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Multi-Strategy Metro Timetable Recovery: A Unified MIQP Approach Integrating Skip-Stop, Holding and Rescheduling

R. Kumar[1] and M. Miyatake[2]

[1]Green Science and Engineering Division, Sophia University, Tokyo, Japan
[2]Department of Engineering and Applied Science, Sophia University, Tokyo, Japan

Abstract

This study proposes an integrated mixed integer quadratic programming-based real-time timetable recovery model for high-frequency metro operations. The objective of our model is to minimise deviations between actual and planned headways, accounting for station importance based on ridership data. Upon disturbance, trains are classified as disturbed, already departed and not yet departed. Based on the classification, recovery measures such as skip-stop, holding and departure offset are applied. We applied this model to the Yokohama Municipal Subway Blue Line in Yokohama, Japan. In the experiments, we tested the model's performance by varying the disturbance location along the route and the number of rescheduled trains. It is observed that skip stops being a dominant recovery strategy effectively reducing the local deviations and improving the headway regularity by 30-49% depending upon the disturbance location, while holding and departure offsets can further improve the headway regularity to 54.6% in line with greater operational flexibility, compared to about 31.8% near terminal stations where recovery options are limited and based on the sensitivity analysis these improvement can be achieved by rescheduling 2-3 trains. The formulation is compared with metaheuristic algorithms, in which the model reliably finds globally optimal solutions in significantly shorter time.

Keywords: metro operations, timetable recovery, mixed-integer programming, skip-stop strategy, holding control, departure rescheduling, disturbance management, ridership weighting, headway regularity.

1 Introduction

Urban rail transit systems generally operate at high service frequencies, where maintaining regular headways is more important than strictly following a fixed timetable. Osuna and Newell [1] showed that large headway variations increase average passenger waiting times. Previous work also reports that passengers dislike waiting on platforms more than travelling inside the train [2], making headway regularity a key concern for service quality [3]. As a result, effective real-time control strategies are required to reduce the impact of operational disturbances as they occur.

In practice, passenger congestion is the most common source of operational disturbances, particularly during peak hour periods when train or platform doors do not close on time [4]. Previous studies report that such disturbances events typically range from a few minutes up to around 15 minutes in duration [4, 5]. Although these delays usually affect only a single train initially, they may accumulate across successive trips, leading to schedule drift and preventing trains from departing as planned [6, 7]. If these localised delays are not addressed, they can propagate downstream, causing wider system disruptions characterised by irregular headways and train bunching [8, 9].

Different control strategies have been explored to address these disturbances. Holding control is one of the most common, with vehicles delayed at stations to regulate headways [10, 11]. This idea has also been used in real-time rolling-horizon settings to limit travel-time variability [12]. Skip-stop operation is another control option, allowing trains to pass selected stations so that lost time can be recovered [13, 14, 15]. A drawback of this approach is that some passengers may not be able to board or alight at the stations they intended to use [6]. Although both strategies are known to be effective, they are usually applied on their own, even though several studies indicate that better results can be achieved when multiple control measures are combined [6, 16].

This paper presents a unified optimisation problem for real-time timetable recovery and demonstrates its application to the Yokohama Blue Line [17]. The recovery model seeks to minimise ridership-weighted deviations from normal headways to find the optimal holding, skip-stop and departure-time operations [3, 7, 18]. The balance between regularity of operations and passenger disutility is modelled using different weights for headway deviation and skipped stops, according to the ridership weightage. The optimisation problem is expressed as a mixed-integer quadratic program (MIQP), which can be solved to global optimality in a reasonable time.

2 Methods

This section includes the formulation, beginning with the problem definition, the objective function, the constraints, the case study, and the conclusion.

2.1 Problem Definition

Consider a metro line composed of N_S stations indexed by $S = \{1,2, \dots, N_S\}$ and N_T trains indexed by $T = \{1,2, \dots, N_T\}$. Each train i operates on the same metro line, sharing identical origin and destination terminals, and travels along a fixed sequence of stations. A disturbance, for example, a door malfunction occurs at station $\hat{s} \in S$, affecting the disturbed train(i^*). Recovery actions are coordinated across i^* and a set of n following trains within the recovery horizon, so that the recovery set $T_r \subseteq T$ contains $|T_r| = n + 1$ trains. Consecutive train pairs are denoted $C = \{(i,j): i,j \in T_r,\ j = i + 1\}$. Stations where skipping is not permitted, because they serve as junctions with other lines, are included in the critical set S_c, and stations downstream from the disturbance make up the recovery scope $S_r \subseteq S$. The model can accommodate operational delays of up to 15 minutes on a single metro line with a fixed station sequence, no train overtaking, and separate operations in each direction.

