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Redesigning urban intermodal transit for passenger and freight co-modal mobility: Metro line planning with integrated truck routing

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A B S T R A C T

Urban transportation systems are under increasing pressure to efficiently accommodate both passenger and freight mobility within limited infrastructure and operational budgets. Operators face growing pressure to make more efficient use of existing infrastructure due to economic and environmental constraints. In this regard, we investigate the capacitated line planning problem with integrated truck routing for passenger and freight co-modal mobility in an intermodal network composed of an urban rail transit (URT) system and road-based truck services. Different from existing research that either focuses on passenger-oriented line planning in a single-modal network or optimizes tactical- and operational-level decisions for passenger and freight co-modal mobility based on fixed line plans, we consider a strategic-level problem where urban planners aim to fundamentally re-optimize the allocation of existing infrastructure resources and budget across the intermodal network. We formulate this problem as a path-based mixed-integer linear programming model. The model determines line plans and frequency for both URT and truck services, as well as the passenger and freight routing, with the aim of optimizing the total weighted travel time of passengers and freight. To solve large-scale instances, we develop a column generation algorithm with a two-phase diving procedure. Our algorithm incorporates acceleration techniques and budget reservation strategies derived from the mathematical properties of the formulation. We evaluate our approaches on both artificial instances and real-world case studies from the Rotterdam intermodal network. The results show that our algorithm obtains solutions with an average optimality gap of 0.77%, while reducing computation time by 95.53% compared to GUROBI. Using the existing Rotterdam URT line plan with optimized frequencies as a benchmark, we demonstrate that our approach improves service quality by 6.50% without increasing operational costs. From a practical perspective, real-life case studies suggest that accommodating the passenger and freight co-modal mobility in existing passenger-oriented metro systems requires redesigning the line plan from scratch, rather than merely adjusting frequencies or incrementally expanding the current network. The results further indicate that effective freight integration depends on reallocating budget across modes, with URT serving as the backbone of the intermodal system and truck services providing a complementary function.

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1. Introduction

With the continuous growth of e-commerce, urban freight demand is increasing rapidly. However, road infrastructure in most major cities around the world is already operating at or near capacity, and urban areas are increasingly affected by severe congestion, air pollution, and a decline in quality of life. Relying solely on trucks for freight transport is therefore becoming increasingly unsustainable (Stokkink and Geroliminis, 2025), creating a growing need to exploit high-capacity public transport systems for freight movement, especially in large cities where road-based deliveries are increasingly constrained by congestion and access restrictions in dense urban areas. One promising solution is *passenger-freight co-modal mobility*, which refers to the shared use of infrastructure or capacity between passenger and freight services (Zheng et al., 2025).

This motivation is increasingly reflected in practice. In addition to long-established examples in other domains, such as postal cargo transport by commercial airlines, recent pilot projects and planning initiatives in Europe and Asia have explored passenger-freight co-modal operations in urban transit systems (see, Dutch Amsterdam, 2011; Guangming Daily, 2024). More recently, urban rail transit (URT) systems have also begun to incorporate freight transport. For example, the Daxing Airport URT Line in Beijing carries both passengers and freight (People's Daily Online, 2024). In addition, the Beijing Metro Line 22, which is currently under construction, has been reported as exploring a passenger and freight co-modal system linking suburban logistics hubs with the urban area. Similar initiatives have also been reported in Shenzhen, where metro services are coordinated with other freight technologies, such as autonomous vehicles, trucks, drones, and buses, to improve logistics efficiency and support low-emission urban freight distribution (Shenzhen Qianhai Shenzhen-Hong Kong Modern Service Industry Cooperation Zone Authority, 2024; Xinhua News Agency, 2025). These developments indicate that the passenger and freight co-modal mobility is emerging as a practically relevant way to exploit public transport for ferrying freight.

However, accommodating additional urban freight demand is not simply a matter of increasing URT services. Freight demand is typically unevenly distributed across space, whereas URT systems are constrained by fixed infrastructure, predefined line layouts, and limited operating flexibility. Although URT can provide high-capacity transport along major corridors and should naturally serve as the main carrier of freight flows, it is neither operationally nor economically reasonable to absorb all additional freight demand by continuously adding rail services. Under a limited budget, doing so would often require excessive service provision on specific corridors and lead to an inefficient use of scarce resources of URT systems. Therefore, URT should play the dominant role in transporting freight, while truck services remain necessary as a complementary mode to serve freight movements for which URT-based transport would be too costly, too capacity-intensive, or spatially unsuitable.

This leads to a fundamental intermodal line planning problem. The key issue is not whether freight should be transported by URT or by trucks, but how the two modes should be coordinated efficiently under limited resources and budget. In particular, URT should function as the high-capacity backbone of the system, while truck services complement it through flexible transport between depots, between depots and metro transfer stations, between two metro stations, and (or) between depots and metro stations. Consequently, the problem is to determine how limited resources should be allocated across URT services, truck services, and transfer facilities between URT and truck services so that URT serves as the freight backbone of the system and truck services provide only targeted and cost-effective supplementation.

To address this strategic-level issue, we study a *Line Planning Problem* in this paper, which is defined as the integration of *line selection* and *frequency setting*, following Schmidt and Schöbel (2024). As indicated in Fig. 1, line planning determines which candidate lines are operated and at what frequencies, yielding a *line concept* (Schöbel, 2012). Consistent with both the majority of the line planning literature and planning practice, we take as input a predefined line pool. In practice, operators typically start from a set of candidate lines that already reflects infrastructure and operational constraints, and then determine the subset of lines to operate together with their service frequencies. The line pool is obtained from a preceding *line generation* step. When line generation is integrated with line selection, the resulting problem is often referred to as the *Network Design Problem*. The full integration of line generation, line selection, and frequency setting is commonly termed the *Network Design and Frequency Setting Problem* in the literature (see, e.g., Durán-Micco et al., 2022; Aktaş et al., 2024).

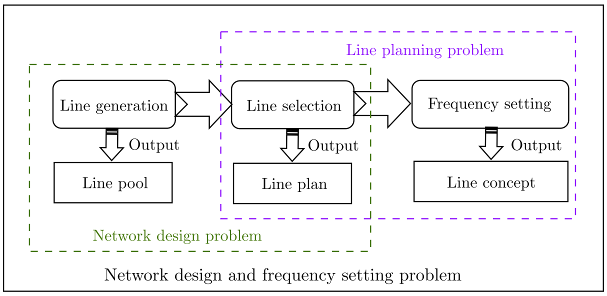


Fig. 1. Illustration of components in the line planning problem investigated in this study.

Existing literature on line planning largely centers on passenger demand, with some studies disregarding in-vehicle capacity limitations altogether (e.g., Schöbel, 2012; Schmidt and Schöbel, 2024; Lu et al., 2025). Research on passenger-freight co-modal transport mainly focuses on tactical and operational decisions. In single-mode URT-based settings, existing studies have explored timetable design, carriage allocation, and related operational adjustments on URT networks with existing passenger-oriented line plans (see, Di et al., 2022; Hörsting and Cleophas, 2023; Tundulyasaree, 2024). In intermodal systems including URT and truck services, the literature typically assumes an exogenously given URT line plan and optimizes truck routing or related operational decisions conditional on this fixed service structure of the URT network (e.g., Mo et al., 2023; Di et al., 2025; Stokkink and Geroliminis, 2025; Di et al., 2026). Strategic-level research on the joint design of URT and truck services remains scarce, especially when both modes are coordinated under a unified budget and jointly serve freight demand in an integrated transportation network.

Motivated by these research gaps, this paper studies the capacitated line planning problem with integrated truck routing for passenger-freight co-modal mobility in an intermodal network. Passengers are served by URT services, while freight can be transported by URT, trucks, or a combination of both. To capture these interactions, we construct a two-layer change-and-go network, in which the URT and truck layers are connected through intermodal freight transfer facilities. Based on this network, we develop a path-based mixed-integer linear programming formulation that jointly determines the URT line plan, the truck line plan, the locations of freight transfer facilities, and routing decisions for passengers and freight under a unified budget constraint. In this way, the model explicitly captures the strategic allocation of limited resources across the two modes, with the aim of making the optimal use of URT for freight transport while retaining truck services as an economical complement where needed. The proposed framework is general to accommodate different truck service patterns through the specification of candidate truck lines. We adopt a system-optimal perspective as a first step toward the capacitated line planning problem in an intermodal network and to establish a proof of concept for the proposed framework.

To solve real-world large-scale instances, we further develop a column generation algorithm with a novel two-phase diving procedure, supported by acceleration techniques and a parallelization approach to improve computational efficiency. The diving framework is general and can be applied to other optimization problems involving two sets of integer decision variables. Extensive numerical experiments based on a widely used dataset based on a grid network and real-life case studies are conducted to demonstrate the effectiveness of the proposed approaches, and gain managerial and practical insights.

The remainder of this paper is structured as follows. Section 2 reviews related literature. Section 3 introduces the capacitated line planning problem with integrated truck routing for co-modal passenger and freight mobility. In Section 4, we present the mathematical formulation of the problem. Section 5 describes the solution methodology, including a column generation algorithm with a novel two-phase diving procedure. In Section 6, we perform extensive computational experiments. Lastly, we conclude in Section 7.

2. Literature review

Line planning for passenger mobility has been studied over the past several decades. The integration of passenger and freight mobility across the tactical- and operational-levels of public transit planning has gained attention only more recently. This literature review examines three main research streams: (i) line planning for passenger mobility, (ii) optimization of passenger-freight integration at the tactical and operational levels within urban rail transit systems, and (iii) line planning approaches for integrated passenger and freight mobility.

2.1. Line planning for the passenger mobility

Line planning is a strategic-level planning problem that has been extensively studied in the public transport literature. Comprehensive surveys of line planning in public transport can be found in Schöbel (2012) and Schmidt and Schöbel (2024). For metaheuristic approaches to the network design problem, we refer the reader to Iliopoulou et al. (2019). Recent developments in the network design and frequency setting problem are reviewed in Durán-Micco and Vansteenwegen (2022). Two main approaches are used to address line planning: one is to pre-compute and input shortest passenger routes into the optimization (e.g., Schiewe et al., 2019). The second is to dynamically generate passenger routes during the optimization (e.g., Borndörfer et al., 2007; Lu et al., 2025).

From the perspective of objective functions, line planning models can generally be divided into cost-oriented, passenger-oriented, and hybrid approaches. Cost-oriented models typically aim to minimize operational costs (Claessens et al., 1998) or maximize revenue (Canca et al., 2017), while ensuring that pre-defined service quality and capacity requirements are met. In contrast, passenger-oriented models focus on enhancing passenger convenience and satisfaction, with objectives such as maximizing the number of passengers who can travel directly (Bussieck, 1998; Bertsimas et al., 2021), minimizing passengers' travel time with the assumption of system-optimal routing (Schöbel and Scholl, 2006), minimizing passengers' travel times with the assumption passengers will always use the shortest route (Wens and Vansteenwegen, 2025), or minimizing perceived travel time by accounting for crowding effects and operational budget constraints (Lu et al., 2025).

A third category of models seeks to balance both perspectives, aiming to develop line concepts that jointly result in low operational costs and reduced passengers' travel times (see, Borndörfer et al., 2007; Goerigk and Schmidt, 2017; Zhou et al., 2021). For example, Borndörfer et al. (2007) proposed a multicommodity flow model that allows passengers to choose routes freely, while disregarding capacity limitations.

We contribute to this stream of literature by extending traditional line planning models for passenger mobility to an intermodal setting that integrates both passenger and freight transportation. Specifically, we develop a novel decision-making framework that jointly optimizes line planning and truck routing within an intermodal transit network. Unlike some prior approaches that assume fixed passenger routes, our model dynamically generates passenger routes during the optimization process. Furthermore, we incorporate strict capacity constraints to realistically capture infrastructure limitations for both passengers and freight. This integrated approach enables the efficient coordination of passenger and freight movements, leading to better utilization of shared infrastructure and reduced travel time for passengers and freight.

