2024 Australian & New Zealand Control Conference (ANZCC)
1-2 February, 2024. Gold Coast, Australia

2024 Australian & New Zealand Control Conference (ANZCC) | 979-8-3503-1497-7/24/$31.00 ©2024 IEEE | DOI: 10.1109/ANZCC59813.2024.10432899

Evolutionary Multi-Objective Optimization for High-Speed Railway Train Timetable Rescheduling with Optimal/Suboptimal Solutions into Initial Population*

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Abstract— **In this paper, the high-speed railway train timetable rescheduling (TTR) problem with disturbances of trains running in sections and stations is analyzed. It is formulated as a multi-objective optimization problem that minimizes the total train delays and the frequency of adjusting train arrival/departure time. In order to solve the problem, a novel nondominated sorting genetic algorithm-II (NSGA-II) is proposed for TTR. A multi-permutation encoding method is developed to decide the departure orders of the trains at different stations. A rule-based decoding method determines the trains' feasible schedule according to the departure orders. The constraints to model the train operation are handled through encoding and decoding. To improve the quality of the initial population, one or more Pareto optimal and suboptimal (near Pareto optimal) solutions are included into the initial population, which achieves the utilization of the information and knowledge of TTR in problem-solving. We investigate the effectiveness of the proposed NSGA-II with multi-permutation encoding and the effects of including one or more Pareto optimal solution(s) in the initial population. The experiment results show that including optimal solutions significantly improves the performance of NSGA-II.**

I. INTRODUCTION

High-speed railway (HSR) intelligent dispatching command is an important part of the HSR operation [1]. The total operating mileage of China's HSR has reached 42000 km by the end of 2022. Due to the large density of HSR, train operations may be affected by train delays when disturbance or disruption occurs. Train timetable rescheduling (TTR) is conducted to help recover to regular operation.

When train operation is disturbed, additional time for trains running in sections or dwelling in stations will be included. Therefore, rescheduling strategies should be conducted, including the adjustments of arrival/departure time in stations and traversing order in sections to minimize the spread of train delays. The TTR problem has been analyzed in many studies, which is belong to non-deterministic polynomial hard (NP-hard) [2]. The problem is formulated with one or multiple objectives. Binder *et al.* [3] formulated an integer programming model optimizing passenger satisfaction, operational costs, and the deviation from the undisrupted timetable. ε-constraint method is adopted to obtain the Pareto front. Shakibayifar *et al.* [4] proposed a multi-objective simulation-based optimization framework for TTR with a partial/full blockage. A multi-objective variable neighborhood search metaheuristic is proposed to minimize the total train delay at destination stations and the total deviation from the original schedule at all stations. Yan *et al.* [5] studied a TTR problem with two objectives, including minimizing the additional train delays due to the disturbance of trains running in section and dwelling in stations and the frequency of adjusting train arrival/departure time. An improved ε-constraint method is adopted to obtain the Pareto front. However, obtaining the entire Pareto front is time-consuming. At the same time, railway dispatcher is only interested in part of the front, and dispatching should be conducted in real time.

Evolutionary algorithm (EA) is usually used to tackle the NP-hard problems [6]. Ding *et al.* [7] developed a memetic algorithm to solve the TTR problem, minimizing the total train delay with a high real-time performance. Wang *et al.* [8] proposed an efficient problem-specific strengthen elitist genetic algorithm. An efficient heuristic strategy is used for population initialization for better convergence. Using Optimal/suboptimal solutions for population initialization is also an effective way for multi-objective optimization problems [9]. We improve the results in [5] with less computation time and only part of the Pareto front for better decision-making. A multi-permutation encoding method and a rule-based decoding method are developed to deal with the constraints of the TTR problem. Moreover, a novel nondominated sorting genetic algorithm-II (NSGA-II) is developed with optimal and suboptimal solutions for initialization and new mechanisms for population crossover and mutation.