In order to keep the problem tractable and real-time implementable, the formulations are restricted to having a finite horizon and a reduced control action space for finding optimal solution within operational time limits. Trains not included in the recovery set are however still handled as envelope trains with their predetermined fixed routes serving as reference trajectories.When a disturbance is detected, trains in T_r are divided into three categories: the disturbed train (i^*) applies skip-stop to recover time, already departed trains (T^+) are en route and can apply holding and skipping, not-yet-departed trains (T^0) which are at the origin can apply departure offset as given in Table 1.

Train Category	Skip-Stop	Holding	Departure Offset
Disturbed	Yes	No	No
Already Departed	Yes	Yes	No
Not-Yet-Departed	No	No	Yes

Table 1: Availability of strategies by train category.

2.2 Objective Function

The objective function minimises squared headway deviations weighted by station ridership, penalising irregular service more heavily considering ridership importance.

$$min\, Z = \underbrace{\sum_{(i,j)\in C} \sum_{s\in S_r} w_b(s)\big(H_{i,j,s} - H^*\big)^2}_{C_H} + \underbrace{\sum_{i\in T_r} \sum_{s\in S_r} w_t(s) \cdot (H^*)^2 \cdot y_{i,s}}_{C_S}$$
$$+\, \alpha \underbrace{\sum_{i\in T_r} \sum_{s\in S_r} h_{i,s}^2}_{C_D} \tag{1}$$

Here $a_{i,s}$ denotes the arrival time (s) of train i at station s, so the headway $H_{i,j,s} = a_{j,s} - a_{i,s}$, and H^* is the target headway. The weights $w_b(s)$ and $w_t(s)$ denote normalised boarding and throughput demands, respectively. The decision variables are: skip decision $y_{i,s} \in \{0,1\}$, which equals 1 if train i skips station s; and holding time $h_{i,s} \geq 0$ (s), the additional dwell at station s. Departure offset $x_i \geq 0$ (s) for not-yet-departed trains is introduced in the constraints. The three cost terms are:

- **Headway deviation cost (C_H):** Squared deviations from the target headway are multiplied by the boarding demand $w_b(s)$. Greater deviations are therefore weighted more heavily, as these have a more detrimental effect on the waiting time of passengers.
- **Skip-stop penalty (C_S):** When station s is skipped, affected passengers which are arriving randomly wait approximately one additional headway (H^*) [1] and wait for next serving train. Throughput-based weight $w_t(s)$ captures both boarding and alighting passengers.
- **Holding penalty (C_D):** Quadratic holding cost with weight α, for encouraging the distribution of small-holding actions across stations rather than concentrated delays.

The station weights are normalised ridership measures derived from operator statistics [19]. Boarding weight $w_b(s)$ is applied to headway deviations since irregular headways primarily affect waiting passengers, while throughput weight $w_t(s)$ is applied to skip penalties since skipping affects both passengers unable to board and those unable to alight:

$$w_b(s) = \frac{\text{Boarding}(s)}{\max\limits_{s'} \text{Boarding}(s')}, \quad w_t(s) = \frac{\text{Boarding}(s) + \text{Alighting}(s)}{\max\limits_{s'}(\text{Boarding}(s') + \text{Alighting}(s'))} \tag{2}$$

2.3 Constraints

The optimisation problem is subject to the following constraints, which ensure operational feasibility and safety throughout the recovery corridor.

$$a_{i,s+1} = a_{i,s} + \tau_{s,s+1} + d_s(1 - y_{i,s}) + h_{i,s}, \quad \forall i \in T_r,\ s \in S_r \tag{3}$$

$$a_{j,s} - a_{i,s} \geq \underline{h}, \quad \forall (i,j) \in \mathcal{C},\ s \in S_r \tag{4}$$

$$y_{i,s} = 0, \quad \forall i \in T_r,\ s \in S_c \tag{5}$$

$$y_{i,1} = 0, \quad y_{i,N_S} = 0, \quad \forall i \in T_r \tag{6}$$

$$\sum_{s \in S_r} y_{i,s} \leq K, \quad \forall i \in T_r \tag{7}$$

$$y_{i,s} + y_{i,s+1} \leq 1, \quad \forall i \in T_r,\ s \in S_r \tag{8}$$

Let s_i^0 denote the current station of train i at the time of disturbance detection.

