Integrated Optimization of Vehicle Scheduling and Passenger Assignment of Demand-Responsive Transit and Conventional Buses under Urban Rail Transit Disruptions

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Abstract: Urban rail transit systems are vital to urban mobility, yet disruptions may cause significant congestion or delays for passengers. Traditional evacuation strategies, predominantly reliant on conventional buses, could not consider the diverse characteristics of passengers. This study proposes an optimization method that integrates the services of demand responsive transit (DRT) and conventional buses to efficiently and passenger-friendly evacuate stranded passengers when urban rail transit disruption occurs. An integer linear programming model is proposed to deliver both a vehicle schedule (including the number of used DRT vehicles and conventional buses, as well as the routes of the vehicles) and a passenger assignment solution simultaneously. The route of the DRT vehicle is considered variable, and passenger assignment with each vehicle depends on the passengers' destination and the route of the assigned vehicle. Moreover, we propose a preprocessing method to generate a set of feasible routes for each vehicle. We consider two objectives: maximize the number of transported passengers and minimize the travel time. An epsilon-constraint-based algorithm is used to find the Pareto optimal solutions for the proposed bi-objective model. The case study is conducted using data from a real-world urban public transportation network in China to evaluate the effectiveness of the proposed method. The experimental results show that the integrated optimization approach achieves a significant average reduction of 73.88% in travel time and 72.39% in the total number of vehicles used compared with single-mode evacuation strategies utilizing only conventional bus services. Furthermore, the experimental results obtained by integrated optimization of the vehicle route scheduling and passenger assignment achieve up to 80.93% reduction of travel time and 11.14% increase of transported passengers, compared with the solutions by fixed vehicle routes. **DOI: 10.1061/JTEPBS.TEENG-8863.** *© 2025 American Society of Civil Engineers.*

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Introduction

Public transit systems are crucial for people's mobility. Urban rail transit (URT) is the backbone of the public transit system due to the large volume of passengers transported. However, unplanned events such as rolling stock breakdowns or infrastructure failures may occur in URT operations, causing major disruption and further stranding a large number of passengers at the station. Thus, an efficient evacuation strategy is paramount to ensure passenger safety and the service quality of public transportation.

Traditional evacuation plans typically rely on a single transportation mode, such as conventional buses. Conventional buses operate on fixed routes, which ensure the predictability and familiarity of the evacuation service to passengers during emergency evacuations (Kepaptsoglou and Karlaftis 2009). This contributes to the orderly evacuation process, thereby reducing uncertainty and chaos. In recent years, researchers have increasingly focused on integrating conventional buses into urban rail transit systems, particularly in response to system disruptions. Zhang et al. (2021) gave a review of the metro system disruption management and substitute bus service, emphasizing the importance of bus bridging services in mitigating disruptions. In response to urban rail transit disruptions, researchers developed a set of models and algorithms to solve the bus bridging service design problem, such as the robust optimization model (Liang et al. 2019; Wang et al. 2022), bilevel optimization model (Itani et al. 2020), multimodal k-shortest route algorithms (Luo and Xu 2021), tabu search heuristic algorithms (Chen and An 2021), and multiobjective genetic algorithms (Zheng et al. 2022). These studies have provided methods to optimize conventional bus bridging schedules for passengers stranded at the disruption points of URT, with decisions such as bus frequency, vehicle scheduling, and bus timetables.

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However, conventional buses are typically operated with fixed routes and destinations, which may limit the service quality for addressing the varied destination demands of passengers. Recently, a new type of public transit system named demand-responsive transit (DRT), also known as dial-a-ride (DAR) (Dong et al. 2020), custom buses (Dou et al. 2021), and flexible buses (Sun et al. 2020), could provide a flexible service for passengers to transport them to their destinations, potentially enhancing the service quality. Research on the flexible route scheduling and personalized demand fulfilment of DRT has yielded significant findings. To enhance the flexibility and operational efficiency of DRT, Xia et al. (2024) have developed a pioneering distributionally robust optimization model which adeptly integrates timetabling and vehicle scheduling within an intermodal transit network, leveraging the dynamic capabilities of modular vehicles to accommodate fluctuating passenger demands and operational uncertainties. Liu and Ouyang (2021) developed a framework that optimizes route planning and scheduling for personalized DRT services, integrating queuing network models with transit network design to accommodate both dispersed and concentrated trip patterns. In terms of DRT scheduling, researchers have conducted studies on route planning, stop scheduling, and timetable optimization to minimize the operational costs of the DRT system (Chen et al. 2021). By developing mixed-integer linear programming models (Lee et al. 2023; Ma et al. 2023; Fu and Chow 2023), employing heuristic algorithms (Galarza Montenegro et al. 2021) and genetic algorithms (Zheng et al. 2020), researchers could satisfy the personalized demands of passengers with less operational costs, thereby enhancing the satisfaction levels of DRT services. For the bridging services of URT provided by DRT vehicles, researchers have proposed some methods to enhance the integration efficiency between DRT and URT, including a genetic algorithm (Deng et al. 2013), bilevel optimization model (Pan et al. 2014), distributed algorithm (Muelas et al. 2015), two-stage vehicle routing model (Shen et al. 2017), and two-stage ant colony algorithms (Tan et al. 2022). In response to URT disruptions, Wang et al. (2024) have proposed a novel two-step optimization model that strategically integrates train timetable rescheduling with the dynamic dispatch of DRT vehicles. This approach ensures a more agile and efficient evacuation of stranded passengers, leveraging the adaptability of DRT services to meet varying passenger demands during URT disruptions.

However, most of the research only considers one type of bus (e.g., conventional bus, DRT) when managing URT disruption with bus service. As a result, the evacuation services by one type of bus may fail to meet the point-to-point passenger travel demand (i.e., conventional bus) or lack evacuation efficiency (i.e., DRT). Moreover, the studies solve the problems of vehicle scheduling and passenger assignment for evacuation services in a sequential or nonoptimized manner, which leaves an open gap in terms of evaluation performance by considering those two aspects simultaneously. To deal with these issues, an integrated optimization method that combines different types of bus services is needed. In the context of urban rail transit disruptions, there is a growing recognition of the importance to collect passenger destination information quickly. Recent technological advancements, as highlighted by He (2023) and Chandakas (2020), have enabled the rapid collection of such data, providing a solid foundation for the effective deployment of DRT services in response to disruptions. These studies underscore the efficacy of dynamic optimization algorithms in reshaping vehicle routing and scheduling to meet the diverse and immediate destination requirements of passengers. Furthermore, our study leverages these advancements by integrating the services of DRT and conventional buses, utilizing real-time passenger destination data as a key input parameter to establish our optimization model. This data-driven approach, which is particularly significant in the context of transit disruptions where a rapid response to passenger needs is essential, as pointed out by Attard et al. (2020), allows us to focus on optimizing the integration and coordination of DRT and conventional bus services based on the actual destination requirements of passengers.

This study proposes an optimization method that integrates the services of DRT and conventional buses. Based on the achievements and gaps in the literature, the main contributions of this study are as follows:

This research integrates vehicle scheduling and passenger assignment by combining the services of DRT and conventional buses to provide evacuation services after urban rail transit disruptions. This method considers the personalized demands of stranded passengers (i.e., the destinations of the passengers) by integrating scheduling vehicle routes of the DRT and passenger assignment. At the same time, the method could achieve efficient evacuation services by using conventional buses with big passenger carrying capacity and short-distance bridging service. The proposed integrated optimization method is innovative, and incorporates the advantages of the DRT system and conventional buses.

A bi-objective integer linear programming optimization model is proposed to construct the evacuation plan by using DRT vehicles and conventional bus vehicles. A vehicle scheduling plan and a passenger assignment plan are obtained simultaneously. Two objectives are considered to minimize total travel time and maximize the number of transported passengers. In the model, the route of the DRT vehicle is considered flexible, which couples with the passenger assignment decisions, according to the passenger destinations, the carrying capacity of the DRT vehicle, and travel time among the destinations.

An extensive experimental study has been conducted to validate the effectiveness of the proposed model. The combination of the evacuation services of DRT and conventional buses yields an average reduction of 73.88% in travel time and 72.39% in the total number of vehicles used, compared with single-mode evacuation strategies utilizing only conventional bus services. Moreover, the experimental results obtained by integrated optimization of the vehicle route scheduling and passenger assignment achieve up to 80.93% reduction of travel time and 11.14% improvement of the number of transported passengers, compared with the solutions by fixed vehicle routes.