2.2. Tactical-level and operational-level optimization of passenger and freight co-modal mobility within urban rail transit systems

Existing research on freight-passenger integration in urban rail transit systems has mainly focused on tactical-level and operational-level optimization, such as train timetabling, carriage allocation, and rolling stock scheduling. This body of work can be broadly categorized into three streams.

The first stream assumes fixed train timetables and focuses on optimizing carriage allocations at the line level for both passengers and freight (e.g., Di et al., 2022). The second stream jointly optimizes train timetables and carriage allocations at the line level, allowing more flexibility in adjusting service schedules (e.g., Hörsting and Cleophas, 2023; Tundulyasaree et al., 2024). The third stream explores network-level carriage allocation under fixed timetables while assuming that the cross-line circulation of rolling stock is out of scope (Li et al., 2024).

In summary, existing studies largely rely on fixed line plans and focus on downstream decisions such as timetabling and carriage allocation. However, enabling effective integration of passenger and freight transport across intermodal networks that combine URT and road systems requires strategic-level planning decisions to optimize resource allocation fundamentally. This need has been increasingly recognized in recent literature. For instance, Stokkink and Geroliminis (2025) highlight the importance of strategic-level decision-making in a multimodal system by optimizing micro-hub locations for last-mile delivery. Nevertheless, strategic-level line planning that integrates both passenger and freight flows within a unified intermodal network remains largely unexplored. Rather than focusing on how freight is accommodated within individual trains, our study revisits how public transport infrastructure, originally designed for passenger services, can be reallocated to support co-modal mobility. To enrich this line of research, we propose a capacitated line planning model that jointly optimizes URT line plans and truck routing for both passenger and freight transport. By coordinating the two systems and reallocating capacity from a strategic perspective, our approach improves the utilization of underused transit resources, facilitates the shift of freight from roads to rail, and supports cost-effective urban mobility.

2.3. Intermodal urban logistics involving public transit systems

Our study is also situated within a broader research context on intermodal urban logistics involving public transit systems. Leveraging public transit systems, a central question is how to recommend trip options for passengers or coordinate passenger and freight flows when capacity and infrastructure are limited. One research stream focuses on demand-side optimization in Mobility-as-a-Service (MaaS) systems, such as multimodal trip planning, with the goal of improving passengers' experience under a given public transport network (e.g., Zhang et al., 2025b; Yao et al., 2026). The second steam focuses on the coordinated scheduling of the intermodal system (e.g., Xia et al., 2024). A third stream studies public-transport-based crowd-shipping, where freight is opportunistically transported by exploiting spare capacity on passenger services under fixed line plans and timetables, while the first-mile and last-mile operations are handled by couriers (see, Kızıl and Yıldız, 2023; Ermağan et al., 2024). These studies provide valuable insights, yet they typically do not revisit the design of the public transit itself.

To sum up, the majority of related literature assumes the line plans of public transit are given and fixed, and optimization is carried out mainly on the demand side and at the operational level. Our study is conceptually connected to this intermodal logistics line of work, but differs fundamentally in research scope and modeling focus. We consider an emerging passenger and freight co-modal setting in which passenger-oriented URT systems are required to systematically accommodate both passenger and freight demands. In such settings, simply managing demand or inserting freight opportunistically on top of an existing passenger-oriented URT line plan can be structurally limiting. We therefore take the supply-side network redesign as the main lever and address a strategic-level line planning problem that starts from redesigning the line plan, while coordinating it with road-based truck services within a unified budget framework. This perspective enables a more efficient allocation of limited infrastructure resources and budget across modes and provides a planning-oriented pathway for URT systems to serve emerging passenger and freight co-modal demands.

2.4. Line planning for integrated passenger and freight mobility

The literature on strategic-level planning for integrated passenger and freight mobility remains scarce. We are only aware of one existing study in this stream, namely Chen et al. (2024). The authors propose a multi-period railway line planning model with pre-defined train modes, including passenger-only, freight-only, and mixed modes. In their numerical experiments, the mixed mode is specified exogenously through a fixed 50/50 split between passenger and freight capacity. However, specifying train modes (or line types) may be premature at the strategic planning stage. Decisions regarding capacity sharing and train mode implementation are more appropriately addressed during the subsequent tactical planning stage (e.g., through carriage allocation optimization). In addition, their approach excludes passenger and freight routes with travel times exceeding a fixed threshold during pre-processing. Although this reduces the problem size, it may exclude feasible routing options whose value depends on broader capacity and cost trade-offs in the integrated system.

In contrast, we consider an intermodal setting that integrates URT and road transport, without assuming fixed train modes. Freight is allowed to flexibly utilize surplus passenger capacity, and truck routing is jointly optimized with URT line planning to enable seamless intermodal coordination. To address the resulting computational challenges, we develop a scalable solution framework for the resulting large-scale problem with multiple sets of integer decisions. Hence, this paper moves beyond the existing single-modal setting and develops a unified strategic-level optimization framework for metro line planning with integrated truck routing, capturing in-vehicle capacity limitations, shared infrastructure utilization, and coordination across transportation modes.

2.5. Paper contributions

Table 1 provides an overview of the aspects covered in the reviewed literature to highlight the contributions of our study. In summary, the line planning problem for single-modal networks has been well studied, mainly in the context of passenger mobility, with some studies focusing on uncapacitated line planning. Most existing studies on the integration of passenger and freight focus on tactical- or operational-level decisions, such as timetabling on a single line, carriage allocation, or rolling stock scheduling. Strategic-level planning and network-level resource optimization have received limited attention. On the basis of the existing literature, this paper aims to make the following contributions to the field of line planning for passenger and freight co-modal mobility in the domain of intermodal network:

Table 1
Overview of relevant publications on line planning and train scheduling for integrated freight-passenger co-modal mobility systems.

Publication	Freight and passenger co-modal mobility	Network-level optimization	Decision-making stage	Truck routing	Capacity
Schöbel and Scholl (2006)	–	Railway	Line planning	–	–
Borndörfer et al. (2007)	-	Railway	Line planning	–	–
Goerigk and Schmidt (2017)	–	Railway	Line planning	–	✓
Schiewe et al. (2019)	–	Railway	Line planning	–	–
Bertsimas et al. (2021)	–	Railway	Line planning	–	–
Durán-Micco et al. (2022)	–	Bus	Line planning	–	✓
Vermeir et al. (2021)	–	Bus	Line planning	–	–
Zhou et al. (2021)	–	URT	Line planning	–	–
Wens and Vansteenwegen (2025)	–	Bus	Line planning	–	–
Lu et al. (2025)	–	URT	Line planning	–	✓
Di et al. (2022)	✓	–	Carriage allocation	–	✓
Hörsting and Cleophas (2023)	✓	–	Timetabling	–	–
Chen et al. (2024)	✓	Railway	Line planning	–	✓
This paper	✓	Intermodal	Line planning	✓	✓

(i) We propose an integrated optimization framework for capacitated line planning with embedded truck routing in an intermodal transit network, aiming to support the passenger and freight co-modal mobility under a unified budget constraint. Intermodal freight transfers are only allowed if the transfer facilities are constructed in the solution. The core objective is to coordinate resource allocation across URT and truck services at a strategic planning stage.

(ii) We construct a two-layer change-and-go network and formulate the model as a path-based mixed-integer program, jointly optimizing the URT line plan, trcuk routing, the frequency allocation across the intermodal network, freight transfer facilities location, and the routing decisions for all passenger and freight demands.

(iii) We propose a column generation algorithm with a novel two-phase diving procedure. This method is generalizable and applicable to other optimization problems involving two sets of integer decision variables. The resulting pricing problems for passenger and freight routing are solved in parallel to improve computational efficiency. To further accelerate pricing, we apply techniques that eliminate redundant nodes and arcs. Additionally, the first-phase diving leverages mathematical properties of the model to enhance solution quality.

(iv) Extensive numerical experiments show that our algorithm achieves an average of 95.53% reduction in computational time while finding solutions with an average gap of only 0.77%. In addition, the algorithm is shown to be scalable and capable of solving real-life instances effectively. From a practical perspective, our findings yield several insights for intermodal line planning, such as the considerably greater benefits of full network redesign under new demand requirements, relative to incremental expansions and frequency adjustments based on the existing line plan.

3. Problem description

In this section, we present a formal description of the *Capacitated Line Planning with integrated truck Routing for Passenger and Freight co-modal mobility in an intermodal network* (CLiPRPF). We then construct a two-layer change-and-go (CGN) network to model the CLiPRPF problem, extending the single-modal CGN originally proposed by Schöbel and Scholl (2006). Lastly, we introduce the assumptions adopted in our model.

3.1. Description of CLiPRPF

Intermodal network. In this paper, we consider an intermodal network comprising URT and road-based truck services to serve both the passenger and freight demands. The network defines the URT stations, the connecting tracks, and the potential of each station to serve as a transfer point for freight between road and rail. We refer to this network as the *Physical intermodal Transportation*

Network (PTN), denoted by $\mathcal{G} = (\mathcal{S}, \mathcal{E})$, where the vertex set $\mathcal{S}$ represents URT stations, and the edge set $\mathcal{E}$ represents the connections between them. The terminal stations are assumed to be depots in URT systems. Specifically, $\mathcal{E} = \mathcal{E}_m \cup \mathcal{E}_u$, where $\mathcal{E}_m$ denotes the set of rail tracks (i.e., physical connections within the URT system), and $\mathcal{E}_u$ denotes the set of road segments between stations used by trucks.

Line, line pool, and intermodal freight transfer facilities. A *line* l is defined as a directed path in the PTN $\mathcal{G}$, represented by a sequence of stations and connecting edges. If l traverses only URT stations and rail tracks (i.e., edges in $\mathcal{E}_m$), it is referred to as a *URT line*; otherwise, if it traverses stations and road segments (i.e., edges in $\mathcal{E}_u$), it is referred to as a *truck line*. Following common practice in line planning, we take as input a predefined candidate URT line pool $\mathcal{L}_m$ and a candidate truck line pool $\mathcal{L}_u$, where each candidate line is represented as a simple path in the PTN (see, Schöbel and Scholl, 2006; Schiewe et al., 2019; Schmidt and Schöbel, 2024). This line pool follows the typical workflow used in real-life operations. Operators first construct a sufficiently large, operationally viable set of candidate lines, then select a subset from it and determine its frequency. Each line $l \in \mathcal{L}_m \cup \mathcal{L}_u$ is associated with a set-up cost e_l, an operational cost b_l per unit frequency, and in-vehicle capacity for passengers and freight, denoted by Q_l^p and Q_l^h.

In addition, freight is allowed to be served through intermodal routes that combine both truck and URT services. When such intermodal transportation occurs, a transfer is required at a station where the freight switches from one mode to the other. To enable this, a dedicated transfer facility must be constructed at the corresponding station, which incurs an additional fixed cost.

Demands and routing. In line with the line planning literature that models aggregated origin-destination (OD) passenger demand (e.g., Borndörfer et al., 2007; Schöbel, 2012; Van Lieshout et al., 2020; Durán-Micco et al., 2022; Lu et al., 2025), we extend the framework to jointly consider passenger and freight OD demand. Let $\mathcal{P} \subseteq \mathcal{S} \times \mathcal{S}$ denote the set of passenger OD pairs, and $\mathcal{H} \subseteq \mathcal{S} \times \mathcal{S}$ the set of freight OD pairs. Each pair $p \in \mathcal{P}$ is associated with a positive passenger demand d_p, and each pair $h \in \mathcal{H}$ with a positive freight demand d_h. No distinction is made between shipment types or shipment-specific attributes for freight. This aggregated manner matches the strategic scope of the line planning problem and is consistent with the commonly adopted modeling method in related studies on the passenger and freight co-modal mobility (e.g., Di et al., 2022; Tundulyasaree, 2024; Di et al., 2025; Stokkink and Geroliminis, 2025; Zhang et al., 2025a; Di et al., 2026).