$$y_{i,s} = 0, \quad \forall s \in \{s_i^0 + 1, \dots, s_i^0 + \beta\},\ \forall i \in T_r \tag{9}$$

$$0 \le h_{i,s} \le \bar{h}, \quad \forall i \in T_r,\ s \in S_r \tag{10}$$

$$h_{i,s} \le \bar{h}(1 - y_{i,s}), \quad \forall i \in T_r,\ s \in S_r \tag{11}$$

$$h_{i,s} = 0, \quad \forall s \le s_i^0,\ \forall i \in T_r \tag{12}$$

$$h_{i,1} = 0, \quad h_{i,N_S} = 0, \quad \forall i \in T_r \tag{13}$$

$\delta_{i,s} = a_{i,s} + d_s(1 - y_{i,s}) + h_{i,s}$ is the departure time of train i from station s.

$$\delta_{j,s-1} \ge \delta_{i,s} - \tau_{s-1,s} - M \cdot y_{i,s}, \quad \forall (i,j) \in \mathcal{C},\ s \in S_r \tag{14}$$

Let x_i denote the departure time offset from origin for train i, so that:

$$a_{i,1} = \tilde{a}_{i,1} + x_i, \quad \forall i \in T^0 \tag{15}$$

where $\tilde{a}_{i,1}$ is the scheduled departure from the origin terminal.

$$0 \le x_i \le \bar{x}, \quad \forall i \in T^0 \tag{16}$$

$$a_{i,s} \ge \underline{a}_s + \underline{h}, \quad \forall i \in T_r,\ s \in S_r \tag{17}$$

$$\overline{a_s} \ge a_{i,s} + \underline{h}, \quad \forall i \in T_r,\ s \in S_r \tag{18}$$

$$x_i \in R_{\ge \mathbb{0}}, \quad y_{is} \in \{0,1\}, \quad h_{i,s} \in R_{\ge \mathbb{0}} \tag{19}$$

Arrival time propagation: Constraint (3) defines how arrival times are carried forward between successive stations, using $\tau_{s,s+1}(s)$ for inter-station travel time and $d_s(s)$ for scheduled dwell time at station s, applied only if the train stops. For the origin station ($s = 1$), the scheduled dwell time is taken as $d_1 = 0$ to ensures that $a_{i,1}$ functions strictly as a departure time especially for not yet departed trains (T^0).

Safety headway: Constraint (4) ensures that the headway between consecutive trains is no smaller than the minimum safety value $\underline{h}(s)$.

Skip-stop constraints: Constraints (5)–(9) govern skip-stop decisions: (5) protects critical stations; (6) prohibits skipping at terminals; (7) limits skips to at most K per train; (8) prevents consecutive station skips; (9) enforces an announcement buffer of β stations downstream of each train's current position s_i^0, ensuring passengers receive advance notice before a skip occurs.

Holding constraints: Constraints (10)– (13) regulate holding: (10)– (11) bound holding times to a maximum $\bar{h}$ (s) and ensure mutual exclusivity with skipping; (12) restricts holding to stations beyond s_i^0; (13) prohibits holding at terminals.

Platform blocking: Constraint (14) ensures train j cannot arrive at station s before train i departs, i.e., $a_{j,s} \ge \delta_{i,s}$. Also $a_{j,s} = \delta_{j,s-1} + \tau_{s-1,s}$, this is equivalent to

$\delta_{j,s-1} \geq \delta_{i,s} - \tau_{s-1,s}$. When train i skips station s, it passes through without occupying the platform, so the Big-M constant M relaxes the blocking constraint.

Departure offset and boundary conditions: Constraint (15) links departure offset x_i to the departure time from the origin. Constraint (16) bounds the offset to $[0, \bar{x}]$ (s). Constraints (17)– (18) ensure minimum headway separation from boundary trains, where $\underline{a}_s$ and $\bar{a}_s$ denote the fixed arrival times of preceding and following boundary trains, respectively. Constraint (19) specifies variable domains.

3 Case Study: Yokohama Municipal Subway Blue Line

To demonstrate the practical application of the proposed timetable recovery model, this study uses official scheduled data from the Yokohama Municipal Subway Blue Line [17]. The line runs between Azamino in the north and Shonandai in the south, serving a dense urban corridor across Kanagawa Prefecture, Japan. Figure 1 shows a schematic diagram of the Yokohama Blue Line (not to geographical scale).