The rest of the paper is organized as follows: Following this introduction, the next section presents the mathematical formulation of our model, detailing the variables, constraints, and objectives pertinent to the integrated optimization of vehicle scheduling and passenger assignment. Subsequently, the solution method section describes the epsilon-constraint-based algorithm for solving the bi-objective model. Additionally, the case study section applies the bi-objective model to a case study based on Kunming Subway Line 1 in China, showcasing the practical application and results. Finally, the concluding section discusses the paper's findings and potential areas for future research.

Mathematical Formulation

Problem Statement

As depicted in Fig. 1, the network consists of a set of nodes and arcs with technical and operational requirements. Regarding the nodes, we give a disruption point in the urban rail transit network (i.e., the station with many evacuation passengers), a set of depots for DRT and conventional buses, the destination station of conventional

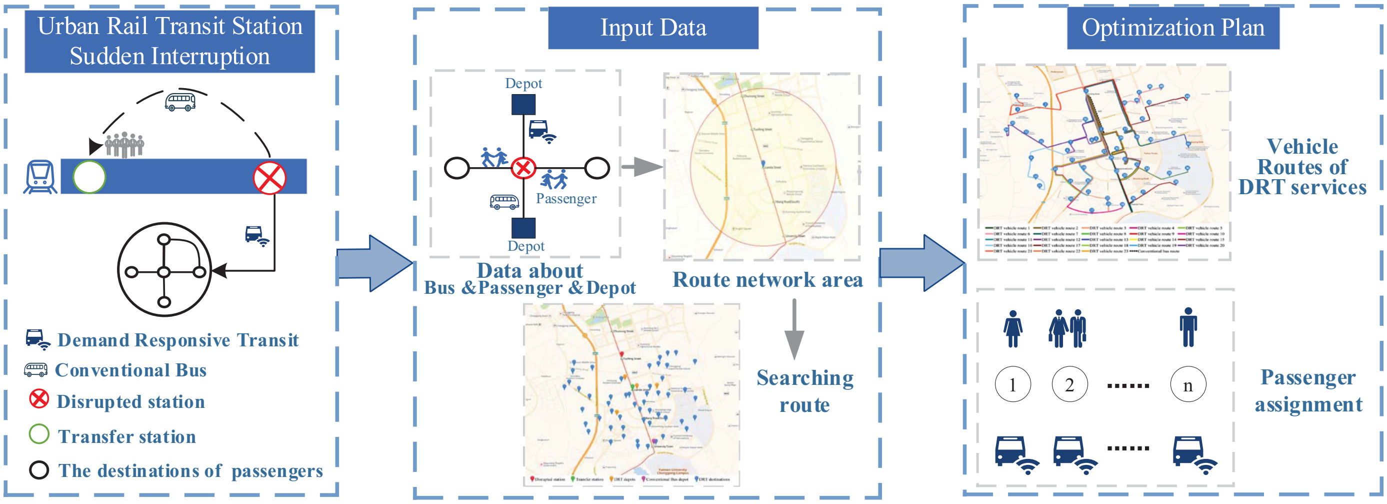

Fig. 1. Problem statement. (Base maps © 2025 AMAP.)

buses, and a set of traveler destinations. An arc is composed of two nodes. Also, we give a set of DRT vehicles and conventional buses with their initial depot, the carrying capacity, and the possible arcs with the travel times. Moreover, the information about the passenger group is provided, i.e., the destination of each passenger group and the number of passengers in each group. Regarding the approach of obtaining passenger destinations, passengers will be encouraged to use an application where they can input their destinations in advance. This will enable our dispatch platform to receive real-time updates on passenger destinations, allowing us to track the travel demands and inform scheduling decisions accordingly.

We focus on the investigation of the operation of the vehicles of DRT and conventional buses to transport passengers by finding the optimal vehicle scheduling plan in order to reduce the travel time and, at the same time, transport more passengers. Thus, we emphasize the details of vehicle scheduling (i.e., the routes and the type of each vehicle) and passenger assignment (i.e., the coupling results between passengers and vehicles). In fact, we propose a preprocessing method to generate the possible routes for each vehicle to accelerate the solution speed. Therefore, in our optimization model, we make the following assumptions: (1) passenger groups waiting for DRT vehicles and conventional buses are considered as indivisible units, with the same destination; (2) each DRT vehicle is assigned multiple predefined feasible routes, with a set of serviceable destinations, predetermined average travel speeds, and predetermined travel times for the entire feasible route; (3) the travel time for each DRT vehicle and conventional bus from the depot to the urban rail transit disruption point is predetermined; and (4) the carrying capacity is consistent across all DRT vehicle, and similarly, it is also consistent across all conventional buses.

Sets, Subscripts, Input Parameters, and Decision Variables of the Model

The definitions of the sets, subscripts, input parameters, and decision variables of the model are presented in the "Notation" section.

Bi-Objective Integer Linear Programming Model

We next formulate the integrated optimization problem of vehicle scheduling and passenger assignment of DRT and conventional buses. The objective function consists of two terms: one is to minimize the total travel time for all vehicles

$$Z^{time} = \left[\left(\sum_{o\in O,k\in K} \alpha_k \times \rho_{k,o} \times t_o^{run} + \sum_{k\in K,r\in\Omega_k} \beta_{k,r} \times x_{k,r}\right) + \left(\sum_{o'\in O',v\in V} t_{o'}^{n_{\text{run}}} \times \rho^n_{v,o'} \times \alpha_v + \sum_{v\in V} \alpha_v \times t_v^{travel}\right)\right] \quad (1)$$

The other one is to maximize the total number of transported passengers

$$Z^{passenger} = \sum_{p\in P^{dial},k\in K} y_{p,k} \times q_p + \sum_{v\in V,p\in P^B} \gamma_{p,v} \times q_p \quad (2)$$

The bi-objective function is expressed by

$$Z = \{\min Z^{time}, \max Z^{passenger}\} \quad (3)$$

In function (1), term $\sum_{o\in O,k\in K} \alpha_k \times \rho_{k,o} \times t_o^{\text{run}}$ represents the total operational time for all DRT vehicles originating from depot o to the disruption point of the urban rail transit system. Term $\sum_{k\in K,r\in\Omega_k} \beta_{k,r} \times x_{k,r}$ represents the total travel time for DRT vehicles along their selected routes. Term $\sum_{o'\in O',v\in V} t_{o'}^{n_{\text{run}}} \times \rho^n_{v,o'} \times \alpha_v$ represents the total travel time for all conventional buses originating from depot o' to the disruption point. Term $\sum_{v\in V} \alpha_v \times t_v^{\text{travel}}$ represents the total single-trip travel time for conventional buses from the disruption point to the transfer station. We clarify that function (1) represents the total travel times for all vehicles. The travel time is composed of several segments: the travel time from the depot to the disruption point, the travel time along the selected routes for DRT vehicles, and the travel time for conventional buses from the disruption point to the transfer station.

In function (2), term $\sum_{p\in P^{\text{dial}},k\in K} y_{p,k} \times q_p$ represents the total number of passengers transported by DRT vehicles. Term $\sum_{v\in V,p\in P^{\text{B}}} \gamma_{p,v} \times q_p$ represents the total number of passengers transported by conventional buses.