*This work was supported in part by the National Natural Science Foundation of China under Grant 62203468, in part by the Young Elite Scientist Sponsorship Program by China Association for Science and Technology (CAST) under Grant 2022QNRC001, in part by the Foundation of China State Railway Group Co., Ltd. under Grant J2023G007, and in part by the Foundation of China Academy of Railway Sciences Corporation Limited under Grant 2023YJ112.

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TABLE I

SUMMARY OF NOTATIONS.

Symbol	Description
	Indices
$i, l \in T$	Index of train
$j \in J$	Index of station
$k \in K$	Index of section
	Parameters
T	Set of trains
J	Set of stations
K	Set of sections
$T^a_{i,j}$	The arrival time of train i at station j in the orignal schedule
$T^d_{i,j}$	The departure time of train i at station j in the orignal schedule
	train i stops at station j and 0 otherwise
$d^{min}_{i,j}$	The minimum dwell time at station j for train i
r^{min}_k	The minimum running time at section k
H_k	The minimum headway between two consecutive trains of the same direction at section k
M	A large positive number
$d^{dis}_{i,j}$	Additional dwell time when disturbance occurs on train i at station j
$r^{dis}_{i,k}$	Additional running time when disturbance occurs on train i at section k
J^{dis}	Set of stations with dwell time disturbance on trains
K^{dis}	Set of sections with running time disturbance on trains
	Decision variables
$t^a_{i,j}$	Actual arrival time of train i at station j
$t^d_{i,j}$	Actual departure time of train i at station j
$q_{i,l,k}$	Actual traversing order which is 1 if train i traverses at section k before train l and 0 otherwise

The remainder of this paper is organized as follows. The proposed model is presented in Section II. Section III presents a novel NSGA-II for solving the TTR. The performance of the proposed algorithm is evaluated in Section IV. Finally, Section V presents the conclusions and future work.

II. PROBLEM FORMULATION

A. Assumptions

1) The upstream and downstream trains are operated separately on their side of tracks and platforms. Therefore, only one side is modeled for rescheduling.
2) The types of disturbance during the train operation are the disturbance of trains running in sections and dwelling in stations, which are reflected as additional running time and dwell time.
3) Multiple disturbances exist with known affected time.
4) The capacity of the station for train platforming is enough.

B. Parameters and Decision Variables

Table I summarizes all the notations used throughout this paper.

C. Objective Function

There are two objective functions of the TTR problem. The first objective function is minimizing the total arrival and departure delay for all trains.

$$\min \ F_1 = \sum_{i\in T}\sum_{j\in J}(t^a_{i,j} - T^a_{i,j}) + \sum_{i\in T}\sum_{j\in J}(t^d_{i,j} - T^d_{i,j}) \quad (1)$$

The second objective function is minimizing the frequency of the train schedule adjustments. It is a rescheduling cost calculated by the total number of train arrival/departure time adjustments.

$$\min \ F_2 = \sum_{i\in T}\sum_{j\in J}\mathrm{sgn}(t^a_{i,j} - T^a_{i,j}) + \sum_{i\in T}\sum_{j\in J}\mathrm{sgn}(t^d_{i,j} - T^d_{i,j}) \quad (2)$$

where $\mathrm{sgn}(\cdot)$ returns 1 when the rescheduled arrival/departure time is later than the original schedule and returns 0 when there is no adjustment on the arrival/departure time.

D. Constraints

1) Dwell Time Constraints: The dwell time at station j should be larger than the minimal dwell time interval to ensure the operations at the station. For trains with dwell time disturbance, the dwell time at the stations should be greater than the original dwell time with the additional dwell time when disturbance occurs.

$$t^d_{i,j} - t^a_{i,j} \geq d^{min}_{i,j} \ \forall i \in T; j \in J; (i,j) \notin J^{dis} \quad (3)$$

$$t^d_{i,j} - t^a_{i,j} \geq T^d_{i,j} - T^a_{i,j} + d^{dis}_{i,j} \ \forall i \in T; j \in J; (i,j) \in J^{dis} \quad (4)$$