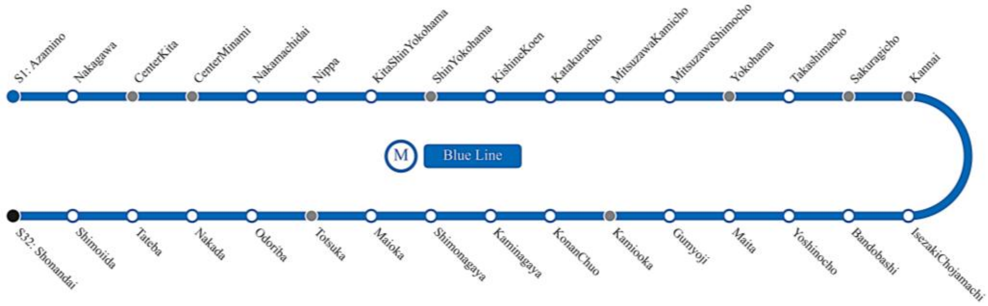

Figure 1: Route diagram of Yokohama Blue Line (S1–S32).

Daily ridership (averaged from monthly statistics, January–December 2024) [19], shown in Figure 2, concentrates at major transfer hubs—Yokohama station handles over twenty times the passenger volume of lower-demand stations such as Maioka. This variation is considered through the station weights $w_b(s)$ and $w_t(s)$ defined in equation (2), ensuring that headway deviations and skip decisions at high-ridership stations are penalised proportionally.

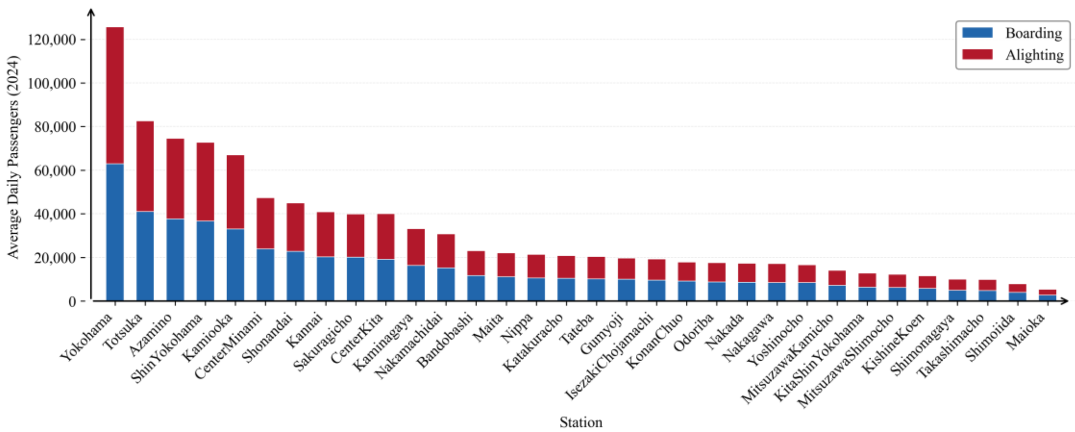

Figure 2: Daily ridership by station [19].

The simulation is single direction, with 21 trains operating in the weekday PM peak (17:00–19:00), using a target headway of 6 minutes ($H^{*} = 360$ s) as found in the operator's service schedule. Consistent with existing literature [20], measurements of service regularity are taken at intermediate stations and not at terminals, as headways at terminals are a means of control rather than a variable that can be optimised.

The MIQP is solved using Gurobi 10.0 with a 0.1% optimality gap on an Intel Core 5 120U CPU @1.40 GHz personal computer with 16 GB RAM. The parameter settings include a minimum headway of $\underline{h}$ =100 s, which is commonly used to maintain safe train separation [5], a maximum holding time of $\bar{h} = 20$ s, and a maximum departure offset of $\bar{x} = 20$ s. These limits constrain the size of control actions and prevent large increases in passenger travel time. The holding penalty is fixed at $\alpha = 20$ to limit excessive holding and to keep such actions small. The maximum number of skipped stations per train is capped at K=2, allowing time recovery to be distributed across several affected trains or applied to a single train category when necessary, while keeping passenger disruption to a minimum. An announcement buffer of $\beta = 1$ station is used to ensure advance notice is available for on-board and platform announcements before a skip is executed. In addition, ten junction stations are designated as non-skippable (S_c). Since no real-time operational data were publicly available, we used scheduled travel and dwell time only [17].

A 300-second delay is introduced at Shin-Yokohama (S8) for Train 2, aligning with empirical observations [4] that more than 90% of dwell time delays in Tokyo are up to 5 minutes. In this case, the delay is severe enough to cause platform blocking, where the following train (Train 3) must wait at S7 until Train 2 departs. Figure 3 shows that, in the do-nothing case, Train 2 (red, original trajectory in light grey) bunches with Train 3, reducing the headway to Train 3 and creating a gap to Train 1.