The constraints for the model are as follows:

$$\sum_{p\in P^{\text{dial}}} y_{p,k} \times q_p \le c_k, \quad \forall\ k \in K \quad (4)$$

For each DRT vehicle k, constraint (4) ensures the total number of passengers assigned must be within the carrying capacity of the vehicle k

$$y_{p,k} \leq \sum_{r \in R} a_{r,d_p} \times x_{k,r}, \quad \forall\ p \in P^{\text{dial}}, \quad k \in K \tag{5}$$

If passenger p is transported by DRT vehicle k (i.e., $y_{p,k} = 1$), constraint (5) can ensure that the route of vehicle k must go through the destination of passenger group d_p

$$\sum_{r \in \Omega_k} x_{k,r} \times \alpha_k = 1, \quad \forall\ k \in K \tag{6}$$

Constraint (6) ensures that each DRT vehicle k can only select one feasible route r

$$\sum_{k \in K} y_{p,k} = 1, \quad \forall\ p \in P^{\text{dial}} \tag{7}$$

Constraint (7) ensures that each passenger group p can only be assigned to one DRT vehicle k

$$\begin{cases} (\alpha_k - 1) \times P^{\text{dial}} \leq \sum_{p \in P^{\text{dial}}} y_{p,k} - 1 + \varepsilon \\ (\alpha_k \times P^{\text{dial}}) \geq \sum_{p \in P^{\text{dial}}} y_{p,k} \end{cases} \quad \forall\ k \in K \tag{8}$$

Constraint (8) links the binary variable α_k and $y_{p,k}$: if vehicle k is selected by one or more passenger groups (i.e., $\sum_{p \in P^{\text{dial}}} y_{p,k} \geq 1$), then vehicle usage variable α_k will be equal to 1; $= 0$, otherwise

$$\sum_{p \in P^B} \gamma_{p,v} \times q_p \leq c_v, \quad \forall\ v \in V \tag{9}$$

For each conventional bus v, constraint (9) ensures the total number of passengers assigned must be within the carrying capacity of the bus v

$$\sum_{v \in V} \gamma_{p,v} = 1, \quad \forall\ p \in P^B \tag{10}$$

Constraint (10) ensures that each passenger group p can only be assigned to one conventional bus v

$$\begin{cases} (\alpha_v - 1) \times P^B \leq \sum_{p \in P^B} \gamma_{p,v} - 1 + \varepsilon \\ (\alpha_v \times P^B) \geq \sum_{p \in P} \gamma_{p,v} \end{cases} \quad \forall\ v \in V \tag{11}$$

Constraint (11) links the binary variable α_v and $y_{p,v}$: if bus v is selected by one or more passenger groups (i.e., $\sum_{p \in P^B} y_{p,v} \geq 1$), then vehicle usage variable α_v will be equal to 1; $= 0$, otherwise.

Solution Method

A Preprocessing Method to Generate a Set of Feasible Routes for Each Vehicle

The efficiency of the integrated optimization approach is highly dependent on the size of the solution space. In the model, we model the vehicle routing problem by a route-based method to accelerate solution speed. In fact, we have designed a preprocessing approach to generate the possible routes for each vehicle by a revised routing formulation. The following pseudocodes give the algorithmic details of the feasible route solution construction procedure. The notations used are presented in the "Notation" section.

Model M_routing. The model for the routing problem with a fixed number of destinations

$$\text{Minimize} \sum_{r \in R, (i,j) \in E} c_{i,j} \times x_{r,i,j} \tag{12}$$

$$\text{s} \cdot \text{t} \cdot \sum_{j:(i,j) \in E} x_{r,i,j} = 1, \quad \forall\ i, r \tag{13}$$

$$\sum_{i:(i,j) \in E} x_{r,i,j} = 1, \quad \forall\ j, r \tag{14}$$

$$\sum_{(i,j) \in E} x_{r,i,j} = n, \quad \forall\ r \tag{15}$$

In model M_routing, objective (12) is the minimization of the overall travel distances. Constraints (13) and (14) ensure that in a route, each destination node is connected to two other nodes, which arc is predecessor and successor. Constraint (15) states that the number of destinations in a route is equal to the predetermined value.

Algorithm 1. Generate a set of feasible routes for each vehicle

Input: max_num_destinations, $c_{i,j}$, v_k
Output: $a_{r,i}$, $\beta_{k,r}$, Ω_k
Initialize $a_{r,i} \to 0$, $\beta_{k,r} \to 0$, $\Omega_k \to \phi$, $\rho \to 0$
While ($\rho <$ max_num_destinations) **do**
  Solve Model B with $n = \rho$
  Output the solutions of $x_{r,i,j}$ for route r
  If ($\sum_{(i,j) \in E} x_{r,i,j} = \rho$)
    $a_{r,i} = 1$; $a_{r,j} = 1$; $\Omega_k \to r$; $\beta_{k,r} = \sum_{(i,j) \in E} c_{i,j} \times x_{r,i,j} / v_k$
  Else
  $\rho + +$;
  end
end
Return $a_{r,i}$, $\beta_{k,r}$, Ω_k

An Epsilon-Constraint-Based Algorithm for Solving the Bi-Objective Model

This section establishes an algorithm for solving the bi-objective integrated optimization problem, utilizing the epsilon-constraint method. The algorithm proceeds by following algorithm.

Algorithm 2. An epsilon-constraint-based algorithm for solving the bi-objective model

Step 1: Construct **a Single-Objective Optimization Model**
Step 1.1: Formulate a single-objective optimization model (Model M_time) that minimizes travel time, i.e., minZ^{time}, and subject to constraints (4) to (11).
Step 1.2: Formulate another single-objective optimization model (Model M_passenger) that maximizes the number of transported passengers, i.e., max$Z^{passenger}$, and subject to constraints (4) to (11).
Step 2: Solve the **models of M_time and M_passenger**
Solve models M_time and M_passenger to obtain the objective values Z^{*}_time and $Z^{*}\_passenger$ of the optimal solutions, respectively.
Step 3: Obtain **Boundary Points of the Pareto Front**

Add constraint $Z^{passenger} \geq Z^{*}\_passenger$ to model M_time. Solve the model and obtain the objective value Z'_{time} and the value of transported passenger number $Z'_{passenger}$ of the optimal solution. Then, $(Z'_{time}, Z'_{passenger})$ is a boundary point of the Pareto front. Similarly, add constraint $Z^{time} \leq Z^{*}\_time$ to model M_passenger to obtain another boundary point $(Z''_{time}, Z''_{passenger})$. Add the solutions of the two boundary points to the Pareto solution set Θ.

Step 4: Construct **a Single-Objective Model with Epsilon-Constraint**

Formulate a single-objective model with epsilon constraint, denoted as model M_time_ε. The objective of the model is to minimize the total travel time, i.e., miZ^{time}. The constraints of the model are as follows:

(1) Constraints (4) to (11);

(2) A set of epsilon constraints, i.e., $Z_{passenger(\omega)} \geq Z'_{passenger} + \omega \times \vartheta$, where $\omega = 1,2, \ldots, \rho - 2$, ρ is the number of desired Pareto solutions, and ϑ is the stepwise of the epsilon between two solutions, i.e., $\vartheta = (Z''_{passenger} - Z'_{passenger})/(\rho - 2)$.

Step 5: Obtain **a set of Pareto-Optimal Solutions**

For $\omega = 1,2, \ldots, \rho - 2$, solve model M_time_$\varepsilon$ to obtain the objective value Z^{time}_{ω} and the corresponding value of transported passenger number $Z^{passenger}_{\omega}$. Add solutions $(Z^{time}_{\omega}, Z^{passenger}_{\omega})$ to the Pareto solution set Θ.

Step 6: Output **the Pareto Front**

Output the Pareto front based on the obtained objective values of the Pareto optimal solutions.

Numerical Experiments

In this section, we first describe the data set. Then, we report the experimental results of the bi-objective model. Further, we investigate the benefits of the integrated optimization services of DRT and conventional buses, by considering a single transportation mode to transport passengers. Moreover, we conduct a comparison between the flexible and fixed routing options for vehicles, to highlight the advantages of flexible routing as evidenced by our experimental results. Lastly, we present a sensitivity analysis of the vehicle carrying capacity.

Description of the Data Set

Upon the occurrence of equipment failure at a subway station, trains are unable to traverse the impacted station, thereby necessitating an immediate halt at this station, which becomes the disruption point. This situation leads to a significant accumulation of passengers stranded at this disruption point. In response to the challenges posed by such a scenario, it is imperative to implement an urgent evacuation procedure.

The majority of impacted passengers have destinations that are significantly distant from the disruption point. For these passengers, it is infeasible to directly evacuate them to their final destinations. In such scenarios, conventional buses can be employed to transport these passengers to a designated transfer station with turnback capabilities—a station equipped with facilities that allow trains to reverse direction and operate in a part route mode between this station and other unimpacted stations. This arrangement enables passengers to resume their journey by transferring from the conventional bus to the subway at the transfer station, where trains can perform a turnback and continue service.

Conversely, for a smaller number of passengers with destinations near the disruption point, the flexibility of DRT services can be leveraged. By considering the personalized demands of these passengers, DRT vehicles can efficiently transport them directly to their intended destinations, thereby providing a personalized evacuation solution and minimizing inconvenience.