2) Running Time Constraints: The running time in section k should exceed the minimum running time. For trains with running time disturbance, the running time at the sections should be greater than the original running time with the additional running time when disturbance occurs.

$$t^a_{i,j+1} - t^d_{i,j} \geq r^{min}_k \ \forall i \in T; j \in J/\{|J|\}; (i,k) \notin K^{dis} \quad (5)$$

$$t^a_{i,j+1} - t^d_{i,j} \geq T^a_{i,j+1} - T^d_{i,j} + r^{dis}_{i,k} \quad \forall i \in T; j \in J/\{|J|\}; (i,k) \in K^{dis} \quad (6)$$

3) Headway Constraints: The headway between any two trains should be larger than the minimum headway to ensure safety. The trains are assumed to have constant speed at sections. Therefore, we need to ensure that the headway is satisfied at the departure and arrival times of trains at stations.

$$t^d_{l,j} - t^d_{i,j} \geq H_k q_{i,l,k} - M(1 - q_{i,l,k}) \quad (7)$$

$$t^a_{l,j+1} - t^a_{i,j+1} \geq H_k q_{i,l,k} - M(1 - q_{i,l,k}) \quad (8)$$

for all $i, l \in T$, $i \neq l$, $j \in J/\{|J|\}$, $k = j$.

4) Traversing Order Constraints: For any two trains, either one can traverse at a section before the other.

$$q_{i,l,k} + q_{l,i,k} = 1 \ \forall i, l \in T; i \neq l; k \in K \quad (9)$$

5) Departure and Arrival Time Constraints: The actual departure time should be larger than the original one with the additional dwell time when disturbances occur. The actual arrival time should be larger than the original arrival time with the additional running time when disturbances occur.

$$t^d_{i,j} \geq T^d_{i,j} + d^{dis}_{i,j} \ \forall i \in T; j \in J \quad (10)$$

$$t^a_{i,j} \geq T^a_{i,j} + r^{dis}_{i,k} \ \forall i \in T; j \in J; k = j - 1 \quad (11)$$

where $r^{dis}_{i,0} = 0$, $\forall i \in T$.

6) Decision Variable Constraints: The following constraints define the domain of the decision variables:

$$t^a_{i,j}, t^d_{i,j} \geq 0 \;\forall i \in T; j \in J \quad (12)$$

$$q_{i,l,k} \in \{0,1\} \;\forall i,l \in T; i \neq l; j \in J/\{|J|\}; k = j \quad (13)$$

E. Model Reformulation

Due to the nonlinear terms $\text{sgn}(\cdot)$ in (2), the linearization method is developed. Two auxiliary variables are introduced, i.e., $\mathbf{r}_1 = [r_1^{i,j}]_{|T|\times|J|}$ and $\mathbf{r}_2 = [r_2^{i,j}]_{|T|\times|J|}$, which are defined as follows:

$$\begin{cases} r_1^{i,j} = \text{sgn}(t^a_{i,j} - T^a_{i,j}) \\ r_2^{i,j} = \text{sgn}(t^d_{i,j} - T^d_{i,j}) \end{cases} \forall i \in T; j \in J \quad (14)$$

Substituting (2) by (14), a reformulated mixed integer linear programming (MILP) model is obtained. The proposed TTR model can be reformulated as follows:

$$\begin{aligned}
&\min \; F_1 \\
&\min \; F_2 = \sum_{i\in T}\sum_{j\in J} r_1^{i,j} + \sum_{i\in T}\sum_{j\in J} r_2^{i,j} && (15)\\
&\text{s.t. } Mr_1^{i,j} \geq t^a_{i,j} - T^a_{i,j} \;\forall i \in T; j \in J && (16)\\
&\quad Mr_2^{i,j} \geq t^d_{i,j} - T^d_{i,j} \;\forall i \in T; j \in J && (17)\\
&\quad r_1^{i,j} \leq t^a_{i,j} - T^a_{i,j} \;\forall i \in T; j \in J && (18)\\
&\quad r_2^{i,j} \leq t^d_{i,j} - T^d_{i,j} \;\forall i \in T; j \in J && (19)\\
&\quad r_1^{i,j}, r_2^{i,j} \in \{0,1\} \;\forall i \in T; j \in J && (20)\\
&\quad \text{Constraints } (3) - (11). && (21)
\end{aligned}$$

III. Proposed Method

A multi-permutation based NSGA-II is proposed in this section. Encoding and decoding are introduced to deal with the constraints of the MILP model. The population of the NSGA-II is initialized with different strategies and updated using selection, crossover, and mutation operators.