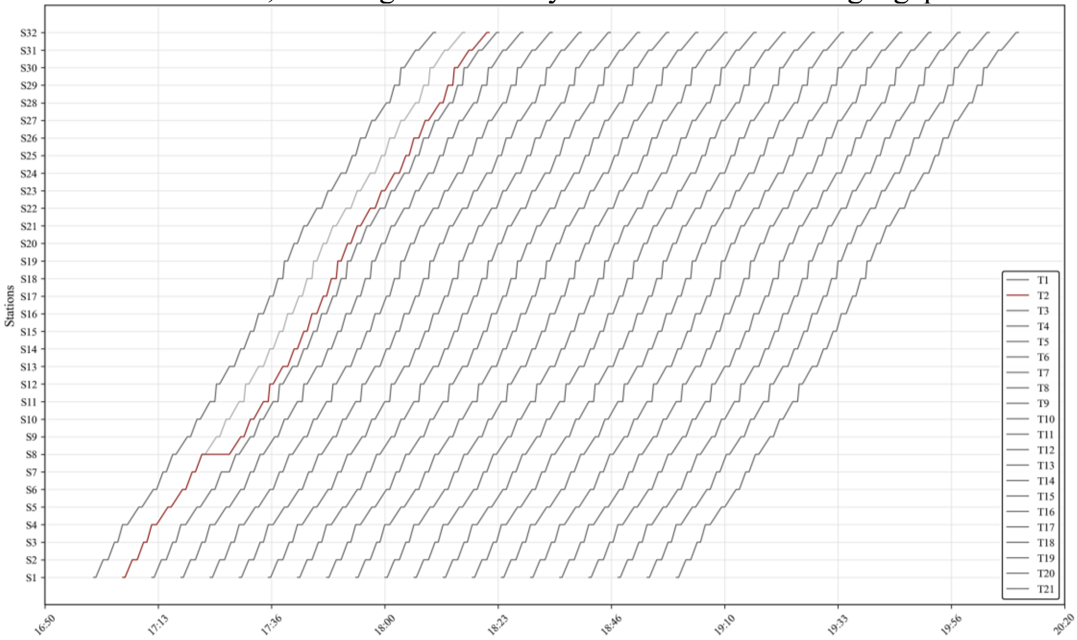

Figure 3: Train trajectories under a disturbed scenario.

When disturbance is detected, the state of train operations is classified. In this given situation, apart from the disturbed train, two trains are already en-route on the commercial service and the rest are still waiting at the origin for departure. The MIQP model allocates recovery measures to the different groups: skip-stop for the affected train, skip and holdings for the trains already in operation, and offsets for the departure times of the trains that have not yet departed.

For our case, we are rescheduling trains by varying n from 0 (disturbed train) to $n = 10$ (following trains), The train trajectories are shown in Figure 4 after optimisation, Mitsuzawa-Kamicho (S11) and Takashimacho (S14) are marked skip stations (marked by red circle at skipped stations) by disturbed train since skipping these stations yields an overall gain in regularity by reducing headway deviation from downstream stations, and further, their ridership is also low compared to other stations. Train 2 recovers some lost time from the initial delay, due to reduced dwell times at the skip stations. Downstream headways become notably more consistent after this operation. The two trains which were already en-route hold at their respective downstream stations. Holding times are concentrated around the disturbance and decrease toward the end station. Departing trains are offset, with smaller delays (offsets) applied to trains that depart later in the schedule. This results in a much more consistent headway distribution along the rest of the line, and the train trajectories are now more uniform.