We assume that passengers are served exclusively by URT services, while freight can be transported via truck services, URT services, or a combination of both. The travel time of a passenger or the freight from origin to destination is computed as the sum of in-vehicle travel time and transfer penalties. The route set in the PTN is defined on the network containing all candidate lines in the line pools $\mathcal{L}_m$ and $\mathcal{L}_u$, i.e., as if every candidate line were operated. This enlarged network is much larger than any realized line plan, while it provides the basis for identifying, in principle, all feasible routes for each passenger and freight OD pair. The routing decisions of both passengers and freight are optimized jointly with the capacitated line planning and truck routing decisions. Example 1 illustrates how both freight and passengers can be routed through either direct routes or routes with transfers. It also emphasizes the importance of strategically located designated freight transfer facilities for enabling intermodal freight operations.

Example 1. Fig. 2 presents an example of passenger and freight routing in an intermodal network, where stations A and D are the origin and destination, respectively. The network consists of two layers: the upper layer represents the truck network, and the lower layer represents the URT network. The URT layer consists of two lines and four stations, namely A, B, C, and D. In contrast, the truck layer includes only three stations: A, B, and D. These three stations are equipped with intermodal freight transfer facilities, which allow freight to switch between the truck and URT networks.

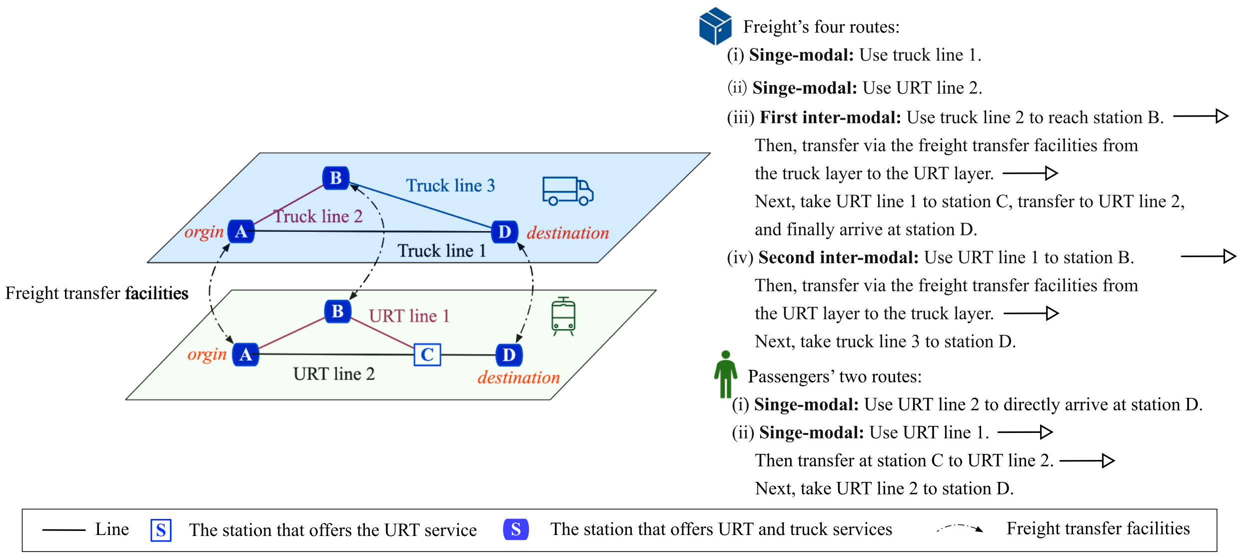


Fig. 2. An illustration of the passengers' and freight's routing in the PTN.

As shown in Fig. 2, freight in this network has two single-modal routing options and two intermodal routing options from station A to station D. Passengers have two single-modal routing options. Moreover, freight transfers within the URT network do not require dedicated transfer facilities. In practice, such transfers can rely on the existing regular elevators, as illustrated by the transfer operations in the Qingdao metro shown in Fig. A.1(a) in Appendix A. There are two possible transfer methods: one is manual handling by logistics company staff, as illustrated in Fig. A.1(a) and (b), and the other is automated transfer using autonomous robots, as illustrated in Fig. A.1(c).

Problem statement. The objective of the CLiPRPF problem is to determine a line plan and the corresponding service frequencies that minimize the total travel time of passengers and freight, subject to a given operational budget and strict in-vehicle capacity constraints. More specifically, the problem is to select a subset of lines from $\mathcal{L}_m \cup \mathcal{L}_u$, each assigned both the optimized frequencies for passengers and for freight. To do so, we introduce a binary decision variable $w_l \in \{0, 1\}$, indicating whether line l is selected ($w_l = 1$) or not ($w_l = 0$). We further define two continuous non-negative variables: f_l^p and f_l^h, representing the frequencies allocated to passenger and freight demand, respectively. We assume $f_l^p \in \mathbb{R}_{\geq 0}$ and $f_l^h \in \mathbb{R}_{\geq 0}$, as URT systems are typically managed based on headways rather than fixed (hourly) integer frequencies (Lu et al., 2025) and truck services typically do not follow evenly spaced dispatch intervals.

Remark 1. These frequencies do not imply the use of separate trains or lines dedicated exclusively to passengers or freight. Instead, they represent the proportion of the total capacity allocated to transport passengers and freight over the study horizon. Accordingly, the total capacity allocated to passengers and freight on line $l \in \mathcal{L}_m \cup \mathcal{L}_u$ during the entire study horizon is given by $f_l^p Q_l^p$ and $f_l^h Q_l^h$, respectively.

Moreover, we model the physical and operational requirements of handling freight in this intermodal system by defining a binary decision variable indicating whether a transfer facility is installed at a candidate station. All incurred costs include line set-up costs, operational costs, and transfer facility installation costs. These costs must collectively satisfy a given budget B, ensuring that the solution remains financially feasible for operators.

3.2. Construction of the two-layer change-and-go network

To model the routing of passengers and freight, we construct a two-layer change-and-go network (CGN) tailored to the problem studied in this paper, building upon the single-layer framework in Schöbel and Scholl (2006). Unlike the single-layer CGN, the proposed two-layer CGN is specifically designed to represent the interactions between the URT system and truck services on the road, and the movements of passengers and freight within the intermodal transit network. The two layers are connected through designated intermodal transfer facilities, whose activation is itself a decision in the CLiPRPF problem. Moreover, the three types of nodes and the five types of arcs are specifically designed to capture the operational characteristics of the passenger and freight co-modal mobility in this intermodal system. In particular, different types of arcs correspond to different travel and transfer processes of passengers and freight, and are defined so as to distinguish whether they are available to passengers, freight, or both. The resulting network (denoted by $G = (\mathcal{V}, \mathcal{A})$) consists of an upper layer representing truck services on the road and a lower layer representing the URT system. The customized structure of this two-layer CGN is reflected in the definitions of its nodes and arcs, which are introduced below.

For the sake of illustration, we present in Fig. 3 the two-layer CGN corresponding to the PTN in Fig. 2. Specifically, for each station $s \in \mathcal{S}$ in the PTN, we construct one *station node*, of which the set is denoted as $\mathcal{V}^s$. Then, for every URT line $l \in \mathcal{L}_m$ and truck line $l \in \mathcal{L}_t$ that passes through station s, we create separate *travel nodes*: (i) *URT travel nodes* $v_{s,l}^m \in \mathcal{V}^m$, representing the travel node at station s of URT line l, and (ii) *truck travel nodes* $v_{s,l}^u \in \mathcal{V}^u$, representing the travel node at station s of truck line l.

On the basis of these nodes, we construct the following five types of arcs (denoted as $\mathcal{A}$) in graph G, where each arc is associated with a corresponding cost c_a for all $a \in \mathcal{A}$:

- **URT travel arcs** $\mathcal{A}^t$: These arcs connect two URT travel nodes $v_{s,l}^m$, representing the movement of trains along URT lines, which transport passengers and freight within the URT system. The cost of each arc corresponds to the in-vehicle travel time in the URT network.
- **Truck travel arcs** $\mathcal{A}^u$: These arcs connect two truck travel nodes $v_{s,l}^u$, representing the movement of freight along truck lines. The cost of each arc corresponds to the in-vehicle travel time provided by truck services.
- **Passenger transfer arcs** $\mathcal{A}^c$: These arcs connect a station node and a URT travel node, representing passenger transfers between URT lines. The cost of each arc is defined as half of the total transfer penalty, since each transfer involves two passenger transfer arcs: one from a URT travel node on the transfer-out line to a station node, and another from the station node to a URT travel node on the transfer-in line.
- **Rail-to-rail freight transfer arcs** $\mathcal{A}^{cr}$: These arcs connect a URT travel node and a station node, representing freight transfers within the URT system. The cost of each arc is defined as half of the freight-related transfer penalty, which is typically higher than that for passenger transfers.
- **Rail-to-road freight transfer arcs** $\mathcal{A}^{ct}$: These arcs connect a truck travel node and a station node at stations that support both URT and truck services, representing intermodal transfers between the two modes.

  For freight-related transfer arcs, transfer penalties are modeled in an aggregated manner. Specifically, we assign different transfer penalties to rail-to-rail and rail-to-road freight transfers, thereby reflecting the higher complexity of intermodal transfers in an aggregated way. Moreover, the penalty for rail-to-road freight transfers is typically higher than that for rail-to-rail freight transfers, which in turn is higher than that for passengers' transfers. This treatment is consistent with the strategic-level planning scope of the problem, where demand is represented at the OD level and service decisions are made at the line level. More detailed transfer-related operations and shipment-dependent transfer costs are more appropriately addressed at the tactical-level planning stage. Similar aggregated treatments are also common in studies related to passenger-freight co-modal transport (Di et al., 2026, 2022; Tundulyasaree, 2024; Di et al., 2025; Stokkink and Geroliminis, 2025; Zhang et al., 2025a).

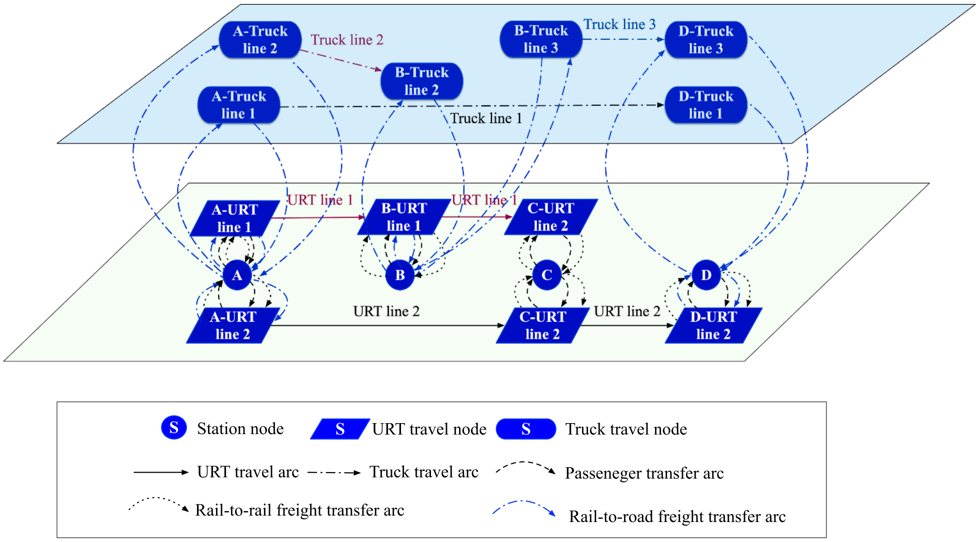


Fig. 3. An illustration of the two-layer CGN.

3.3. Assumptions

To formulate the described problem, without loss of generality, we adopt the following assumptions throughout this paper.

Assumption 1. Passenger and freight demands are deterministic and known a priori. In urban transit planning, this assumption is widely adopted for strategic-level planning models and the field of passenger and freight co-modal mobility, where demands are obtained based on historical data and statistical models (see, Schöbel and Scholl, 2006; Di et al., 2022; Bertsimas et al., 2021).