In our case study, we focus on Kunming Subway Line 1 in China, designating Tuofeng Street Station as the disruption point and Lianda Street Station as the transfer station with turnback capabilities. Moreover, the network includes the passenger's destinations, which are generated by real-world API data via AMap. The nodes of the network are shown in Fig. 2. The network is composed of 54 nodes and 129 arcs; detailed data about the network can be found in the Supplemental Materials. 27 DRT vehicles and 20 conventional buses are considered for dispatching. 635 feasible routes for each DRT vehicle are generated by Algorithm 2. 120 passenger groups are considered, with a total of 1,003 passengers who required evacuation services at the disruption point. This configuration allows us to explore the effectiveness of integrating DRT and conventional bus services in managing passenger evacuation during disruptions.

We use the CPLEX solver version 12.10 with default settings to solve the ILP model to optimality. The following experiments are all performed on an Intel(R) Core (TM) i9-13900K CPU @3.00GHz processor and 128 GB RAM. CPLEX can solve the model quickly (i.e., less than 180 seconds). To facilitate practical application, the model incorporates a strategy for efficient passenger grouping and vehicle assignment. The integration of our proposed approach, the Passenger Information System (PIS), and a mobile notification system will inform the assigned vehicles for passengers and the selected route for vehicles, ensuring a smooth and organized evacuation process. The Fig. 3 provides a step-by-step visualization of the application program's workflow.

Experimental Results, Trade-Off between Travel Time and Transported Passengers

In this section, we investigate the bi-objective aspect of our integrated optimization problem. We use Algorithm 2 to produce the Pareto frontier depicted in Fig. 4. We obtain 27 Pareto solutions with a stepwise value of 40. Table 1 summarizes the relevant information about the travel time, the number of vehicles, and the failed transported passenger percentage of the obtained Pareto solutions. Solutions 1 and 27 are the two boundary points. Solution 1 in the table indicates the travel time is zero (there is no vehicle used to transport passengers); thus, the passengers cannot leave the disruption point. By moving from solution 1 to 20, an additional travel time of 10 minutes can reduce the failed transported passengers by 4%, and the failed transported passenger percentage is linearly reduced by the increased travel time and the number of vehicles. Further, the more we move to the right in the frontier, the more travel time (i.e., an average of 67 minutes) and vehicles (i.e., an average of 4 vehicles) it takes to reduce the percentage by 4%.

The extreme of the Pareto frontier in the upper right corner (marked with a solid dot) of Fig. 4. has a maximum number of transported passengers of 1,003 and a total travel time of 677.5 minutes. Fig. 5 reports the routes of DRT vehicles of this solution, and its detailed information is shown in Table 2. These experimental results show that, in our case study, 79.76% of passengers are transported by conventional buses as it is with high efficiency in transporting a large number of passengers, and the other passengers can be transported by DRT vehicles to their destinations.

Benefits of the Integrated Services of DRT and Conventional Buses

We now compare the performance of the integrated services with the single-mode service. The single-mode service is the traditional

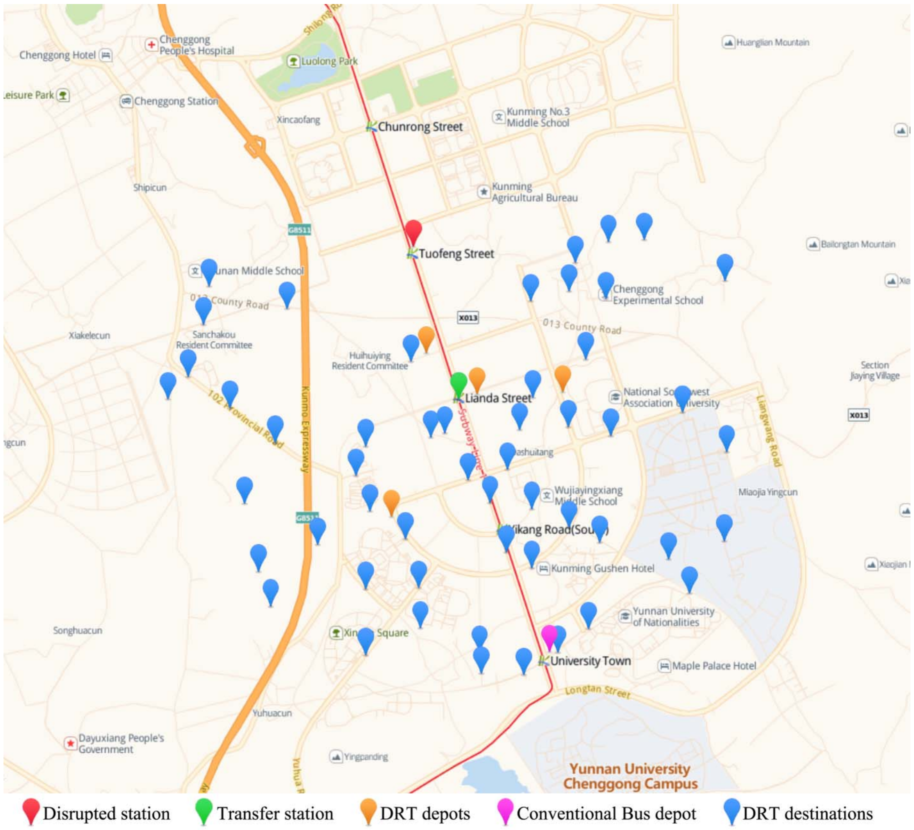

Fig. 2. Real-world experimental network. (Base map © 2025 AMAP.)

evacuation strategy, which typically relies on a single transportation mode, such as conventional buses or taxis. We design two sets of experiments to evaluate the benefits of the integration. We are interested in solution quality (i.e., total evacuation time reduction, number of vehicles reduction) for the following two scenarios:

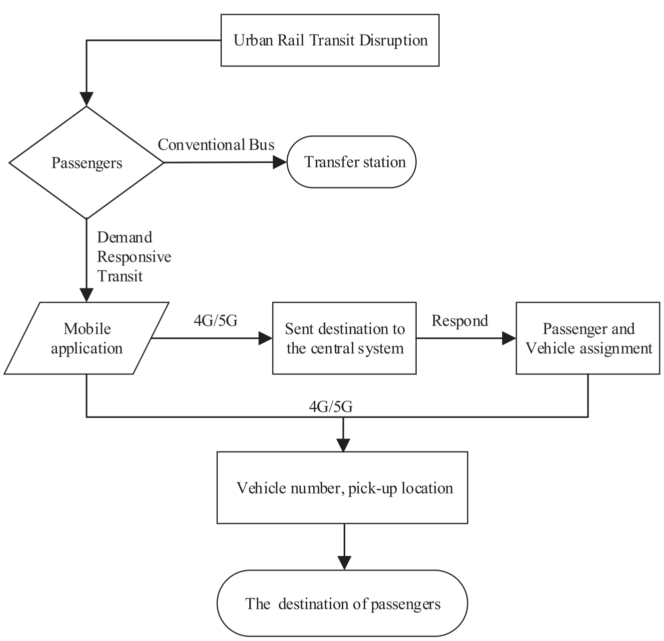

Fig. 3. Passenger data collection and evacuation process.

DRT+C (this work): using the proposed MIP model with integrated services of DRT and conventional buses.

DRT: using the MIP model with only DRT service.

We first focus on the total travel time reduction of two scenarios, as shown in Fig. 6. The solution quality using the MIP model with integrated services of DRT and conventional buses (i.e., DRT+C, this work) is better than the MIP model with only DRT service (i.e., DRT), i.e., the travel time of the line with solid square symbols is significantly reduced compared to the corresponding line with solid circle symbols. Moreover, we present the percentage of

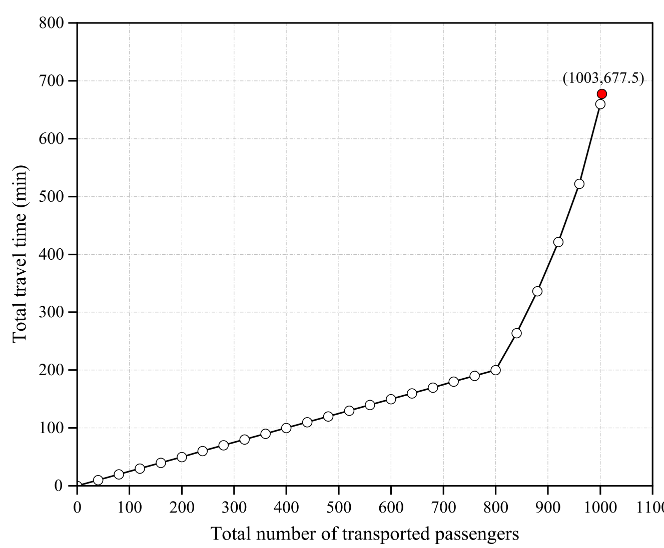

Fig. 4. Pareto frontier.