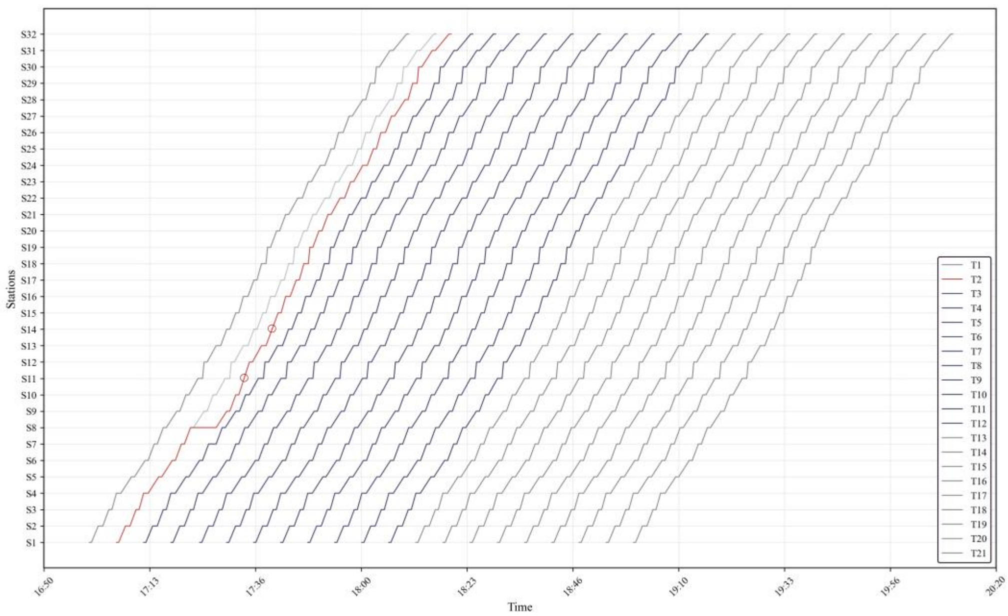

Figure 4: Train trajectories under optimised schedule.

To quantify the effect of the number of coordinated trains on recovery performance, a sensitivity analysis is conducted by varying n from 0 (disturbed train) to 10 (following trains). The plot shows two metrics: 'served stations only', which measures headway improvement at stations where trains provided service, and 'effective headway', which additionally considers increased waiting times at skipped stations by analysing the gaps (from the previously served train to the next serving train) created by skipping stations, as illustrated in Figure 5.

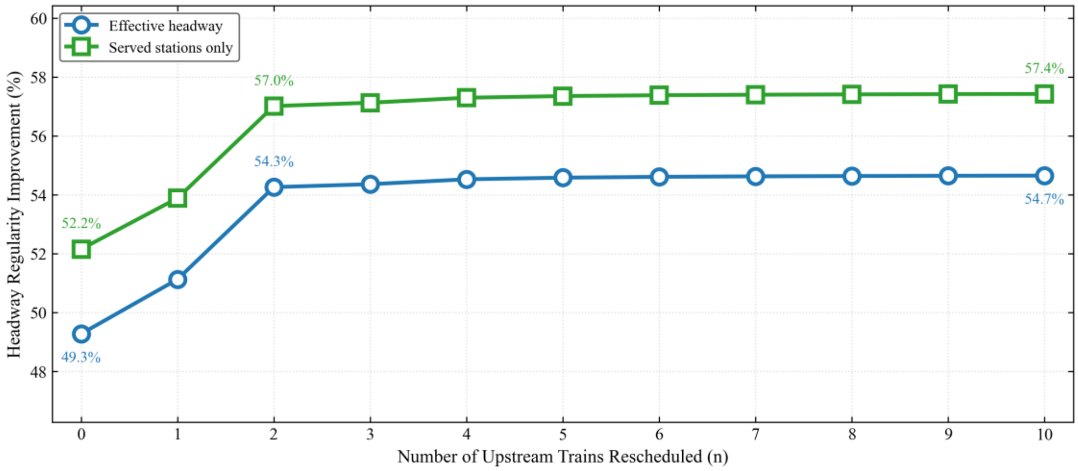

Figure 5: Headway regularity improvement vs n.

As shown in Figure 5, it is observed that if only the disturbed train is optimised with skip-stop ($n = 0$). The improvement in headway regularity relative to the disturbed baseline is approximately 49%. This substantial improvement occurs because skip-stop recovers actual travel time rather than merely redistributing delays. Further, it simultaneously reduces the headway gap to the preceding train while increasing separation from the following train, thereby improving both adjacent headways in a single action.

As more following trains are added to the optimisation, performance continues to improve but with diminishing returns. For $n \geq 2$, the improvement is about 54%, and for $n = 10$, it is close to 55%. Holding and departure offsets add another 4–5% on top of that by spreading the changes across multiple trains. These levels of improvement align with the quadratic nature of the objective function, which punishes the magnitude of the deviation increasingly severely as it was squared. For comparison, Gkiotsalitis and Cats [20] reported around a 30% improvement in headway regularity using dispatch-time rescheduling alone on the Washington, D.C., metro. The larger improvements in our case are due to the integrated use of skip-stop control, holding and departure offsets in a single optimisation problem. Improvements do, however, depend on the location of the disturbance and the recovery actions available, as will become evident from the following analyses.