Assumption 2. Line frequencies are bounded within a pre-defined range. Bounding line frequencies within a predefined range is a common practice in transit planning to reflect physical and operational constraints. Previous line planning studies have also adopted similar constraints to ensure operational feasibility (e.g., Borndörfer et al., 2007; Lu et al., 2025).

Assumption 3. Passenger and freight volumes on arcs and routes are modeled as continuous variables, since they represent aggregated demand at the strategic-level planning level. Moreover, as these volumes are typically large, the approximation error introduced by relaxing integrality is negligible. This is a commonly adopted assumption in related literature (see, Borndörfer et al., 2007; Hartleb et al., 2023; Lu et al., 2025; Xia et al., 2026).

Assumption 4. We consider system-optimal routing for both passengers and freight. Similar assumptions have been widely adopted in previous studies on line planning problems (e.g., Schöbel and Scholl, 2006; Borndörfer et al., 2007; Schöbel, 2017; Chen et al., 2024). In other related studies on passenger and freight co-modal systems, such as timetabling problems, passenger and freight demand are also typically assigned to trains from a system-optimal perspective (e.g., Di et al., 2022; Hörsting and Cleophas, 2023; Stokkink and Geroliminis, 2025).

4. Mathematical formulation

Based on the proposed two-layer CGN, we introduce the notations including sets, parameters, and decision variables, formulate the CLiPRPF as an MILP model.

4.1. Notations

Table 2 summarizes the sets and parameters used in the model. To formulate the CLiPRPF, we define the following seven sets of decision variables:

- w_l: Binary variable equal to 1 if line $l \in \mathcal{L}_m \cup \mathcal{L}_u$ is operated; 0 otherwise.
- f_l^p, f_l^h: Continuous variables representing the service frequencies of line $l \in \mathcal{L}_m \cup \mathcal{L}_u$ allocated to passenger and freight services, respectively. For truck lines $l \in \mathcal{L}_u$, we set $f_l^p = 0$.

Table 2
Sets and parameters in CLiPRPF.

Sets	
$\mathcal{S}$	Set of stations in the PTN
$\mathcal{E}$	Set of edges between stations in the PTN, where $\mathcal{E} = \mathcal{E}_m \cup \mathcal{E}_u$ and $e \in \mathcal{E}$
$\mathcal{E}_m$	Set of tracks in the URT system between stations in the PTN
$\mathcal{E}_u$	Set of segments on road between stations used by trucks in the PTN
$\mathcal{L}_m$	Line pool of the URT system for integrated passenger and freight mobility
$\mathcal{L}_u$	Line pool of the truck system for freight mobility
$\mathcal{L}(e)$	Set of lines passing through edge e
$\mathcal{P}$	Set of passenger OD pairs
$\mathcal{H}$	Set of freight OD pairs
$\mathcal{A}$	Set of travel and transfer arcs in the CGN, where $\mathcal{A} = \mathcal{A}^t \cup \mathcal{A}^c \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u$ and $a \in \mathcal{A}$
$\mathcal{A}^t$	Set of travel arcs used by trains in the URT system
$\mathcal{A}^c$	Set of transfer arcs for transporting passengers in the URT system
$\mathcal{A}^{cr}$	Set of rail-to-rail transfer arcs for transporting freight within the URT system
$\mathcal{A}^{ct}$	Set of rail-to-road transfer arcs between URT and trucks for transporting freight
$\mathcal{A}^u$	Set of travel arcs used by trucks
$\mathcal{R}$	Set of routes in CGN for all OD pairs $\mathcal{P} \cup \mathcal{H}$
$\mathcal{R}_a$	Set of routes passing through arc $a \in A$
$\mathcal{R}^p$, $\mathcal{R}^h$	Set of routes for OD pair $p \in \mathcal{P}$ and $h \in \mathcal{H}$, respectively
$\mathcal{R}^p_a$, $\mathcal{R}^h_a$	Set of routes for OD pair p or h that pass through arc a, respectively
Parameters	
e_l	Set-up cost of line $l \in \mathcal{L}_m \cup \mathcal{L}_u$
e_a	Set-up cost of each rail-to-road transfer arc $a \in \mathcal{A}^{ct}$
b_l	Operational cost of line $l \in \mathcal{L}_m \cup \mathcal{L}_u$
f_l^{min}, f_l^{max}	Lower and upper bounds on the service frequency for line $l \in \mathcal{L}_m \cup \mathcal{L}_u$
B	Budget for operating the optimized line plans
Q_l^p	Capacity of each train on $l \in \mathcal{L}_m$ for transporting passengers
Q_l^h	Capacity of each train or truck on $l \in \mathcal{L}_m \cup \mathcal{L}_u$ for transporting freight
d_p, d_h	Number of passengers with OD pair $p \in \mathcal{P}$ and freight with OD pair $h \in \mathcal{H}$
$l(a)$	Line $l \in \mathcal{L}_m \cup \mathcal{L}_u$ that arc a belongs to
c_a	Travel time on arc $a \in \mathcal{A}$
σ_p, σ_h	Weight coefficients in the objective function for travel times related to passengers and freight

- u_a: Binary variable equal to 1 if the rail-to-road transfer arc $a \in \mathcal{A}^{ct}$ is activated for transferring freight between the URT system to trucks; 0 otherwise.
- x_a: Continuous variable representing the total number of passengers using arc $a \in \mathcal{A}$.
- y_a: Continuous variable representing the total amount of freight using arc $a \in \mathcal{A}$.
- z_r: Continuous variable denoting the number of passengers assigned to route $r \in \mathcal{R}$.
- m_r: Continuous variable denoting the amount of freight assigned to route $r \in \mathcal{R}$.

4.2. Path-based MILP formulation of CLiPRPF

Based on the aforementioned definitions, we formulate the CLiPRPF problem as the following path-based MILP model:

$$\min \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^c} \sigma_p c_a x_a + \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u} \sigma_h c_a y_a \tag{1a}$$

$$\text{s.t. } f_l^{min} w_l \le f_l^p + f_l^h \le f_l^{max} w_l \qquad \forall l \in \mathcal{L}_m \cup \mathcal{L}_u, \tag{1b}$$

$$\sum_{l\in\mathcal{L}(e)} w_l \ge 1 \qquad \forall e \in \mathcal{E}_m, \tag{1c}$$

$$\sum_{l\in\mathcal{L}_m\cup\mathcal{L}_u} \left[b_l(f_l^p + f_l^h) + e_l w_l\right] + \sum_{a\in\mathcal{A}^{ct}} e_a u_a \le B, \tag{1d}$$

$$y_a \le M_a u_a \qquad \forall a \in \mathcal{A}^{ct}, \tag{1e}$$

$$x_a \le \sum_{l\in\mathcal{L}(a)} Q_l^p f_l^p \qquad \forall a \in \mathcal{A}^t, \tag{1f}$$

$$y_a \le \sum_{l\in\mathcal{L}(a)} Q_l^h f_l^h \qquad \forall a \in \mathcal{A}^t \cup \mathcal{A}^u, \tag{1g}$$

$$x_a = \sum_{r\in\mathcal{R}_a} z_r \qquad a \in \mathcal{A}^t \cup \mathcal{A}^c, \tag{1h}$$

$$y_a = \sum_{r\in\mathcal{R}_a} m_r \qquad \forall a \in \mathcal{A}^t \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u, \tag{1i}$$

$$\sum_{r\in\mathcal{R}_a^p} z_r \leq d_p f_{l(a)}^p \qquad \forall a \in \mathcal{A}^t \cup \mathcal{A}^c, p \in \mathcal{P}, \tag{1j}$$

$$\sum_{r\in\mathcal{R}_a^h} m_r \leq d_h f_{l(a)}^h \qquad \forall a \in \mathcal{A}^t \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u, h \in \mathcal{H}, \tag{1k}$$

$$\sum_{r\in\mathcal{R}^p} z_r = d_p \qquad \forall p \in \mathcal{P}, \tag{1l}$$

$$\sum_{r\in\mathcal{R}^h} m_r = d_h \qquad \forall h \in \mathcal{H}, \tag{1m}$$

$$w_l \in \{0,1\} \qquad \forall l \in \mathcal{L}_m \cup \mathcal{L}_u, \tag{1n}$$

$$u_a \in \{0,1\} \qquad \forall a \in \mathcal{A}^{ct}, \tag{1o}$$

$$f_l^p, f_l^h \geq 0 \qquad \forall l \in \mathcal{L}_m \cup \mathcal{L}_u \tag{1p}$$

$$x_a, y_a \geq 0 \qquad \forall a \in \mathcal{A}, \tag{1q}$$

$$z_r, m_r \geq 0 \qquad \forall r \in \mathcal{R}. \tag{1r}$$

(i) Objective function. Objective function (1a) minimizes the total weighted travel time of passengers and freight. For each arc $a \in \mathcal{A}$, c_a denotes the travel time on arc a. The variables x_a and y_a represent the total passenger flow and freight flow using arc a, respectively. The first term $\sum_{a\in\mathcal{A}^t\cup\mathcal{A}^c} \sigma_p c_a x_a$ is formulated to calculate passengers' travel time over URT travel arcs $\mathcal{A}^t$ and passengers' transfer arcs $\mathcal{A}^c$, weighted by a coefficient σ_p. The second term $\sum_{a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u} \sigma_h c_a y_a$ accounts for total travel time of freight over the arcs available to freight, including URT travel arcs $\mathcal{A}^t$, rail-to-rail transfer arcs for transporting freight $\mathcal{A}^{cr}$, rail-to-road transfer arcs $\mathcal{A}^{ct}$, and travel arcs used by trucks $\mathcal{A}^u$, weighted by a coefficient σ_h.

(ii) Line planning constraints. Constraints (1b) ensure that the frequency of each operated line in both the URT and truck systems remains within the lower and upper bounds. These constraints are directly related to the opening of lines, as each selected line must operate within feasible frequency limits. For URT lines, the minimum frequency is required to maintain acceptable service standards, while the maximum frequency is limited by infrastructure capacity. For truck lines, upper bounds reflect practical limitations including road capacity, traffic congestion on the road, and environmental concerns such as emissions and noise. Excessive truck operations may exacerbate urban congestion, whereas a minimum frequency ensures adequate freight transport capacity. Constraints (1c) require that each existing track $e \in \mathcal{L}(e)$ in the URT system be served by at least one operated line in the solution. This guarantees full utilization of the infrastructure and avoids underused or disconnected segments in the network, which is essential when deciding which lines to open.

(iii) Budget constraints governing the operation of lines and the construction of transfer facilities between the URT system and trucks. Constraints (1d) ensure the budget limit B. Specifically, for each line $l \in \mathcal{L}_m \cup \mathcal{L}_u$, $e_l w_l$ represents the fixed setup cost of activating the line and $b_l(f_l^p + f_l^h)$ denotes the operational costs of the selected URT and truck lines. For each transfer facility $a \in A^{ct}$, $e_a u_a$ denotes its setup cost. Constraints (1e) govern the use of transfer facilities between the URT and trucks. If a rail-to-road transfer arc $a \in \mathcal{A}^{ct}$ carries freight flow (i.e., $y_a > 0$) in the solution, then the corresponding facility must be constructed, that is, $u_a = 1$; otherwise, $u_a = 0$.

(iv) In-vehicle capacity constraints. Constraints (1f) and (1g) are hard-capacity constraints imposed on travel arcs. They ensure that the passenger flow x_a and the freight flow y_a on each arc a do not exceed the capacity provided by all lines traversing the arc for passengers and freight, respectively.

(v) Passenger and freight routing constraints. Constraints (1h)–(1i) connect the arc-based flow variables x_a and y_a with the route-based routing variables z_r and m_r, where x_a and y_a denote passenger and freight flows on arc a, and z_r and m_r denote passenger and freight routing decisions on route r. Specifically, the passenger flow x_a on arc a equals the sum of z_r over all passenger routes using arc a, and the freight flow y_a equals the sum of m_r over all freight routes using arc a.