A. Encoding and Decoding

Instead of using real-coded encoding to represent the arrival and departure time of the timetable, this paper adopts a multi-permutation encoding method to represent the traversing order of the trains in different sections. With a given traversing order of trains for each section, we only need to determine the arrival and departure times of trains satisfying the constraints. The advantage of this encoding method is that all constraints are handled, and no constraint violations will be generated. This encoding method includes multiple permutations, each representing the order of trains in one section between two train stations. The value for each permutation is within the range [1, $|T|$] with no repeated values. The length for each permutation is $|T|$, which is the total number of trains. The total number of permutations is $|K|$, which is also the total number of sections.

With determined train orders in different sections, a rule-based decoding method is conducted to determine the arrival and departure times of trains. A key issue in the decoding process is to avoid large train delays with less change in the arrival and departure time as well as the number of schedule adjustments. Therefore, the arrival and departure times are determined according to the minimum dwell time, running time, and headway.

The arrival and departure time of the trains at the first station is determined only considering the dwell time disturbance, the headway between two consecutive trains, and the original arrival/departure time. The arrival time is set for trains at other stations as early as possible, considering the running time disturbance in the last section, section running time constraints, headway between two consecutive trains, and the original arrival time. The departure time is set considering the dwell time disturbance in the current station, station dwell time constraints, headway between two consecutive trains, and the original departure time.

The corresponding rescheduled timetable is obtained through the above decoding strategy based on the multiple permutations of the train traversing orders.

B. Population Initialization

Random initialization is usually adopted in EAs to ensure diversity. However, a good initial population may improve the solution's performance and speed up the convergence. Therefore, the information and knowledge of the TTR are utilized in problem-solving by adding one or more Pareto optimal (near Pareto optimal) solutions into the initial population. Three Pareto optimal solutions and one near Pareto optimal solution are generated. Since there are two objectives in the TTR problem, the weighted method is adopted to obtain the optimal solutions with three different weight vectors. Three weight vectors are: weight vector 1 (0.98, 0.02), weight vector 2 (0.2, 0.8), and weight vector 3 (0.02, 0.98). The corresponding Pareto optimal solutions are denoted as op1, op2, and op3, respectively. The near optimal solution is obtained using the first-come-first-served (FCFS) strategy, denoted as nop. The initial population is generated by one or more optimal or near optimal solutions and randomly initialized ones.

C. Selection, Crossover, and Mutation Operators

When selecting the individuals for crossover and mutation, the crowding distance is used to rank the parent and child individuals within the size of the population. The crossover and mutation operations are different for the proposed multi-permutation encoding scheme compared with traditional NSGA-II. We randomly select one permutation from $|K|$ permutations for crossover and mutation, respectively. Modified order crossover and swap operators are used for the selected permutation for crossover and mutation in the individual, respectively [7].

IV. Computational Experiments

This section discusses the performance of the proposed NSGA-II along with nine variants by including one or more Pareto optimal and near Pareto optimal solution(s). All experiments were conducted on a PC with an Intel Core i5-8265U CPU 1.60GHz and 8 GB internal memory.

TABLE II

THE MINIMUM RUNNING TIME AT SECTIONS.