Table 1. Travel time and transported passengers for the obtained Pareto solutions

Pareto solution number	Travel time (min)	The number of vehicles	Failed transported (%)
1	**0**	**0**	**100**
2	10	1	96
3	20	2	92
4	30	3	88
5	40	4	84
6	50	5	80
7	60	6	76
8	70	7	72
9	80	8	68
10	90	9	64
11	100	10	60
12	110	11	56
13	120	12	52
14	130	13	48
15	140	14	44
16	150	16	40
17	160	16	36
18	170	17	32
19	180	18	28
20	190	19	24
21	**200**	**20**	**20**
22	264	25	16
23	336	29	12
24	421	33	8
25	522	37	4
26	659	42	0.3
27	677	43	0

Note: Solutions 1 and 27 are the two boundary points which are denoted in bold font.

improvement in solution quality from the scenario DRT as a function of the number of transported passengers. This percentage of improvement is calculated by the formula $(Z_{DRT}^{time} - Z_{DRT+C}^{time})/Z_{DRT}^{time}$. As shown, when transporting 1,003 passengers, the total travel time of scenarios of DRT+C and DRT is 677.5 and 1,656.5 respectively, resulting in a 59.10% reduction. Particularly, scenario DRT + C achieves a maximum reduction of 80.93% compared to scenario DRT when transporting 800 passengers. In summary, the average improvement in solution quality of our proposed MIP model with integrated services is 73.88%, thereby enhancing evacuation efficiency at the disruption point.

Furthermore, we analyze the number of vehicles used for the two scenarios. Fig. 7 shows the number of vehicles used and the percentage of the improvement in solution quality of two scenarios. The percentage of improvement in this figure is calculated by the formula $(\sum_{k:k\in \mathrm{DRT}} \alpha_k - \sum_{k:k\in \mathrm{DRT+C}} \alpha_k)/\sum_{k:k\in \mathrm{DRT+C}} \alpha_k$. As illustrated, the number of vehicles used for scenario DRT increases linearly with the increase of transported passengers, which is much higher than the corresponding scenario DRT+C. For instance, when transporting 1,003 passengers, scenario DRT+C uses a total of 43 vehicles, and scenario DRT needs 103 vehicles, achieving an improvement in solution quality of 58.25%. Overall, compared with the results of scenario DRT, the minimum, maximum, and average improvement of scenario DRT+C is 58.25%, 75%, and 72.39%, respectively; 26 out of 27 sets of experimental results indicate an improvement of more than 50%; 24 sets achieve an improvement exceeding 60%.

In summary, the experimental results demonstrate the benefits of integrating DRT and conventional bus services. These benefits are reflected by the reduced travel time and vehicles used.

Benefits of Flexible Vehicle Routes

This section aims to study the impact of flexible vehicle routes on the solution quality. Recall that the proposed MIP model considers the vehicle routes designed for flexibility to better accommodate passenger demands.

Five cases are generated by considering different maximum numbers of destinations for the route of each vehicle, denoted as Case A, Case B, Case C, Case D, Case E, respectively, as presented in Table 3. Column 3 gives the number of possible routes for each vehicle; column 4 shows the number of all possible routes of the vehicle services. For Cases A to E, 10 sets of numerical experiments are conducted by considering different random routes for each vehicle.

Fig. 8 shows the results of the six cases. The objective values of 10 experiments for Cases A to E are distinguished by symbols: squares for Case A, inverted triangles for Case B, upright triangles for Case C, pentagrams for Case D, and diamonds for Case E, respectively. Moreover, the average objective values of 10 experiments for Cases A to E are drawn as a solid line with square symbols and the results of Case F is indicated by a dashed line with circle symbols.

We first focus on the comparison of results with flexible and fixed vehicle routes. The solution quality of Case F with flexible vehicle routes is better than the results of Cases A to E with fixed vehicle routes, i.e., the dashed line is obviously higher than the solid line. This demonstrates the benefits of flexible vehicle routes, i.e., more passengers can be transported with fewer evacuation times by variable vehicle routes. The improvement in the number of transported passengers for Case F is 11.14%, 8.15%, 7.65%, 8.05%, and 8.20%, respectively, when comparing with the average objective values of Cases A to E with same travel time.

Furthermore, we analyze the impact of the number of destinations for the fixed vehicle route, presented as discrete points and solid lines in Fig. 8. As shown, the travel time and the number of transported passengers increase with the number of destinations. By moving from Case A to Case C, an additional destination of a route can improve the number of transported passengers by 0.75%–5.34%, which is a significant improvement, with an average increase of travel time by 8.40%. However, the more we move to the right of the line (i.e., Cases D and E), the lower improvements (i.e., 0.46%–0.87%) in transported efficiency it becomes to add one destination, with the increase of travel time of 2.25%–3.78%. To conclude, we may consider more destinations of a route with longer travel time to transport more passengers. However, it is not a good idea to consume a much longer travel time for obtaining a small improvement in transported passengers only.

Performance Evaluation for Different Carrying Capacities of Vehicles

In this section, we investigate the model performance under different carrying capacities of vehicles. We consider four cases with carrying capacity of 30, 15, 10, and 5 persons, respectively. Fig. 9 shows the experimental results of the four cases, indicated as bars with different patterns. A missing bar means that no feasible solution could be found to transport the given number of passengers. For example, the maximum number of transported passengers with a carrying capacity of 5 persons per vehicle is 935. Thus, the crosshatched bars are missing when the number of transported passengers exceeds 900. As we can see from the figure, the travel time decreases with an increase of carrying capacity. When the carrying capacity per vehicle increases from 10 to 15, the average reduction in travel time is 9.47%. When the carrying capacity is