(vi) Interactions between line planning and passenger/freight routing decisions. Constraints (1j)–(1k) ensure that flow can only be assigned to arcs associated with activated lines. Constraints (1l)–(1m) guarantee that all passenger and freight demand are routed. Lastly, constraints (1n)–(1r) define the domains of the decision variables.

Remark 2. Although Formulation (1) is developed for the intermodal line planning problem with the passenger and freight co-modalmobility considered in this paper, its structure is more broadly applicable to multi-modal transportation systems that integrate line planning with passengers' routing, or with joint routing of both passengers and freight. For example, the same framework can be extended to emerging urban air mobility-metro integration for passenger and freight transportation using electric vertical take-off and landing (eVTOL) and metro services. In such a system, passengers may be served by both eVTOL vehicles and metro services, whereas freight may be transported mainly by metro because of the limited capacity and high operating costs of eVTOLs. Under this extension, the current freight transfer facility decision can be reinterpreted as a vertiport location decision, and the remaining structure can support the joint design of line planning and routing decisions. Naturally, additional mode-specific extensions would be required, such as constraints related to the capacity and operational costs of eVTOLs.

5. Solution approach

The main challenge in solving Formulation (1) lies in the enormous number of potential routes in the sets $\mathcal{R}_p \cup \mathcal{R}_h$, associated with each passenger OD pair $p \in \mathcal{P}$ and freight OD pair $h \in \mathcal{H}$, particularly in large-scale intermodal networks. This results in an excessive number of decision variables z_r and m_r, making direct enumeration computationally infeasible. To address this challenge and solve the CLiPRPF problem efficiently, we develop a column generation algorithm integrated with a novel two-phase diving heuristic to obtain high-quality integer solutions. Additionally, we incorporate model-driven lower and upper bound estimations to accelerate convergence.

In this section, we begin with a high-level overview of the proposed solution approach in Section 5.1. Thereafter, we present the column generation approach with acceleration techniques for solving the linear relaxation of the CLiPRPF problem in Section 5.2. In Section 5.3, we introduce the novel two-phase diving approach.

5.1. Overview

Column generation is a decomposition-based solution method for linear programs with an intractable number of variables, commonly used in large-scale and real-life optimization applications (e.g., Liang et al., 2018; Stokkink et al., 2024; Lu et al., 2025; Xia et al., 2025). Algorithm 1 provides an overview of the column generation algorithm integrated with our proposed two-phase diving approach, which incorporates the budget reservation strategy for the URT system. In our implementation, the RMP is solved using GUROBI, and the two pricing problems are solved in parallel using Dijkstra's algorithm.

Algorithm 1 Column generation with the two-phase diving approach.

Input: Initial route pool $\overline{\mathcal{R}}_p$ and $\overline{\mathcal{R}}_h$ for each $p \in \mathcal{P}$ and $h \in \mathcal{H}$ ▷ Section 5.2.1
// **Column Generation Initialization**
repeat
    Solve the RMP over current route pool to obtain dual variables ▷ Section 5.2.2
    Parallelize PPs to identify routes with negative reduced costs ▷ Sections 5.2.3 and 5.2.5
    Add the route with the smallest reduced cost to the route pool
until no more columns with negative reduced cost
Save fractional solution (w^*, u^*) ▷ Section 5.2
Initialize feasible budget B, threshold τ_w, and $B_{\text{URT}}^{\text{reservation}}$ from Proposition 1
// **First-phase diving on line planning variables** w_l
while budget not exhausted and unfixed w_l exist **do**
    if URT budget spent $< B_{\text{URT}}^{\text{reservation}}$ **and** any unfixed URT line has $w_l > \tau_w$ **then**
        Fix the URT line l with highest w_l to 1 ▷ Section 5.3.3
    else
        Fix the line (URT or truck) l with highest w_l to 1 ▷ Section 5.3.1
    end if
    repeat
        Solve RMP over current route pool
        Parallelize PPs and add columns with negative reduced cost to the route pool
    until no more columns with negative reduced cost
end while
// **Second-phase diving on transfer facility variables** u_a
while budget not exhausted and unfixed u_a exist **do**
    Fix transfer facility a with highest u_a value to 1 ▷ Section 5.3.2
    repeat
        Solve RMP over current route pool
        Parallelize PPs and add columns with negative reduced cost to the route pool
    until no more columns with negative reduced cost
end while
Output: Final solution for the CLiPRPF problem

5.2. Column generation

We now focus on the column generation framework used to solve the linear relaxation of the CLiPRPF problem. Instead of generating all possible passengers' and freight's routes a priori, we begin by solving a *restricted master problem* (RMP) defined over a limited subset of all potential routes. The RMP is a linear program that determines line planning, truck routing, and demand routing decisions.

Based on the optimal dual values of the RMP solution, we then solve two separate pricing problems: one for passengers and one for freight. These dual values guide the generation of new routes with negative reduced costs that can improve the objective value. To further improve computational efficiency, we propose a reduction technique that removes redundant nodes and arcs when solving the pricing problems. Notably, the passenger and freight pricing problems are independent of each other and can therefore be solved in parallel to improve computational efficiency. If any routes with negative reduced cost are found, the one with the most negative value is added to the RMP, which is then re-solved. This iterative process continues until no route with a negative reduced cost can be found, indicating optimality of the linear relaxation. To obtain a feasible solution for the CLiPRPF problem with integer variables $\mathbf{w}$ and $\mathbf{u}$, we propose a novel two-phase diving heuristic that alternates between column generation and incremental variable fixing until integrality is achieved. As will be shown in Section 6.2.2, this framework, when combined with the proposed two-phase diving method, achieves small optimality gaps within short computational times.

We next present the details of the column generation algorithm, including initialization, the RMP, the two pricing problems, and the calculation of reduced costs.

5.2.1. Initialization

To ensure the initial feasibility of the RMP, two separate subsets of feasible routes are generated for passengers and freight and provided to the RMP. These initial routes serve as the starting point for the column generation procedure. Specifically, for each passenger and freight OD pair, the shortest route is identified in the PTN obtained when all lines in both line pools are assumed to be operated, and then mapped onto the two-layer CGN. All resulting routes in the CGN are used to initialize the RMP.

5.2.2. RMP formulation

The RMP is a linear relaxation of Formulation (1), in which the decision variables $(\mathbf{w}, \mathbf{u}, \mathbf{f}, \mathbf{x}, \mathbf{y}, \mathbf{z}, \mathbf{m})$ are treated as continuous. We define two sets, $\overline{\mathcal{R}}^p \subset \mathcal{R}^p$ and $\overline{\mathcal{R}}^h \subset \mathcal{R}^h$, to represent the subsets of all possible routes for passengers and freight, respectively. In addition, we define $\overline{\mathcal{R}} \subset \mathcal{R}$, $\overline{\mathcal{R}}_a \subset \mathcal{R}_a$, $\overline{\mathcal{R}}_a^p \subset \mathcal{R}_a^p$, and $\overline{\mathcal{R}}_a^h \subset \mathcal{R}_a^h$ to denote the corresponding subsets of all route-arc incidence sets for passengers and freight. The RMP can now be formulated as follows:

$$\min_{\mathbf{w},\mathbf{u},\mathbf{f},\mathbf{x},\mathbf{y},\mathbf{z},\mathbf{m}} \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^c} \sigma_p c_a x_a + \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u} \sigma_h c_a y_a \tag{2a}$$

$$\text{s.t. } (1b)-(1g), (1p)-(1q), \tag{2b}$$

$$x_a = \sum_{r\in\overline{\mathcal{R}}_a} z_r \quad a \in \mathcal{A}^t \cup \mathcal{A}^c, \tag{2c}$$

$$y_a = \sum_{r\in\overline{\mathcal{R}}_a} m_r \quad \forall a \in \mathcal{A}^t \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u, \tag{2d}$$

$$\sum_{r\in\overline{\mathcal{R}}_a^p} z_r \leq d_p f_{l(a)}^p \quad \forall a \in \mathcal{A}^t \cup \mathcal{A}^c, p \in \mathcal{P}, \tag{2e}$$

$$\sum_{r\in\overline{\mathcal{R}}_a^h} m_r \leq d_h f_{l(a)}^h \quad \forall a \in \mathcal{A}^t \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u, h \in \mathcal{H}, \tag{2f}$$

$$\sum_{r\in\overline{\mathcal{R}}^p} z_r = d_p \quad \forall p \in P, \tag{2g}$$

$$\sum_{r\in\overline{\mathcal{R}}^h} m_r = d_h \quad \forall h \in \mathcal{H}, \tag{2h}$$

$$w_l \in [0,1] \quad \forall l \in \mathcal{L}_m \cup \mathcal{L}_u, \tag{2i}$$

$$u_a \in [0,1] \quad \forall a \in \mathcal{A}^{ct}, \tag{2j}$$

$$z_r, m_r \geq 0 \quad \forall r \in \overline{\mathcal{R}}. \tag{2k}$$

5.2.3. Pricing problems

In each iteration of the column generation algorithm, two *pricing problems* (PPs) are solved in parallel: one for passengers and one for freight. Each PP becomes finding the shortest path from the source node to the sink node in the connected network to minimize the reduced cost, which is equivalent to the length of the shortest path found. We can, for instance, use Dijkstra's algorithm to solve PPs. The objective of each PP is to check whether a route with a negative reduced cost exists or not, which is computed by using the duals of the RPM solution. If such a route exists, the corresponding column is added to the RMP; otherwise, the current solution is optimal.

5.2.4. Reduced cost calculation

For any route r corresponding to passenger OD pair $p \in \mathcal{P}$, the reduced cost $\psi_p(r)$ is given by

$$\psi_p(r) = -\lambda_p + \sum_{a\in\mathcal{A}_r} \left(\pi_a + \mu_a^p\right), \tag{3}$$

where π_a is the dual variable associated with constraints (2c), μ_a^p corresponds to constraints (2e), and λ_p to constraints (2g). For each $p \in \mathcal{P}$, the PP seeks the route $r^\star$ that minimizes the reduced cost by solving a shortest-path problem on the single-modal CGN. If $\psi_p(r^\star) < 0$, the corresponding column is added to the passenger route pool $\overline{\mathcal{R}}^p$.

For any route r corresponding to freight OD pair $h \in \mathcal{H}$, the reduced cost $\phi_h(r)$ is defined as

$$\phi_h(r) = -\theta_h + \sum_{a \in \mathcal{A}_r} \left(\eta_a + \delta_a^h\right), \tag{4}$$

where η_a corresponds to constraints (2d), δ_a^h to constraints (2f), and θ_h is the dual variable associated with constraints (2h). For each $h \in \mathcal{H}$, the PP identifies the route $r^\star$ that minimizes the reduced cost by solving a shortest-path problem on the two-layer CGN excluding passenger-related arcs. If $\phi_h(r^\star) < 0$, the corresponding column is added to the freight route pool $\overline{\mathcal{R}}^h$.

If no route with negative reduced cost is found for any $p \in \mathcal{P}$ or $h \in \mathcal{H}$, the initial linear relaxation for the CLiPRPF problem is solved to optimality. We then enter a diving procedure, in which integer solutions are progressively constructed by continuously adding new columns and gradually fixing integer decision variables.

5.2.5. Acceleration techniques

To accelerate the solution process, we propose a dedicated CGN for each PP to eliminate redundant nodes and arcs. Table 3 provides the detailed comparison of the CGNs used in Formulation (1), the PPs for passengers and freight. For passengers, the PP is solved on a single-modal CGN, which only includes the URT network and consists of URT travel arcs $\mathcal{A}^t$ and passenger transfer arcs $\mathcal{A}^c$. For freight, the PP is solved on a two-layer CGN without passenger-related arcs, which includes URT travel arcs $\mathcal{A}^t$, truck travel arcs $\mathcal{A}^u$, rail-to-rail transfer arcs $\mathcal{A}^{cr}$, and rail-to-road transfer arcs $\mathcal{A}^{ct}$. The costs of arcs are adjusted using the dual values obtained from the current RMP solution.