No.	Section	Time/min
1	Beijing South – Langfang	15
2	Langfang – Tianjin South	14
3	Tianjin South – Cangzhou West	14
4	Cangzhou West – Dezhou East	21
5	Dezhou East– Jinan West	17
6	Jinan West – Tai'an	15

A. Performance Metric

To verify the ability of the proposed method, two performance metrics are considered, which both measure the diversity and convergence of the solutions. They are the inverted generational distance (IGD) and hypervolume (HV) [10]. HV is obtained by calculating the hypervolume of the approximation front with a reference point (nadir point in this paper). The true Pareto front can be computed by the improved ε-constraint method [5].

B. Test Instances

We adopt the instances in [5]. The Beijing–Tai'an section of Beijing–Shanghai HSR line is considered. It is a double-track railway with altogether 7 stations and 6 sections. 40 trains downstream from 6:00 to 16:00 are considered in the railway timetable.

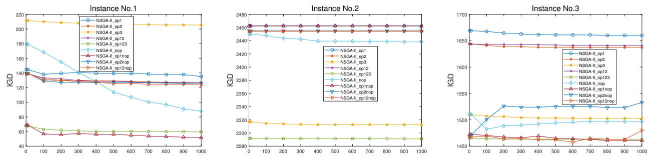
The minimum section running time is shown in Table II. The minimal dwell time for trains at stations is set according to the original timetable. It is set to 2 min for train stops at stations and no dwell time for pass-through stations, origin stations, and destination stations. The minimal headway between two consecutive trains is set to 4 min. M is set to 1000.

Three test instances are generated based on the difference of the disturbances as follows:

Instance No.1: There are only dwell time disturbances when trains stop at stations. The additional dwell time for train 2 at Beijing South is $d^{dis}_{2,1} = 20$ min. The additional dwell time for train 20 at Langfang is $d^{dis}_{20,2} = 20$ min. The additional dwell time for train 30 at Beijing South is $d^{dis}_{30,1} = 20$ min.

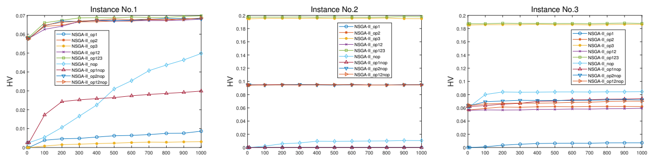
Instance No.2: There are only running time disturbances when trains run at sections. The additional running time for train 4 at Beijing South – Langfang section is $r^{dis}_{4,1} = 15$ min. The additional running time for train 18 at Langfang – Tianjin South section is $r^{dis}_{18,2} = 20$ min. The additional running time for train 32 at Beijing South – Langfang section is $r^{dis}_{32,1} = 20$ min.

Instance No.3: There are both dwell time and running time disturbances. The additional dwell time for train 3 at Beijing South is $d^{dis}_{3,1} = 20$ min. The additional dwell time for train 25 at Langfang is $d^{dis}_{25,2} = 10$ min. The additional dwell time for train 33 at Beijing South is $d^{dis}_{33,1} = 15$ min. The additional running time for train 6 at Beijing South – Langfang section is $r^{dis}_{6,1} = 15$ min. The additional running time for train 15 at Langfang – Tianjin South section is $r^{dis}_{15,2} = 20$ min. The additional running time for train 28 at Beijing South – Langfang section is $r^{dis}_{28,1} = 20$ min.



(a) (b) (c)

Fig. 1. Performance of the NSGA-II variants over 20 runs on the average IGD.



(a) (b) (c)

Fig. 2. Performance of the NSGA-II variants over 20 runs on the average HV.

C. Algorithm Settings

In this paper, NSGA-II is used as the algorithm framework. Different variants of NSGA-II are proposed by modifying the initialization with one or more Pareto optimal (near Pareto optimal) solutions. Nine subsets of the three Pareto optimal and one near Pareto optimal solutions are used to develop the NSGA-II variants. They are {op1}, {op2}, {op3}, {op1, op2}, {op1, op2, op3}, {nop}, {nop, op1}, {nop, op2}, {nop, op1, op2} where solution op1-3 are the Pareto optimal solutions with different weight vectors, and solution nop is a near Pareto optimal solution which is obtained by FCFS. The variants of NSGA-II with a different initialization population are named by the included solutions, which are NSGA-II_op1, NSGA-II_op2, NSGA-II_op3, NSGA-II_op12, NSGA-II_op123, NSGA-II_nop, NSGA-II_op1nop, NSGA-II_op2nop, and NSGA-II_op12nop. The performance of the original NSGA-II and the nine variants were evaluated based on the three test instances.