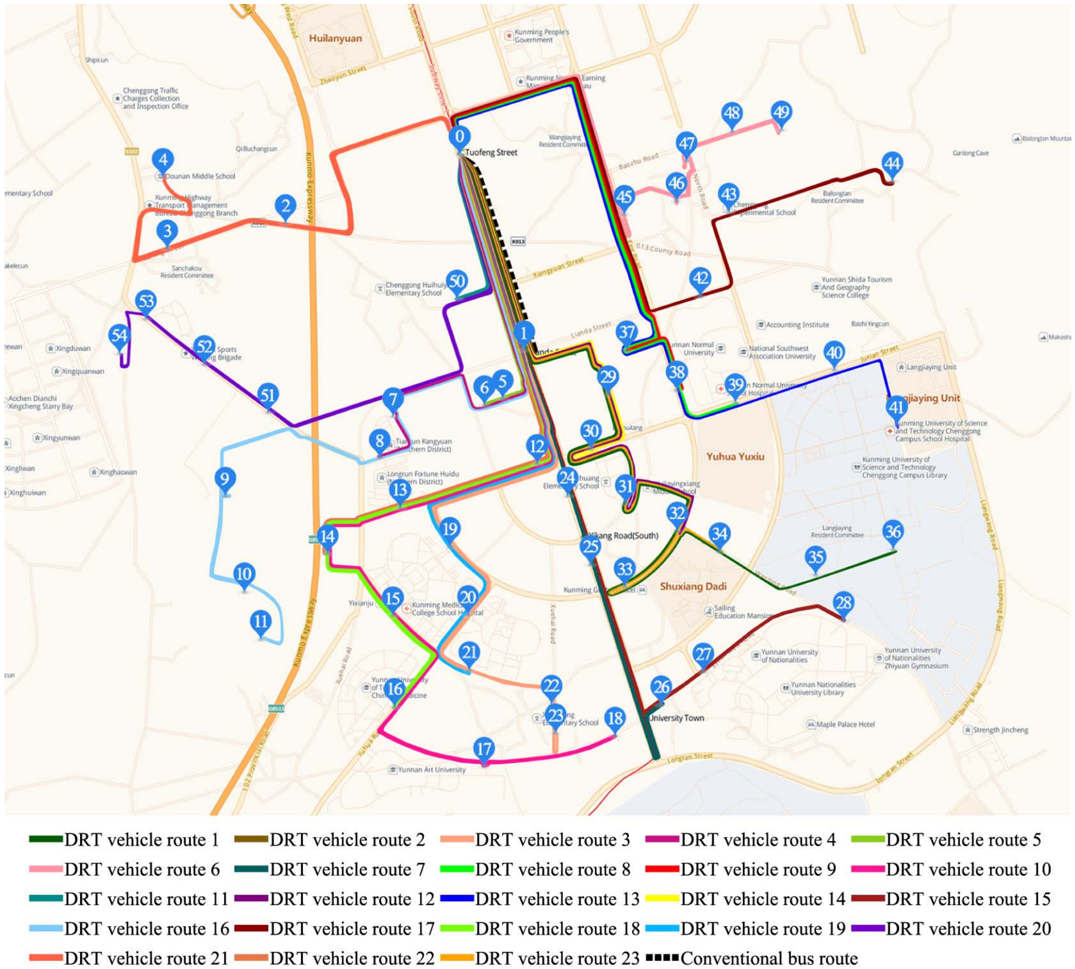

Fig. 5. Routes for vehicles (Pareto solution number 27). (Base map © 2025 AMAP.)

Table 2. Routes for DRT vehicles and the number of transported passengers (Pareto solution number 27)

Vehicle ID	Route	Number of transported passengers
1	0-35-36	10
2	0-1	4
3	0-20-22-23	10
4	0-7-8	9
5	0-5-6	8
6	0-45-46-47-48-49	10
7	0-24-26	7
8	0-38-39	10
9	0-37-38	9
10	0-13-17-18	10
11	0-50	3
12	0-29-31-32	10
13	0-38-40-41	10
14	0-29-30	6
15	0-25-27-28	10
16	0-9-10-11	10
17	0-42-43-44	10
18	0-12-15-16	10
19	0-19-20-21	10
20	0-51-52-53-54	9
21	0-2-3-4	9
22	0-12-13-14	10
23	0-32-33-34	9
Total number of transported passengers		203

further increased from 10 to 30, the average reduction in travel time is 18.52%.

Computational Speed on Instances with Different Scales

In this section, we assess the performances of our proposed approach among the instances within different scale networks shown in Fig. 10, i.e., a small-scale network with 20 nodes and 318 routes, a medium-scale network with 50 nodes and 1,601 routes, a large-scale network with 100 nodes and 2,403 routes. Moreover, we conduct experiments regarding the influence of the quantity of passenger groups and the number of DRT vehicles, to comprehensively analyze the impact on computational efficiency. For each scale of network, we consider 50, 100, and 150 passenger groups with the dispatching of 5, 10, 20, and 50 DRT vehicles. As a result, a total of 30 experiment instances are implemented. Table 4 shows the experimental results for each instance, specifically including the number of variables and constraints, the maximum percentage of transported passengers, and the computational time for obtaining the optimal solutions.

As shown, the number of variables differs among instances with different network scales, disparate numbers of passenger groups, and variant numbers of DRT vehicles. However, the number of constraints only increases with an increasing number of passenger groups and DRT vehicles. The reason for this

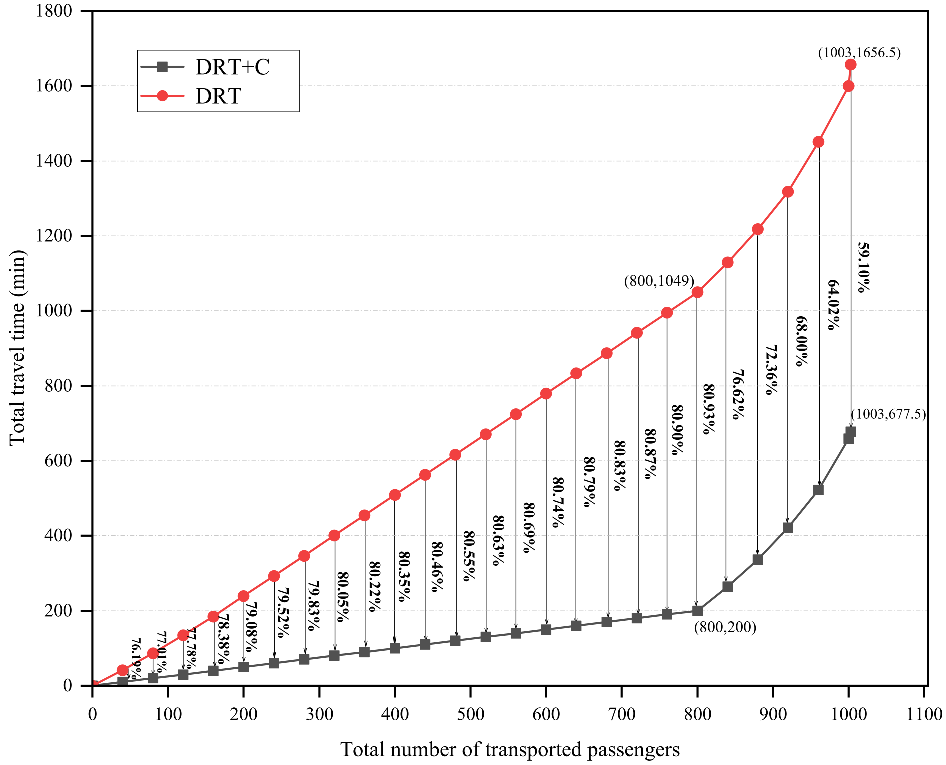

Fig. 6. Travel time and percentage of the improvement in solution quality of two scenarios.

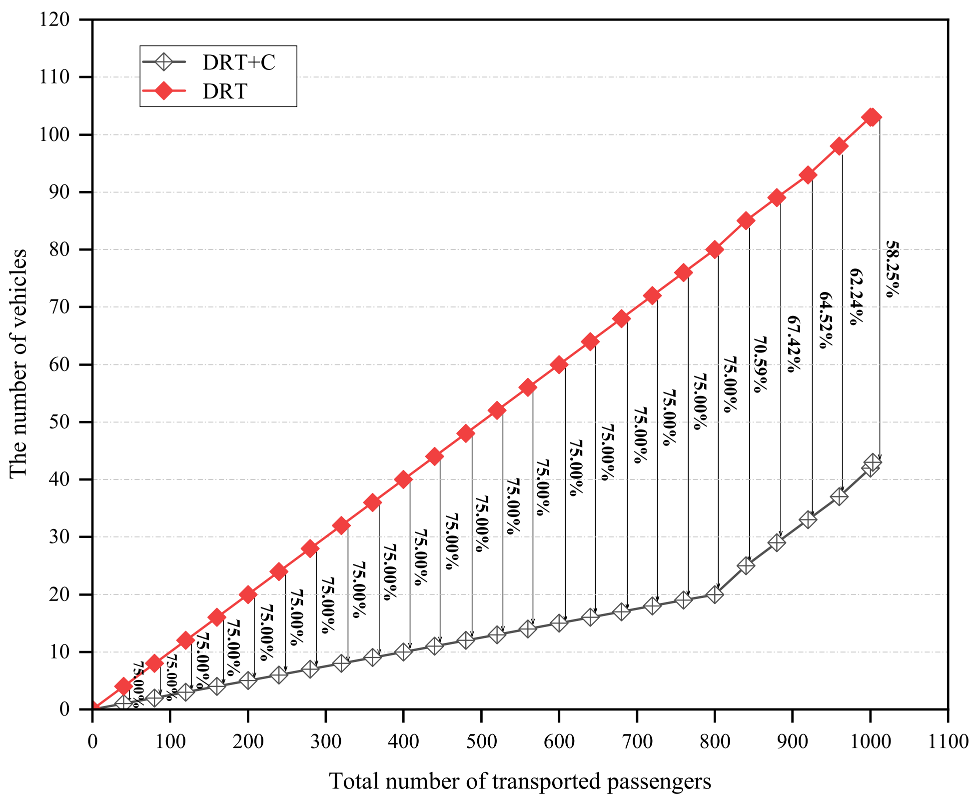

Fig. 7. Number of vehicles used and percentage of the improvement in solution quality of two scenarios.

issue is as follows. We have developed a preprocessing method to generate feasible routes for the vehicles. Subsequently, the optimization model merely needs to select the best route for each vehicle and couple the passenger group with the vehicle, which does not precipitate an increment in the number of constraints.

