796.40±15.44	**753.60±1.64**	752.00
3	5/55/1	796.10±2.02	785.60±2.74	826.00±11.88	**779.95±2.95**	777.00
4	6/60/1	863.65±1.90	847.55±2.39	888.95±13.77	**843.30±1.49**	842.00
5	6/70/1	1170.40±3.75	1144.25±3.89	1213.15±12.60	**1137.85±3.44**	1135.00
6	6/79/1	1356.75±3.09	1324.25±4.93	1391.00±16.40	**1311.65±2.58**	1308.00
7	5/45/10	1538.15±16.06	1508.90±15.91	1611.80±28.62	**1507.10±8.49**	1501.00
8	5/50/10	1693.45±24.19	**1671.10±0.31**	1801.15±46.16	1672.60±4.44	1671.00
9	5/55/10	1826.40±33.44	1773.50±2.24	1946.55±27.96	**1773.00±0.00**	1773.00
10	6/60/10	2069.00±26.63	**1958.60±2.23**	2172.10±36.52	1962.65±6.71	1958.00
11	6/70/10	2610.20±29.67	**2414.75±7.37**	2738.05±43.55	2416.35±5.51	2413.00
12	6/79/10	3087.50±24.84	2740.85±5.47	3147.80±49.53	**2739.60±6.28**	2738.00

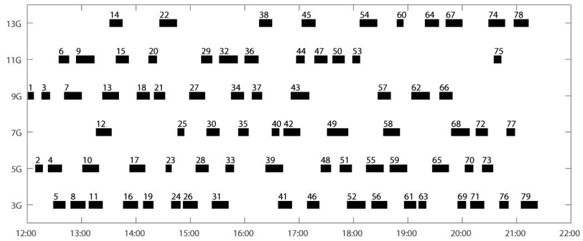


Fig. 2. Original train platform schedule for instance No.6.

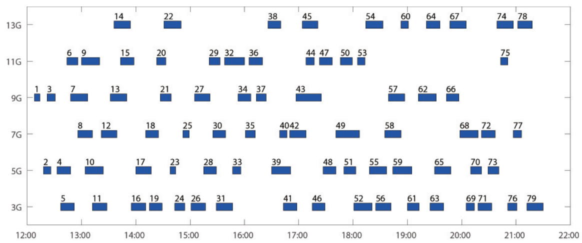


Fig. 3. Rescheduled train platform schedule for instance No.6.

were not designed for mixed encoding with integer and permutation values. All the results of the metaheuristics were obtained within 1 min, which guarantees real-time rescheduling.

Figures 2 and **3** show the original and rescheduled train platform schedules for instance No.6, which were obtained using the proposed GA with an objective value of 1308. In these figures, the rectangle in **Fig. 2** and that in **Fig. 3** represent the occupations of different trains on the platform tracks and arrival/departure routes, respectively. The horizontal length of the rectangle represents the occupation time of the tracks and routes. The number of trains is indicated above the rectangle. The horizontal and vertical axes represent the time and name of the occupied track, respectively. The rectangle in **Fig. 2** represents the non-adjusted platform schedule of the train, whereas the rectangle in **Fig. 3** represents the adjusted platform track or arrival/departure time.

For instance, for No.6, the rescheduling cost was 160 (including 79 adjustments in arrival time, 79 adjustments in departure time, and two adjustments in the platform track), and the total train delay was 1148 min. Based on **Figs. 2** and **3**, the unoccupied resources in the platform track were used more effectively. For example, the tracks were less unoccupied from 12:00 to 15:00 on track 7G (see **Fig. 2**). In the rescheduled train platform schedule, these tracks were used more effectively by assigning train Nos.8 and 18.

Figure 4 shows the convergence curves of the different algorithms for all test instances. The horizontal and vertical axes represent the number of fitness evaluations and the mean of the objective function for 20 trials, respectively. As shown, the proposed GA converged faster than the other algorithms initially. In addition, both the proposed GA and CLPSO exhibited high convergence speeds. The CLPSO demonstrated good searching ability and performed better than the proposed GA on instances 8, 10, and 11. The final result yielded by the proposed GA was better than those of the other algorithms for most test instances.