The parameters for the proposed NSGA-II were set through empirical testing. The population size N_p was set to 50. The maximum number of generation $MaxGen$ was set to 1000. Therefore, the maximum number of fitness evaluations $MaxFes$ was set to 5×10^4. The crossover rate p_c was set to 0.7. The mutation rate p_m was set to 0.5. The number of independent trials for each algorithm for each instance was set to 20.

D. Result Analysis

1) Comparison on IGD and HV: We first analyze the results of the algorithms based on the performance metrics IGD and HV. The performance of the NSGA-II variants over 20 independent runs is shown in Figs. 1 and 2. Since the results of the NSGA-II on instances Nos.1-3 are not

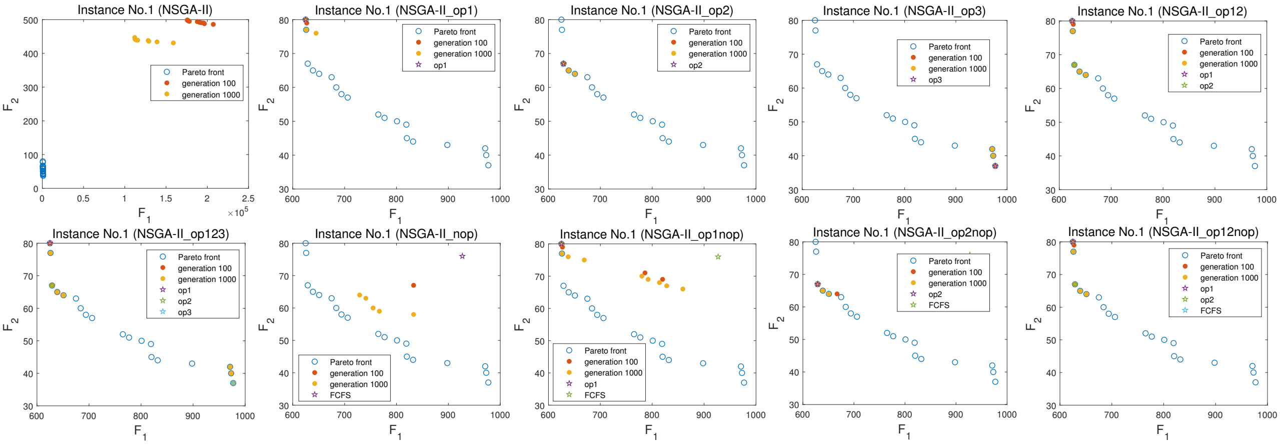


Fig. 3. Population of NSGA-II and its variants at some generations on instances No.1.