Basically, an increased number of variables and constraints typically leads to a prolonged computation time. Overall, optimal

Table 3. The maximum number of destinations, number of possible routes for each vehicle, and the number of all possible routes for all vehicle services of six cases

Case	Maximum number of destinations	Number of possible routes for each vehicle	Number of all possible routes for the vehicle services
Case A	1	54	1,458
Case B	2	129	3,483
Case C	3	175	4,725
Case D	4	162	4,374
Case E	5	85	2,295
Case F (this work)	1–8	635	17,145

solutions can be achieved within 180 s for most of the instances (i.e., 20 out of 30 instances). Moreover, under any network size, the method can obtain the optimal solutions within 180 seconds to serve different numbers of passenger groups. Although an increase number of vehicles gives rise to solution time, it enables to transport a greater number of passengers. Nevertheless, the increase in computational time is not always directly proportional to the percentage of transported passengers. For illustrative purposes, in instances 4 and 5, the computational time increases from 50 to 356 s, yet the percentage of transported passengers only experiences a 5% increment. Computational time is a critical factor in solving real-time problems, and the problem of vehicle scheduling and passenger assignment under urban rail transit disruptions is such a case. Therefore, the determination of an appropriate number of vehicles based on the number of passenger groups can substantially enhance computational efficiency.

Conclusions and Future Research

This paper studies the problem of integrating services of DRT and conventional buses to evacuate stranded passengers when urban rail transit disruption occurs. We have proposed an ILP model to deliver both a vehicle schedule solution and a passenger assignment solution simultaneously. In the optimization problem, the vehicle routes are considered variable, and it couples with the passenger assignment decisions (according to the passenger destinations, the carrying capacity of the DRT vehicle, and travel time among the destinations). Two objectives are considered as to minimize the total travel time and to maximize the total number of transported passengers. In terms of the solution approaches, we have designed a preprocessing method to generate a set of feasible routes for each vehicle to speed up the solution process. Moreover, an algorithm for solving the bi-objective optimization problem is proposed by utilizing the epsilon-constraint method. The performance of the proposed optimization approach is evaluated from the viewpoints of the benefits of the integration and benefits of flexible vehicle routes, based on a real-world urban public transportation network. According to the experimental results, the proposed integrated services of DRT and conventional buses are better than traditional single-mode evacuation strategies, as they could reduce travel time by an average of 73.88%. Moreover, the benefits of flexible vehicle routes are demonstrated: the

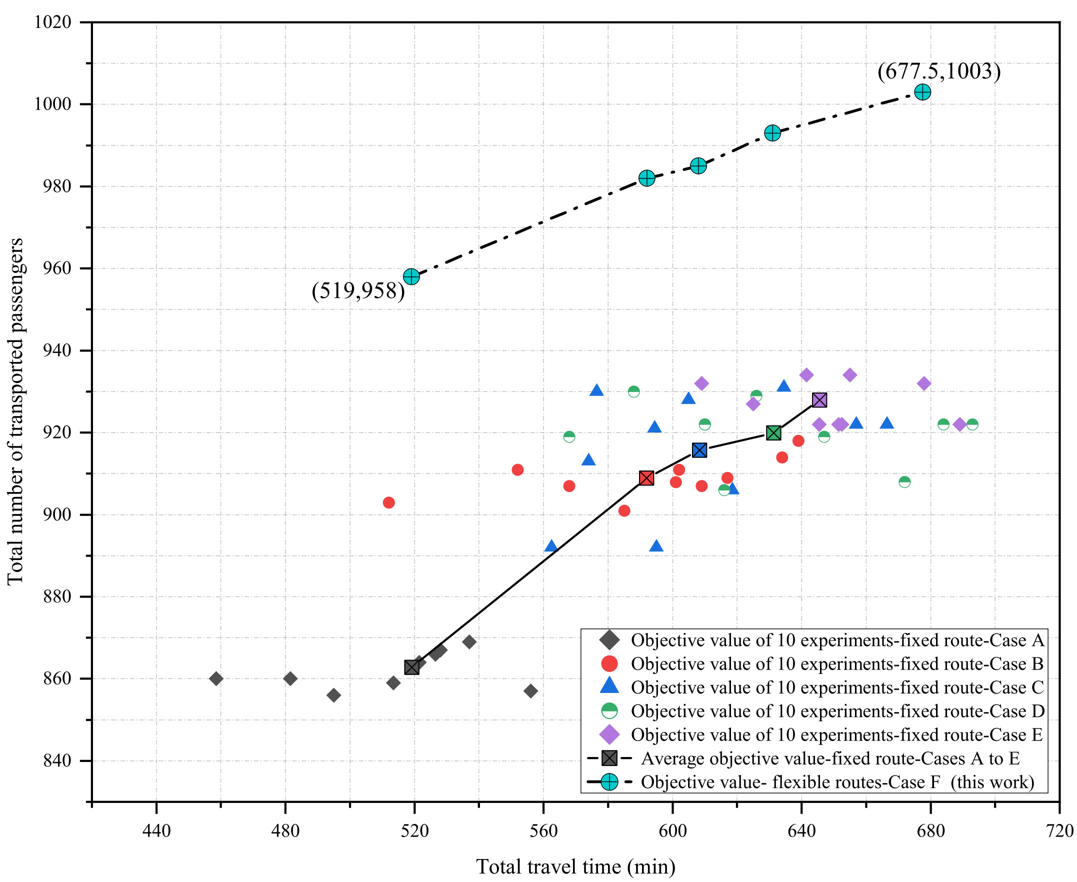

Fig. 8. Experimental results of the 6 cases.

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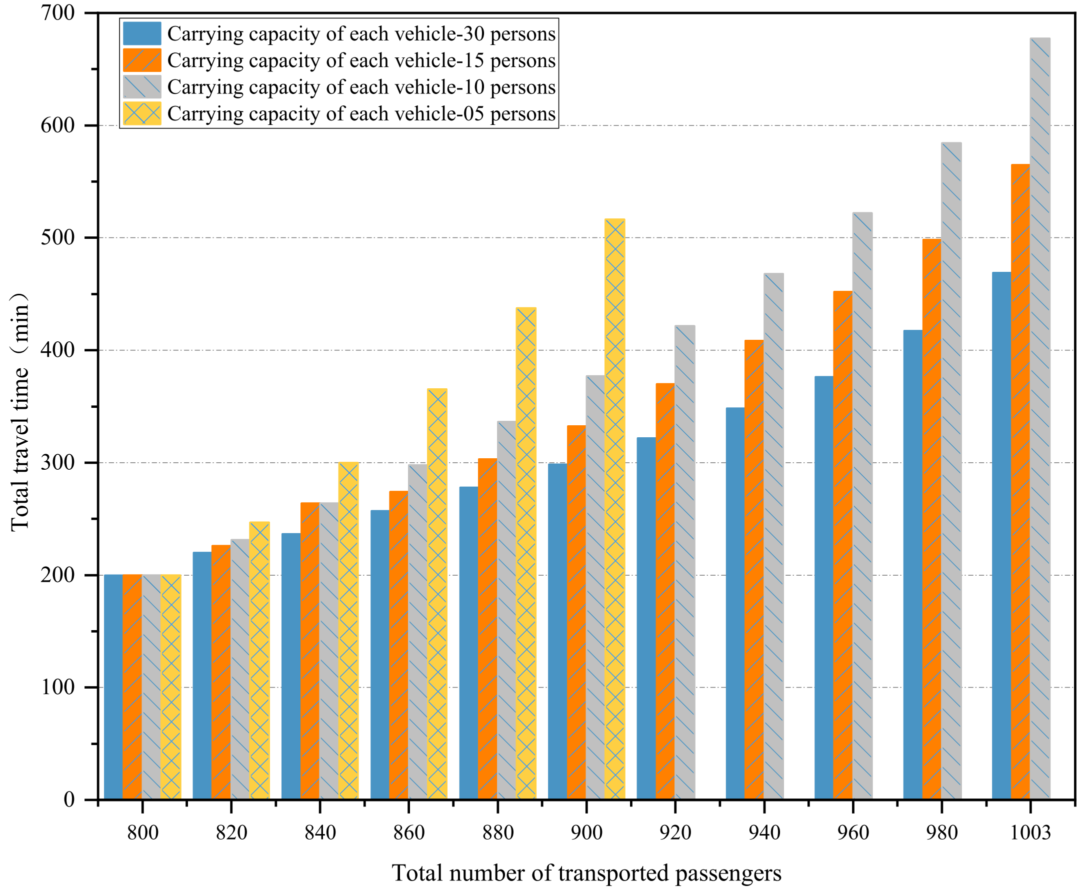

Fig. 9. Results under different carrying capacities of vehicle.