5. Conclusion

In this study, train platform rescheduling at a high-speed railway station under train delays was formulated as an MINLP problem and linearized to an MILP model. A mixed-encoding GA was designed to solve the TPRP. A novel encoding and decoding method was designed by transferring the original problem to an unconstrained one, thus avoiding numerous ineffective searches in the solution space. Tests performed based on 12 test instances showed that the proposed GA outperformed the other algorithms in most instances and was more effective than CPLEX. The results were obtained within 1 min, which demonstrated the feasibility of the proposed GA for real-time rescheduling.

In future, we will consider more complex railway stations with more arrival and departure directions. Consid-

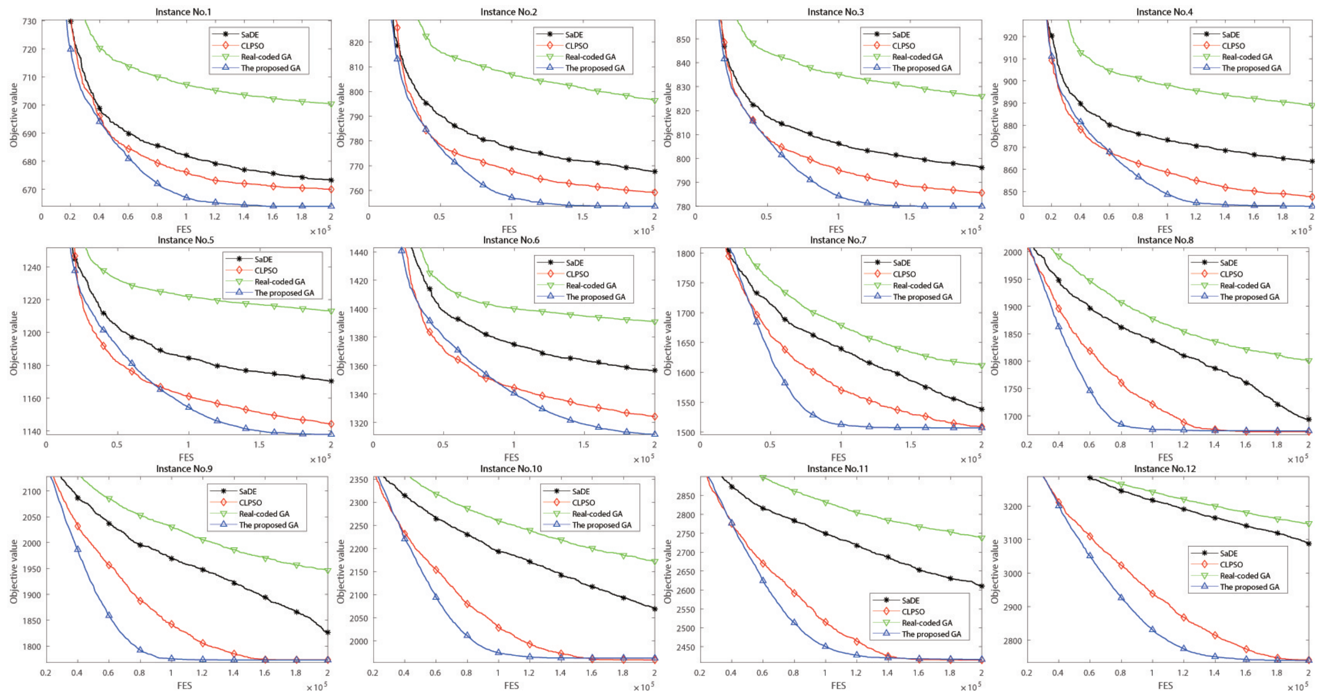


Fig. 4. Convergence curves of different algorithms.

ering the uncertainties in a dynamic environment renders the model more practical [16]. In addition, the crossover and mutation operators of the proposed GA can be further improved. Finally, the rescheduling of the train timetable and train platform can be further analyzed using an integrated model [17].

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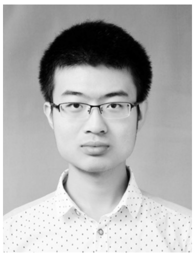

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