To examine how disturbance location affects recovery performance, three representative cases are considered: near the origin (CenterKita, S3), near the middle of the line (ShinYokohama, S8), and near the destination (Kaminagaya, S24). These locations are chosen because they lead to different distributions of train categories at the time the disturbance is detected, which in turn affects the set of available recovery strategies (Table 1). At near-origin disturbances, most following trains have not yet departed from the terminal, restricting available actions to skip-stop and departure offset. Holding cannot be applied because no trains are currently en route downstream.

At near mid-route disturbances, the detection timing creates a mix of already-departed and not-yet-departed trains, enabling all three control strategies to work in combination. At near-destination disturbances, the downstream scope is inherently limited regardless of train categories, constraining the cumulative benefit that any recovery action can achieve. The recovery performance for each scenario is presented as shown in Table 2.

Location	n	Baseline	Optimised	Impr. (%)	Skip	Hold	Offset
Near-Origin (S3)	0	42.34	22.34	47.2	Yes	—	—
Near-Origin (S3)	6	42.34	20.68	51.1	Yes	—	Yes
Near-Mid (S8)	0	34.78	17.64	49.3	Yes	—	—
Near-Mid (S8)	6	34.78	15.79	54.6	Yes	Yes	Yes
Near-Dest. (S24)	0	14.11	9.86	30.1	Yes	—	—
Near-Dest. (S24)	6	14.11	9.62	31.8	Yes	Yes	—

Table 2: Recovery performance by disturbance location. Baseline/Optimised = weighted sum of squared headway deviations ($\times 10^5$ s^2); Impr. = improvement; Skip = skip-stop; Hold = holding; Offset = departure offset.

Observed improvements vary across the three disturbance locations. For S3, located near the origin, an improvement of 51.1% is achieved at $n = 6$, with a downstream scope of 28 stations and limited holding options. For S8, located near the middle of the line, the improvement reaches 54.6%, with skip-stop, holding, and departure offsets all permitted. And for the S24, which is located near the destination, the improvement is 31.8%, with a downstream scope of 7 stations and a reduced set of recovery actions. These values are not directly comparable across locations due to differences in baseline deviations and feasible solutions. However, it is observed that location and recovery scope jointly affect the outcomes.

To further verify the contribution of skip-stop decisions, Table 3 compares recovery performance when the maximum skip limit is reduced from 2 to 1 station only, evaluated at n=0, where skip-stop is the only available strategy.

Location	Station	Skip=1 Impr.	Skip=2 Impr.	2nd Skip Benefit
Near-Origin	S3	27.2%	47.2%	+20.0%
Mid-Route	S8	33.1%	49.3%	+16.1%
Near-Dest	S24	23.0%	30.1%	+7.1%

Table 3: skip-stop sensitivity at n=0 (pure skip effect).

The findings demonstrate that skip-stop decisions account for the largest share of the recovery improvement. Even with only one skipped stop applied to the delayed train ($n = 0$), the resulting improvement ranges between 23% to 33% depending on the disturbance's location, aligning closely with the 30% reported [20]. Further benefits are gained from adding one additional skip, especially for longer downstream runs, where the savings can be accrued over multiple stations.

3.1 Comparison with Metaheuristic Solution Approaches

While the previous analysis demonstrates the recovery gains from the integrated control strategy, the practical implementation of a method must also be viable for real-time use. Metaheuristic methods, such as genetic algorithms (GA) and simulated annealing (SA), are popular in rail rescheduling because they are well-suited to work with nonconvex and complex constraints. To evaluate how well the MIQP formulation performs, its results are compared with those obtained by GA and SA. In all cases, the candidate solutions take the form of vectors of skip-stop decisions, holding times, and departure offsets, and algorithm parameters are selected so that each method can be compared on equal footing.

As shown in Figure 6, we compare the objective function values and computation times for all three algorithms for recovery horizons from 0 to 10. The bars indicate solution quality (lower is better for headway regularity), while the line indicates computation time, shown on the secondary axis.