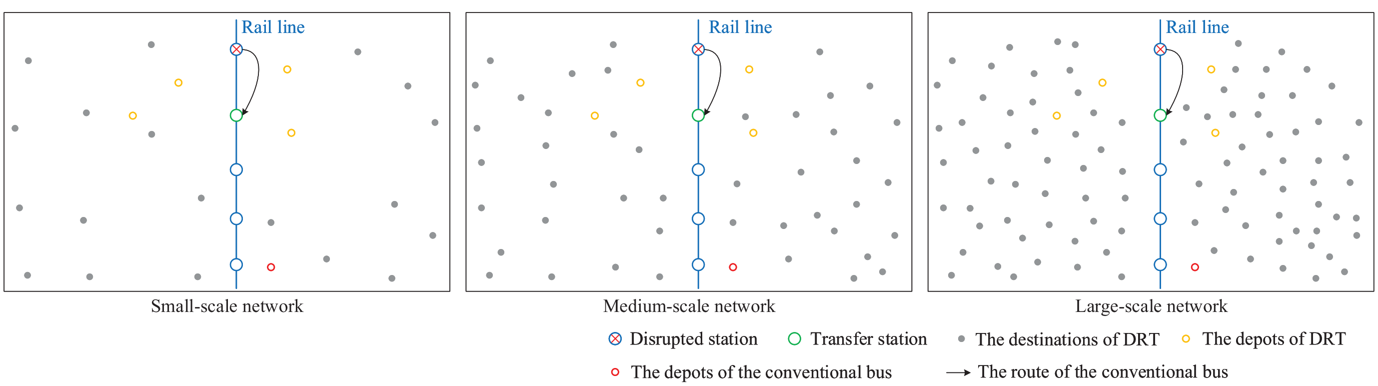

Fig. 10. Networks with different scales.

number of transported passengers can be improved by 7.65%–11.14% by variable vehicle routes.

However, the model has some limitations. While it effectively addresses the integration of DRT and conventional buses during evacuation scenarios, it currently does not account for human factors such as passenger anxiety or crowding at transfer points, which may impact evacuation efficiency. Additionally, the model does not incorporate a diverse range of transportation modes beyond DRT and conventional buses, such as taxis and shared bicycles, which could provide more flexible and comprehensive evacuation options in various real-world scenarios. Finally, regarding vehicle scheduling, the model provides a robust framework for optimizing evacuation routes but does not yet integrate a detailed timetable for vehicle operations.

Our future research will focus on the following main extensions. First, an analysis of human factors and passenger behavior will be incorporated to better understand the dynamics evacuation process. Second, more efficient and high-quality algorithm such as a decomposition method could be developed, to further increase the applicability of the proposed method in the real world. Third, the integration service could include more transportation modes like taxis and shared bicycles. Finally, a more detailed method that includes the schedule of the vehicles should be considered, offering a comprehensive view of the

Table 4. Performance of instances under different scales of network

Index of instance	Network scale	Number of passenger groups	Number of DRT vehicles	Number of variables/constraints	Maximum percentage of transported passengers (%)	Computational time to obtain the optimal solutions(s)
1	Small	50	5	2,169/284	94	7
2			10	3,914/454	100	19
3		100	5	2,419/584	81	7
4			10	4,414/1,004	86	17
5			20	8,404/1,844	95	50
6			50	20,374/4,364	100	356
7		150	5	2,669/884	70	8
8			10	4,914/1,554	75	13
9			20	9,404/2,894	83	37
10			50	22,874/6,914	100	421
11	Medium	50	5	8,584/284	95	23
12			10	16,744/454	100	68
13		100	5	8,830/584	81	23
14			10	17,244/1,004	85	47
15			20	34,064/1,844	95	97
16			50	84,524/4,364	100	393
17		150	5	9,084/884	71	25
18			10	17,744/1,554	75	123
19			20	35,064/2,894	84	424
20			50	87,024/6,914	100	585
21	Large	50	5	12,594/284	96	34
22			10	24,764/454	100	64
23		100	5	12,484/584	82	32
24			10	24,764/1,004	88	66
25			20	50,104/1,844	100	248
26			50	124,624/4,364	100	471
27		150	5	13,094/884	74	37
28			10	25,764/1,554	78	127
29			20	51,104/2,894	86	491
30			50	127,124/6,914	95	694

entire process from the vehicle's departure to the completion of passenger boarding.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

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Notation

The following symbols are used in this paper:

$a_{r,i}$ = binary input parameter, $=1$ indicating route r serves destination i; $=0$, otherwise;
c_k = carrying capacity of vehicle k;
$c_{i,j}$ = travel distance of arc (i, j);
c_v = carrying capacity of vehicle v;
d_p = destination of passenger group p;
e = arc index, denoted by (i, j), $e \in E$, E is the set of all arcs;
i, j = index of points, where $i, j \in S$, and S is the set of all passenger destinations;
k = index of DRT vehicle, where $k \in K$, and K is the set of all DRT vehicles;
n = number of destinations in a route;
o' = conventional bus depot index, $o' \in O'$, O' is the set of all depots for conventional buses;
o = DRT vehicle depot index, $o \in O$, O is the set of all depots for DRT vehicle;
P^{dial} = $P^{\mathrm{dial}} \subset P$, P^{dial} is the set of all passenger groups that require DRT services;
P^B = $P^B \subset P$, P^B is the set of all passenger groups that require conventional bus services;
p = passenger group index, $p \in P$, P is the set of all passenger groups designated for evacuation;
q_p = number of passengers in passenger group p;
r = index of feasible routes, $r \in R$, R is the set of feasible routes;
t_o^{run} = travel time of the vehicle from depot o to the disruption point;
$t_{o'}^{\mathrm{n}_{\mathrm{run}}}$ = travel time of the conventional bus from depot o' to the disruption point;
t_v^{travel} = travel time of vehicle v from the disruption point to the transfer station;
$x_{r,i,j}$ = 0-1 binary decision variable, $=1$ indicating route r selects arc (i, j); $=0$, otherwise;

$x_{k,r}$ = binary decision variable, = 1 indicating vehicle k selects route r; = 0, otherwise;
α_k = binary decision variable, = 1 indicating DRT vehicle k is utilized; = 0, otherwise;
$a_{r,i}$ = 0-1 binary variable, = 1 indicating route r serves destination i; = 0, otherwise;
α_v = binary decision variable, = 1 indicating vehicle v is utilized; = 0, otherwise;
$\beta_{k,r}$ = total travel time for route r of vehicle k;
$\beta_{k,r}$ = total travel time for route r of vehicle k;
v = index of conventional bus, where $v \in V$, V is the set of all conventional bus vehicles;
Ω_k = set of feasible routes for vehicle k;
$\rho_{k,o}$ = binary input parameter, = 1 indicating vehicle k is at depot o; = 0, otherwise;
$\rho^{n}_{v,o'}$ = binary input parameter, = 1 indicating bus v is at depot o'; = 0, otherwise;
$y_{p,k}$ = 0-1 passenger-to-DRT vehicle matching decision variable, = 1 indicating passenger group $p \in P^{dial}$ is evacuated by vehicle k; = 0, otherwise;
$\gamma_{p,v}$ = 0-1 passenger-to-conventional bus vehicle matching decision variable, = 1 indicating that passenger group $p \in P^B$ is evacuated by vehicle v; = 0, otherwise;
v_k = average speed of vehicle k; and
Ω_k = set of feasible routes for vehicle k.

Supplemental Materials

Model Code S1 and Data Code S1 are available online in the ASCE Library (www.ascelibrary.org).

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