Table 3
Comparison of the CGNs used in various problems.

Nodes and arcs	The two-layer CGN used in Formulation (1)	The single-modal CGN used in PP for passengers	The two-layer CGN used in PP for freight
Station node	✓	✓	✓
URT travel node	✓	✓	✓
Truck travel node	✓	–	✓
URT travel arcs	✓	✓	✓
Passenger transfer arcs	✓	✓	-
Truck travel arcs	✓	–	✓
Rail-to-rail transfer arcs	✓	–	✓
Rail-to-road transfer arcs	✓	–	✓

5.3. Two-phase diving procedure

It is challenging to obtain high-quality integer solutions by directly rounding the fractional decision variables in the LP relaxation. This is particularly true for the CLiPRPF problem, which involves two sets of binary decision variables: w_l, indicating whether line $l \in \mathcal{L}$ is operated, and u_a, indicating whether a freight transfer facility is constructed on arc $a \in \mathcal{A}^{ct}$. The route set generated during the column generation process is typically tailored to support fractional solutions and is therefore too limited to ensure good performance under integer constraints. Simply rounding down the fractional values of these variables may lead to under-utilization of available resources, leaving budget unused and resulting in suboptimal solutions. Conversely, rounding up may violate budget constraints (1d) and produce infeasible solutions.

To address these issues, we adopt a diving approach that incrementally constructs integer-feasible solutions by successively fixing decision variables. In this approach, a column generation procedure and a fixing procedure are executed iteratively until an integral solution is found. The diving approach can be interpreted as a heuristic traversal of an LP-based branch-and-bound tree. Unlike exact methods that explore both branches at each node, or rounding-based methods that assign fractional variables to their nearest integer values, the diving approach proceeds along a single path in a depth-first manner, selecting the most promising branch at each step. The objective is not to exhaustively enumerate the solution space, but rather to quickly identify a feasible and high-quality primal solution. Taking the fixing of $\mathbf{w}$ variables as an example, Fig. 4 illustrates such a heuristic trajectory in the decision space. The figure shows how fractional w variables are fixed one at a time, and how RMP and PP are repeatedly solved to improve the solution. For a more detailed discussion of diving-based heuristics within branch-and-price frameworks, we refer the reader to Sadykov et al. (2019).

We find that using a single-phase diving strategy, as commonly employed in the literature, may lead to infeasibility under certain conditions, particularly when the budget is tight. As shown in the analysis in Section 6.2.3, the single-phase diving method may result in infeasible solutions due to the interdependence between the binary decision variables. To overcome this challenge, we propose a novel two-phase diving procedure. In the first phase, we apply diving to the $\mathbf{w}$ variables while keeping $\mathbf{u}$ relaxed. In the second phase, we fix the $\mathbf{w}$ variables and then apply diving to the $\mathbf{u}$ variables, taking into account the remaining budget and the updated route set.

Remark 3. The proposed two-phase diving procedure can, in principle, be further extended by allowing iterative refinement between the two sets of binary variables. Specifically, after fixing the $\mathbf{u}$ variables in the second phase, one could re-relax the $\mathbf{w}$ variables and

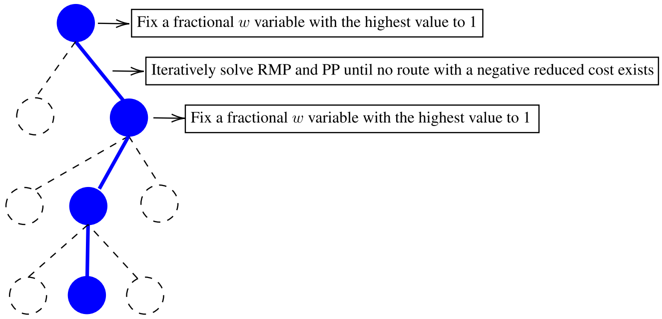


Fig. 4. An illustration of the diving heuristic in an enumeration tree.

re-enter the diving phase on **w**, and vice versa. This process could continue iteratively until no further improvement is found. While such a multi-phase refinement may enhance solution quality in problems with strong interdependencies or tighter coupling between integral variables, our computational results show that the two-phase procedure already yields solutions with typically very small optimality gaps for the CLiPRPF problem. Nevertheless, this extension may be worth exploring in other applications that adopt our proposed solution framework.

While the two-phase approach is heuristic in nature, it typically yields solutions with very small optimality gaps, as we will see in the numerical results. Moreover, based on the theoretical properties of the model, we can derive lower and upper bounds for the budget used in each phase, which can be incorporated to further improve the performance of the proposed two-phase diving method. We now describe each phase in detail, beginning with the standard procedure, followed by the properties that can be incorporated into this two-phase diving method to enhance its performance.

5.3.1. First-phase diving

In the first phase, we aim to obtain integral values for the **w** variables by applying the diving approach. At each iteration, we solve the RMP and the two PPs for both passengers and freight to identify new promising routes until no route with a negative reduced cost is found. Based on the current LP solution, we select the most promising unfixed metro or truck line, namely the one with the highest fractional value, and fix its value to 1.

After each fixation, a budget check is performed to verify whether the decision remains feasible. Let $\mathcal{L}_{\text{fixed}}$ denote the set of already activated lines. The total cost is computed as the sum of (i) the set-up and operating costs of all currently fixed lines $\hat{l} \in \mathcal{L}_{\text{fixed}}$, evaluated at their current LP frequencies, and (ii) the estimated cost of the candidate unfixed line $l \in \mathcal{L} \setminus \mathcal{L}_{\text{fixed}}$ with the cheapest operational cost b_l, assuming it operates at its minimum frequency $f_l^{\min}$. The fixation is accepted and the process continues only if the total cost satisfies the following inequality:

$$\sum_{\hat{l} \in \mathcal{L}_{\text{fixed}}} \left[e_{\hat{l}} + b_{\hat{l}} (f_{\hat{l}}^p + f_{\hat{l}}^h) \right] + \left(e_l + b_l f_l^{\min} \right) \;\leq\; B. \tag{5}$$

If inequality (5) is violated, the diving process terminates and no further variables will be fixed as 1. Otherwise, the procedure proceeds to the next iteration. The solution obtained from the first-phase diving procedure yields integral values for the **w** variables but may still contain fractional values for the **u** variables, and is therefore not guaranteed to be feasible for the original formulation (1). Its objective value provides a valid lower bound on the optimal objective of the original problem.

5.3.2. Second-phase diving

In the second phase, we perform diving on the **u** variables using a procedure similar to that employed in the first phase for the **w** variables. The metro and truck line operating decisions obtained from the first-phase diving are now fixed and denoted by $\hat{\mathbf{w}}$ while the frequency-realted variable is still a decision variable. We iteratively solve the current RMP and the PPs defined in Section 5.2.3, where the current RMP is formulated as

$$\min_{\mathbf{u},\mathbf{f},\mathbf{x},\mathbf{y},\mathbf{z},\mathbf{m}} \sum_{a \in \mathcal{A}^t \cup \mathcal{A}^c} \sigma_p c_a x_a + \sum_{a \in \mathcal{A}^t \cup \mathcal{A}^{cr} \cup \mathcal{A}^{ct} \cup \mathcal{A}^u} \sigma_h c_a y_a \tag{6a}$$

$$\text{s.t. } (1b), (1e) - (1g), (1p) - (1q), (2c) - (2h), (2j) - (2k), \tag{6b}$$

$$\sum_{l \in \mathcal{L}_m \cup \mathcal{L}_u} \left[b_l (f_l^p + f_l^h) + e_l \hat{w}_l \right] + \sum_{a \in \mathcal{A}^{ct}} e_a u_a \leq B. \tag{6c}$$

At each iteration, we identify the unfixed transfer facility variable u_a with the highest fractional value and fix it to 1. After each fixation, a budget feasibility check is performed to determine whether the inclusion of one additional facility would exceed the total budget B. Specifically, we compute the total cost incurred by all previously activated lines and facilities, including the newly fixed u_a, and estimate the minimum additional cost of one more candidate facility. If the resulting cost remains within the budget, the procedure continues to the next iteration. Otherwise, the process terminates, and all remaining unfixed **u** variables are set to zero.

5.3.3. Budget reservation strategies for the first-phase diving

When performing the proposed two-phase diving over the two binary decision variables, a critical concern is the potential over-activation of low-cost truck lines at the expense of URT lines. This imbalance not only undermines the spatial coverage required for passenger mobility but may also trigger excessive investments in freight transfer facilities during the second phase. Since URT lines are essential for maintaining network connectivity, service regularity, and accessibility, especially for dense and distributed passenger demand, their baseline provision must be safeguarded in the first-phase decision process.

To further enhance the performance of the two-phase diving approach, we introduce a URT-first budget reservation strategy that earmarks a minimal portion of the total budget specifically for URT operations. The theoretical basis of this strategy is formalized in Proposition 1, and its integration into the diving procedure is detailed in the discussion that follows. Section 6.2.2 presents numerical results showing that the two-phase diving approach with this budget reservation strategy consistently outperforms the baseline one introduced in Sections 5.3.1 and 5.3.2, yielding smaller optimality gaps.

Proposition 1 (Baseline preserving budget threshold for URT). *Let B_{pass} denote the optimal value of the optimization problem that considers using the URT system to serve all passenger demand (hereafter Problem (i)).*

Problem (1) holds the following separability: URT feasibility is affected by the truck-related decisions only through the total budget constraint (1d). Then, for any total budget $B \geq B_{\text{pass}}$, reserving at least B_{pass} for URT is necessary and sufficient to preserve the baseline URT service.

Proof. Consider Problem (i) that excludes all freight-related variables and constraints and minimizes the URT operational cost $\sum_{l\in\mathcal{L}_m}(e_l w_l + b_l f_l^p)$ over variables $(w_l, f_l^p, x_{a,p})$ while serving all passenger demand. Let $(\hat{w}, \hat{f}, \hat{x})$ be an optimal solution with objective value B_{pass}.

(Necessity.) Any solution that preserves the baseline URT service must finance $(\hat{w}, \hat{f}, \hat{x})$. By optimality of Problem (i), the minimal required URT budget equals B_{pass}.

(Sufficiency.) If $B \geq B_{\text{pass}}$, allocate B_{pass} to URT and fix the URT variables in the integrated model to $(\hat{w}, \hat{f}, \hat{x})$. By separability, these URT decisions remain feasible regardless of the non URT variables. The remaining budget $B - B_{\text{pass}}$ can be used for trucks and transfer facilities without affecting the baseline URT operations. Hence, the baseline is preserved. □

Corollary 1 (Conservative URT budget reservation rule). *Let B_{total} be the minimal operating cost to serve both passenger and freight when the URT concept is fixed to that from Problem (i). If $B \geq B_{total}$, then reserving*

$$B_{URT}^{reservation} := \frac{B_{pass}}{B_{total}} B$$

is sufficient *to preserve the passenger baseline (i.e., to implement the baseline URT solution from Problem (i)), since $B_{URT}^{reservation} \geq B_{pass}$. This share is not minimal in general and does not guarantee preservation when $B < B_{total}$.*

Incorporating the conservative URT Budget reservation rule into the first-phase diving. We incorporate the budget reservation strategy proposed in Proposition 1 into the first-phase diving procedure in a flexible, non-restrictive manner. Rather than imposing a hard budget constraint, this strategy prioritizes the early selection of URT lines while still allowing additional cost-effective URT lines to be selected later if the budget allows.

Specifically, we begin by computing a reserved budget share for URT lines, denoted by $B_{\text{URT}}^{\text{reservation}}$, as defined in Proposition 1. The diving procedure initially focuses on URT lines only, fixing one w_l at a time with the highest fractional values. This continues until one of the following two termination criteria is met: (i) the cumulative operational cost of the activated URT lines reaches the reserved threshold $B_{\text{URT}}^{\text{reservation}}$; or (ii) all remaining unfixed URT lines have w_l values below a predefined threshold τ_w, indicating low marginal importance.