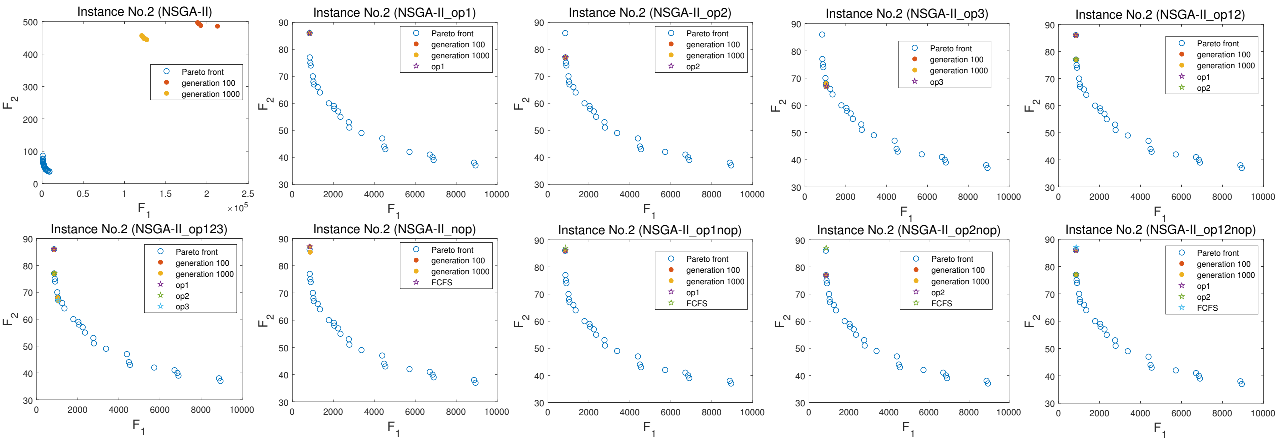


Fig. 4. Population of NSGA-II and its variants at some generations on instances No.2.

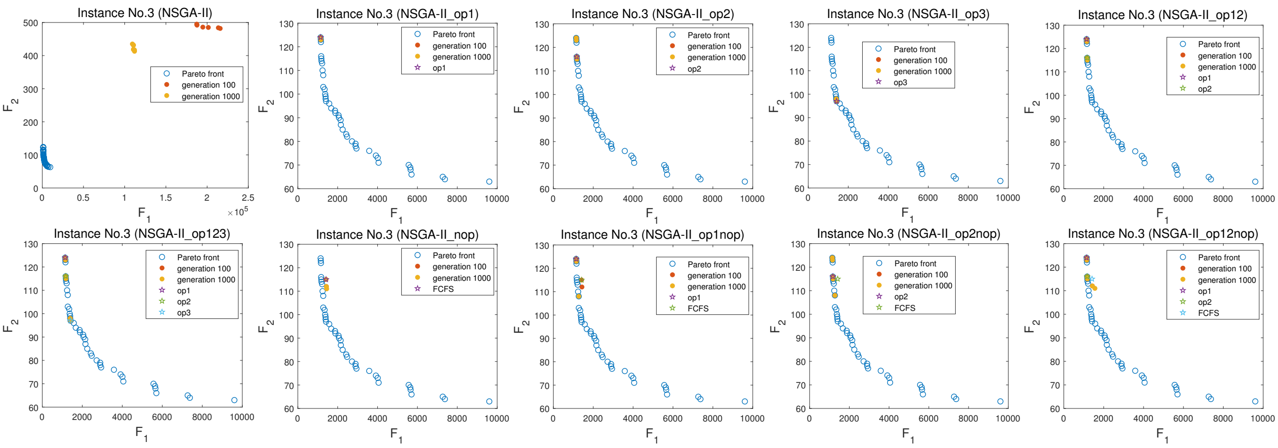


Fig. 5. Population of NSGA-II and its variants at some generations on instances No.3.

competitive (IGD over 1×10^5 and HV = 0), they are not shown in the figures. The results of the NSGA-II with one or more Pareto optimal (near Pareto optimal) solutions for initialization are better than the original NSGA-II with random initialization. Compared with NSGA-II variants with or without additional near Pareto optimal solution nop (FCFS) besides Pareto optimal solutions for initialization, solutions from NSGA-II variants with nop are mostly better in terms of IGD and HV. For example, in terms of IGD and HV, NSGA-II_op1nop, NSGA-II_op2nop, and NSGA-II_op12nop are better than NSGA-II_op1, NSGA-II_op2, and NSGA-II_op12 on instances Nos.1 and 3, and the same on instances

TABLE III

RESULTS OF THE COMPARISON ON THE COMPUTATION TIME AND OBTAINED PARETO OPTIMAL SOLUTIONS ON THREE TEST INSTANCES.