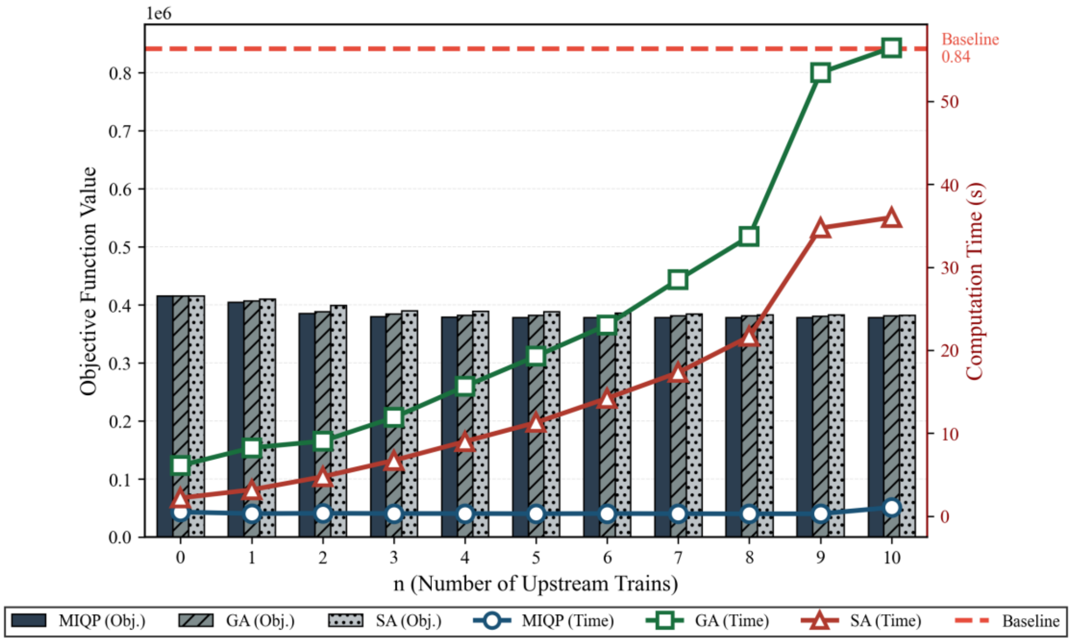

Figure 6: Algorithm comparison—objective values (bars) and computation times (lines) across recovery horizons. GA/SA: representative run (Table 4 for 10-runs).

In terms of solution quality, all three methods achieve comparable results. At $n = 0$, the algorithms converge to identical solutions since the skip-stop decision dominates, and the solution search space is small. For $n \geq 1$, the bars remain nearly equal in height, confirming that metaheuristics can find near-optimal solutions for this problem class. Since GA and SA are stochastic algorithms, 10 runs were conducted to assess solution quality variation. As shown in Table 4, GA averages 0.82% ± 0.23%

above MIQP optimal and SA averages 1.80% ± 0.35%, demonstrating consistent convergence to near-optimal solutions.

	Optimality Gap (%)	Computation Time (s)
MIQP	0.00	0.87
GA	0.82 ± 0.23	46.49
SA	1.80 ± 0.35	29.07

Table 4: Algorithm performance comparison. Results are averaged over 10 runs, with n ranging from 0 to 10.

The main difference between the approaches is in the computational time required. The MIQP solver performs relatively well on all test instances, with average solution times of less than one second and little dependence on the number of trains. In contrast, the solution times for GA and SA grow rapidly with the size of the solution space. While the proposed approach obtains speedups of 30-50 times on the test instances, this is mainly due to the proposed formulation, which contains linear operational constraints and a convex quadratic objective function that can be effectively solved by a branch-and-bound-based MIQP solver, rather than by metaheuristics.

4 Conclusions

In this paper, we propose a real-time recovery strategy for high-frequency metro services based on an integrated model that uses MIQP formulations for the skip-stop, holding, and departure rescheduling strategies. The results indicate that rescheduling a few trains using the combined strategies can efficiently recover from disturbances. In particular, the skip-stop strategy has played an important role in improving the regularity of headways for both the preceding and succeeding trains. In this regard, the regularity of the headways improves by 23 to 33 % when one stop is skipped and by 30 to 49 % when two stops are skipped, depending on the location of the disturbance and the horizon of recovery.

In the near-mid-route disturbance case, we identified sections with more downstream track and train options, and as a result, the recovery strategies led to up to a 54.6% improvement in headway regularity. Near the terminals, improvements peak at approximately 31.8% where downstream flexibility is limited. However, this improvement can further vary depending on the number of skips allowed, the announcement buffer limit, and the holding or departure offset limits.

Finally, the MIQP formulation finds global optima in sub second, 30–50 times faster than near-optimal solutions from SA and GA that converge within 1–2% of the optima over 10 iterations. The framework produces good results for minimal rescheduling of operational trains, even with just two or three trains, making it suitable for real-time operations.

Future work could explore more complex disruption patterns, such as cascading delays involving connecting lines and round-trip operations, where delays spread to the opposite direction through shared terminal turnback processes. Adding speed control, congestion-based dwell times, and passenger origin–destination data would further enhance the modelling of passenger inconvenience and detouring costs, especially in skip-stop scenarios.

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