Once either of these criteria is met, the procedure continues by applying the diving method introduced in Section 5.3.1 to all remaining unfixed lines, including both URT and truck lines.

6. Numerical experiments

In this section, we evaluate the performance of the proposed methodologies through extensive experiments on two sets of instances: (i) the well-known 5×5-grid network, which is a widely used benchmark in the line planning literature (e.g., Friedrich et al., 2017b; Lu et al., 2025), and detailed in Friedrich et al. (2017a), Schmidt and Schöbel (2024); and (ii) real-life instances based on the Rotterdam intermodal network comprising URT and trucks on the road.

We begin by introducing the test instances in Section 6.1, which are used to evaluate both algorithmic performance and strategic insights. We then evaluate the computational efficiency of our column generation algorithm with two-phase diving in Section 6.2, followed by an exploration of key managerial insights in Section 6.3. Lastly, we apply our framework to real-world case studies to evaluate its practical applicability and derive practical insights in Section 6.4.

When analyzing the solutions to the instances, we aim to answer the following questions:

(i) How does the proposed column generation algorithm with two-phase diving perform compared to the state-of-art solver? What are the benefits of incorporating the conservative URT budget reservation rule into our diving procedure? How much does the two-phase diving method help in improving the solution quality? (Section 6.2)
(ii) What are the benefits of integrated intermodal line planning under equal budget conditions? What is the value of reserving part of the budget for URT development? How does overall travel time respond to changes in the total available budget? What are the effects of relaxing truck frequency limits? (Section 6.3)

(iii) Does our algorithm have scalability to address the real-life large-scale problems? Under practical budget constraints, what are the relative advantages of frequency reallocation, network expansion, and full re-optimization? How should transit agencies adapt their line planning strategies when transitioning from passenger-only to integrated passenger and freight services? (Section 6.4)

All experiments are conducted in Python and solved using GUROBI 12.0.2. The computational tests are carried out on a personal computer with Windows 11 (version 23H2), a 14th-generation Intel Core i9-14900HX processor (24 cores / 32 threads, 2.20 GHz base frequency), and 64 GB of RAM.

6.1. Instances

First, we focus on the 5×5-grid network to assess the benefits of our modeling framework and the effectiveness of the proposed solution algorithm. Then, we apply our approaches to real-life instances based on the intermodal transit system of Rotterdam to derive practical insights and validate the applicability of our methods in realistic urban environments. Detailed descriptions of both sets of instances are provided below.

6.1.1. 5×5-grid network

We use the data set based on the 5×5 grid network and adopt parameter settings from the open source Public Transport Networks repository (FOR 2083 Research Group, 2018). To extend this dataset into an intermodal setting, we incorporate a truck layer and corresponding freight demand.

The extended network is illustrated in Fig. 5. As shown in Fig. 5(a), it consists of 25 physical stations. Each station offers both URT and truck services and is modeled as two separate nodes: one for URT (station_m) and one for truck (station_t), resulting in a total of 50 nodes across the two-layer public transport network (PTN). Fig. 5(b) presents the URT layer, which adopts a standard 5×5 grid topology with 40 arcs connecting adjacent URT nodes. Each arc has a travel time of 6 min, following the settings provided in the open-source Public Transport Networks repository. Transfers between URT lines incur a penalty of 5 min for passengers and 7 min for freight. Transfers between the URT and truck layers are permitted only for freight and are penalized by 10 min. The truck layer, shown in Fig. 5(c), replicates the URT structure, with each arc assigned a fixed travel time of 10 min.

The passenger and freight demands are summarized in Table 4. The dataset comprises 571 passenger OD pairs with a total of 6,459 passengers, and 567 freight OD pairs corresponding to 2,913 freight. Passenger demand is exclusively served by the URT system, with OD pairs restricted to URT nodes. In contrast, freight demand can be routed through the URT system, the truck system, or a combination of both, with OD pairs involving any mix of URT and truck nodes.

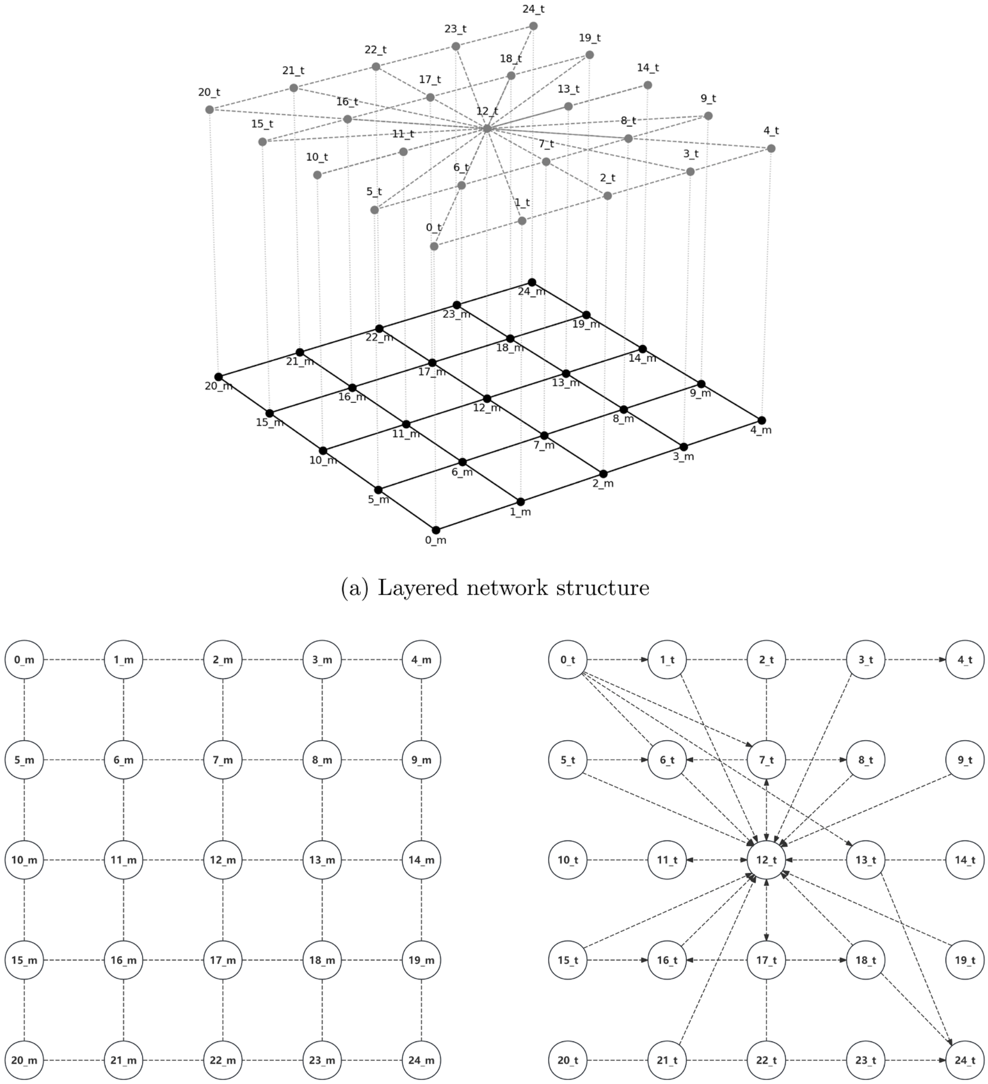
Table 4
Demands in the 5×5-grid network.

Network	# of candidate lines		# of OD pairs		# of demand	
	URT	Truck	Passenger	Freight	Passenger	Freight
5×5-grid network	14	37	571	567	6,459	2,913

We construct two separate line pools: 14 candidate lines for the URT system and 37 for the truck system. For instance, the URT line pool is clarified in Table 5. Following Lu et al. (2025), the operational cost of a line l is set as $b_l = 8N_l$ for URT lines and $b_l = 0.8N_l$ for truck lines, where N_l denotes the number of travel arcs traversed by line l. Each line also has a set-up cost $e_l = 1.5b_l$. Additionally, transfer arcs between metro and truck modes (rail-to-road arcs) has a set-up cost of $e_a = 0.12$. The weights for passengers and freight in the objective function are set to $\sigma_p = 1.0$ and $\sigma_h = 0.8$, and the frequency bounds to $f_l^{\min} = 1$ and $f_l^{\max} = 20$. In addition, to set a reasonable baseline budget, we solve a minimum-cost version of the CLiPRPF model.

Table 5
Line definitions in the 5×5 grid network.

Line	Type	# of stations	Index of involved stations
L1	M	5	0, 1, 2, 3, 4
L2	M	5	5, 6, 7, 8, 9
L3	M	5	10, 11, 12, 13, 14
L4	M	5	15, 16, 17, 18, 19
L5	M	5	20, 21, 22, 23, 24
L6	M	5	0, 5, 10, 15, 20
L7	M	5	1, 6, 11, 16, 21
L8	M	5	2, 7, 12, 17, 22
L9	M	5	3, 8, 13, 18, 23
L10	M	5	4, 9, 14, 19, 24
L11	M	7	5, 6, 7, 12, 17, 18, 19
L12	M	7	1, 6, 11, 12, 13, 18, 23
L13	M	7	15, 16, 17, 12, 7, 8, 9
L14	M	7	21, 16, 11, 12, 13, 8, 3



(a) Layered network structure

(b) URT network

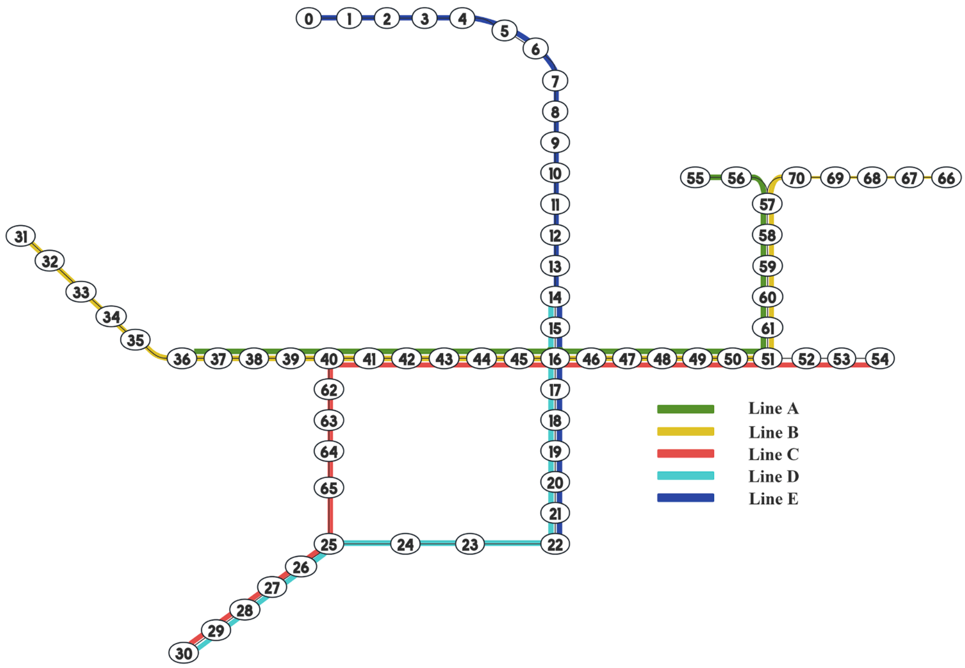
(c) Truck network

Fig. 5. 5 × 5-grid networks used in the computational study.