Instance		NSGA-II	NSGA-II_op1	NSGA-II_op2	NSGA-II_op3	NSGA-II_op12	NSGA-II_op123	NSGA-II_nop	NSGA-II_op1nop	NSGA-II_op2nop	NSGA-II_op12nop
	Time (s)	9.42	10.33	11.59	9.82	13.57	15.18	8.35	10.40	11.62	13.58
1	# of Optimal Solutions	0	2	3	3	5	8	0	2	3	5
	Time of solver (s)	n.a.	5.50	9.55	13.05	15.05	28.10	n.a.	5.50	9.55	15.05
	Time (s)	9.75	11.23	11.44	21.43	14.23	27.12	8.58	11.28	11.47	14.36
2	# of Optimal Solutions	0	1	1	2	2	4	0	1	1	2
	Time of solver (s)	n.a.	2.61	3.13	44.08	5.75	49.82	n.a.	2.61	3.13	5.75
	Time (s)	9.78	16.10	20.51	31.95	27.91	51.25	8.66	16.12	20.58	27.99
3	# of Optimal Solutions	0	2	4	2	4	6	0	3	5	4
	Time of solver (s)	n.a.	22.98	45.61	72.04	45.61	117.66	n.a.	43.51	66.16	45.61

No.2, respectively.

2) Population Distribution: We plot the population of the NSGA-II and its variants at different generations for all 20 runs in Figs. 3 – 5. The figures show that the solutions of NSGA-II are far from the Pareto front on all instances. However, if Pareto optimal or near Pareto optimal solutions are included, the obtained solutions are close to the Pareto front and even similar to parts of the Pareto front. For example, on instance No.1, five solutions are obtained with the initial solution FCFS in NSGA-II_nop, which are close to the Pareto front and better than FCFS. With Pareto optimal solutions for initialization, NSGA-II variants are more likely to obtain high-quality solutions, which are parts of the Pareto front. For example, on instance No.3, six solutions are obtained with the initial solution op1, op2, and op3. Therefore, three additional Pareto optimal solutions are generated.

Meanwhile, as a multi-objective optimization problem, both objectives must be optimized. The obtained solutions are more likely to have a lower value of total arrival and departure delay for all trains, which may be selected for decision-making. A dispatching strategy with a smaller delay is suitable for the actual application of HSR.

3) Analysis of Computation Time and Obtained Pareto Optimal Solutions: The average computation time of NSGA-II and its variants on 20 runs, the number (#) of obtained Pareto optimal solutions for all 20 runs, and the time to obtain the same amount of Pareto optimal solutions consumed by the solver are shown in Table III. The computation time of NSGA-II without Pareto optimal or near Pareto optimal solutions for all three instances are within 10s. Since no Pareto optimal solutions are obtained by NSGA-II and NSGA-II_nop, the number of obtained Pareto optimal solutions are zero, and the corresponding time of solver are not avaliable (n.a.).

As for NSGA-II variants with Pareto optimal solutions, the average computation time is greater than that of NSGA-II and NSGA-II_nop because of the time for obtaining the optimal solution by the solver. For instance No.1, the time of the solver may be less than the time by NSGA-II_op1, NSGA-II_op2, NSGA-II_op1nop, and NSGA-II_op2nop.

For instance No.2, additional optimal solutions are only obtained in NSGA-II_op3 and NSGA-II_op123, where the time of the solver is larger than that of the proposed algorithms.

The NSGA-II variants (except for NSGA-II_nop) perform better on instance No.3, where the time of the solver is larger than that of NSGA-II variants. Therefore, we demonstrate that good solutions in the initial population can significantly improve the performance of the NSGA-II, especially for more complex scenarios.

V. CONCLUSION

The TTR problem with disturbance in sections and stations for HSR is analyzed in this paper. A multi-objective optimization problem is modeled, and a multi-permutation based NSGA-II is proposed. An encoding and decoding method is specially developed for the problem, which successfully deals with the constraints. To improve the performance of the algorithm, one or more Pareto optimal and near Pareto optimal solutions are included into the initial population. By including good initial solutions, Pareto optimal solutions can be obtained, and the computation time is less than the solver on several instances. In the future, we will develop more efficient operators for NSGA-II and consider other EAs to obtain more Pareto optimal solutions.

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