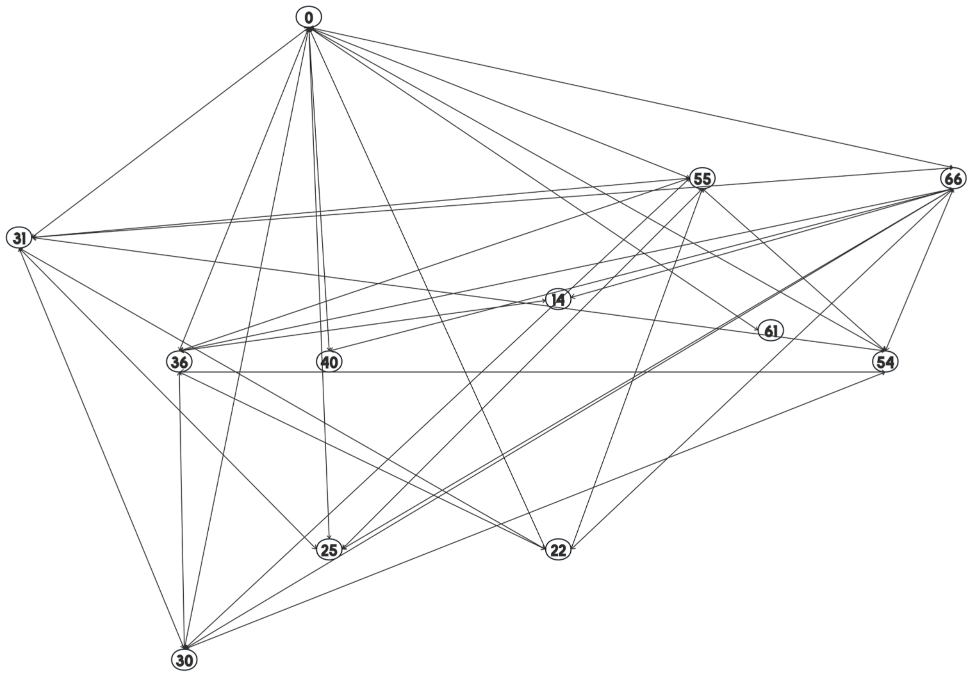
6.1.2. *Rotterdam intermodal network*

To demonstrate the practical applicability of our approaches, we construct a realistic intermodal dataset based on the Rotterdam URT system, using real-life infrastructure layouts and travel times for both URT and truck services. For each currently operated URT line, we use the observed service frequency from the official RET timetables (RET, 2025), where all active lines run with a frequency of 6 per hour.

As illustrated in Fig. 6(a), the existing citywide URT network in Rotterdam consists of 71 stations and 71 track segments. Each travel arc in the URT-layer CGN is weighted by the real-life travel time, which is derived from publicly available infrastructure and timetable data. To construct the URT line pool, we first build the URT network based on the real-world infrastructure layout. We then identify nine terminal stations as candidate line endpoints, corresponding to the termini of the five existing Rotterdam metro lines, namely stations 31, 36, 30, 22, 14, 54, 55, 66, and 0. These terminal stations are spatially distributed across the network to ensure network-wide coverage. The URT line pool is generated using a pairwise shortest-path strategy. Specifically, all pairwise combinations of the nine terminal stations are considered, and for each pair, the shortest path on the URT layer is computed using Dijkstra's algorithm. Each resulting candidate line is represented by its two terminal stations and the ordered sequence of intermediate stations, thereby forming a data-driven initial line set. In addition, the five existing Rotterdam metro lines are explicitly included in the pool by mapping them onto the same underlying network, so that the final line pool contains both synthetic candidate alignments and real-world operating lines. Finally, candidate lines with fewer than seven stations, i.e., lines with one to six stations, are removed.



(a) Overview of the existing citywide URT network in Rotterdam



(b) Truck line pool used in the experiments

Fig. 6. Citywide intermodal network in Rotterdam.

Additionally, we construct a truck line pool to complement the URT line pool. To identify promising truck lines, we analyze all pairwise combinations between the nine selected URT depots and the main transfer stations in the Rotterdam URT network. For each pair, we calculate travel times on both the URT network and the road network. URT travel times are obtained by processing publicly available timetable and infrastructure data, and truck travel times are retrieved from Google Maps under typical operating conditions. We observe that in this dataset, the travel times of trucks are typically shorter than those of URT services since URT has to stop at many station. Therefore, we retain truck line candidates where the URT travel time exceeds the truck travel time by more than 15 min, indicating a clear advantage for truck operations. Based on this criterion, 33 truck lines are selected, as illustrated in Fig. 6(b). To support these truck lines, we introduce 12 dedicated truck stations labeled with the suffix "_t". These include stations 0_t, 14_t, 22_t, 25_t, 30_t, 31_t, 36_t, 40_t, 54_t, 55_t, 61_t, and 66_t.

Furthermore, based on the real-life Rotterdam network, we generate passenger and freight demand using a simple gravity model, with additional adjustments to account for major hubs such as Rotterdam Central and the relative attractiveness of transfer stations. As summarized in Table 6, the dataset includes 4,970 passenger OD pairs with a total demand of 32,493, and 3,422 freight OD pairs representing a total freight demand of 15,358.

Table 6
Line pools and demands used in the Rotterdam case studies.

Network	# of candidate lines		# of OD pairs		# of demand	
	URT	Truck	Passenger	Freight	Passenger	Freight
Rotterdam network	72	66	4,970	3,422	32,493	15,358

The operational cost b_l for each URT line l is computed as $0.8T_l$, where T_l is the total in-vehicle travel time of line l. For truck lines, the operational cost is set to $0.08T_l$. The setup cost is defined as $e_l = 2.5b_l$. A set-up cost of $e_a = 0.012$ is assigned to rail-to-road arcs enabling freight transfers between URT and truck services. To ensure consistency with the experiments based on the 5×5-grid network, we apply the same transfer penalties in the Rotterdam instances. Each passenger transfers between URT lines has a 5-min penalty, each freight transfers between URT lines has a 7-min penalty, and each freight transfer between URT and truck modes at the same station has a 10-min penalty.

In the following, we first demonstrate the effectiveness of the proposed column generation algorithm by comparing it with benchmark solution methods on the 5×5-grid network in Section 6.2. We then present managerial insights derived from the results on the 5×5-grid network in Section 6.3. In Section 6.4, we focus on the real-life case study and provide practical insights based on the Rotterdam network.

6.2. Algorithm performance

6.2.1. Benchmarks

In this section, we define four benchmarks to evaluate the effectiveness of the proposed algorithm. First, to show the benefits of our algorithm, we use GUROBI as the benchmark solution method. Specifically, Formulation (1) is solved to optimality with a sufficiently large number of pre-generated routes per OD pair. Second, to evaluate the impact of the conservative URT budget reservation rule in the first-phase diving procedure, we implement a benchmark that omits this strategy. In this benchmark, the diving follows the method described in Section 5.3.1, without enforcing a reserved budget for the URT system.

Third, to assess the advantage of the two-phase diving approach, we design a benchmark that includes only the first-phase diving. After running column generation and performing first-phase diving on the line planning variables $\mathbf{w}$, we fix the resulting route pool and the line concept (i.e, the line plans and the frequency), and solve Formulation (1) with GUROBI to obtain an integer solution for the $\mathbf{u}$ variables. This serves as a baseline for comparing against our full two-phase diving framework.

Lastly, we compare the proposed column generation solution method with a hybrid algorithm that combines local search and GUROBI, referred to as Hybrid-LS. A detailed description of Hybrid-LS is provided in Appendix B. In Hybrid-LS, Formulation (1) is decomposed into two subproblems. The first subproblem searches the line planning decision variables w_l for lines $l \in \mathcal{L}_m \cup \mathcal{L}_u$ by means of a local search procedure. The second subproblem solves Formulation (B.1) with fixed w_l values to evaluate the candidate line plans generated by the first subproblem. Starting from an initial line plan, the local search iteratively explores neighboring solutions through add, drop, and swap moves on the selected lines. In each iteration, a sampled subset of neighboring solutions is evaluated by solving Formulation (B.1), and the incumbent solution is updated if the best sampled neighbor improves upon the current incumbent. Preliminary experiments showed that, it is difficult to find feasible solutions to the second subproblem because the capacity constraints are frequently violated. To address this issue, capacity constraints are relaxed by introducing nonnegative violation variables, which are penalized in objective function (B.1a) through large coefficients.

6.2.2. Performance comparison among various solution methods

To show the benefits of the proposed algorithm, three sets of experiments based on the 5×5-grid network are conducted. The first set investigates how the performance of GUROBI on Formulation (1) varies with the numbers of the incorporated routes. This aims to identify a sufficient number of routes for high-quality solutions to establish a suitable benchmark for the algorithm and explore the computational boundary of GUROBI in solving instances to optimality. The second set compares the solution quality and computational efficiency of our algorithms, both with and without the conservative URT budget reservation rule applied in the first-phase diving, against the benchmark solution obtained by solving Formulation (1) to optimality using GUROBI with sufficient number of routes.

Finding 1. Adding more routes per OD pair considerably reduces the travel time of passengers and freight up to a point, but shows diminishing returns beyond 10 routes. Nevertheless, the optimized travel time continues to slightly improve when 12 routes per OD pair are incorporated into the PTN. To ensure a strong benchmark for evaluating our algorithm, we adopt the 12-route setting in the subsequent experiments using GUROBI.

For the first experiment, we vary the number of routes in the PTN per OD pair from 2 to 12 and, for each setting, solve the model to optimality using GUROBI. Fig. 7 presents the results, showing the travel time of passengers and freight under different route counts. We observe that total travel time decreases sharply as the number of routes increases from 2 to 10, after which the marginal improvement diminishes. These results suggest that incorporating a sufficient number of passenger and freight routes into the capacitated line planning with integrated truck routing is essential to adequately capture routing flexibility. Consequently, in all subsequent experiments, we use GUROBI to solve Formulation (1) with 12 routes per OD pair, which serves as the benchmark for evaluating the proposed algorithm.

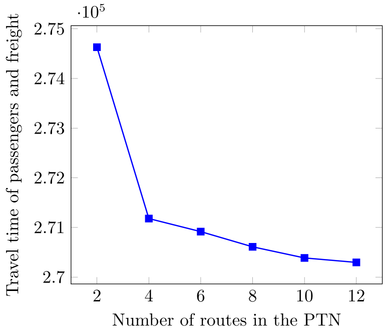


Fig. 7. Comparison of passengers' and freight's travel times among various numbers of routes.

Finding 2. The proposed column generation algorithm with two-phase diving solves the CLiPRPF problem significantly faster than GUROBI, with over 95% time savings, while maintaining optimality gaps below 1%. The inclusion of the conservative URT budget reservation rule further improves performance by reducing the optimality gap, and provides more stable solutions under various parameter settings.

For the second set of experiments, we vary the weight parameters in the objective function as well as the maximum frequency constraints. We use GUROBI and the algorithm without the conservative URT budget reservation rule as two benchmarks. Table 7 reports the optimal values and run times achieved by GUROBI, alongside the results from our algorithm and the benchmark without the conservative URT budget reservation rule. The relative gaps in both objective value and solution time, compared to GUROBI, are also provided to evaluate the performance of each algorithm.

From the results shown in Table 7, we observe that GUROBI requires substantial computational time, taking several hours even for the small-scale 5×5-grid instances to solve the problem to optimality. In contrast, both variants of our algorithm - with and without the conservative URT budget reservation rule - produce high-quality solutions within minutes, achieving over 95% time savings on average while maintaining optimality gaps below 1%. Notably, our algorithm with the conservative URT budget reservation rule consistently yields smaller optimality gaps, with an average gap of 0.77%, compared to 0.85% for the variant without the strategy. Although the 0.08% improvement in average solution quality is modest, it highlights the effectiveness of the conservative URT budget reservation rule. In addition, when the budget is more constrained (e.g., $B = 5,618$), the version with the reservation strategy tends to achieve more noticeable improvements in both solution quality and computational efficiency.

To further show the benefits of our proposed conservative URT budget reservation rule, Fig. 8 presents a detailed performance comparison of the two algorithmic variants relative to GUROBI. It can be seen that the variant with the conservative URT budget reservation rule consistently achieves lower optimality gaps compared to the variant without it. The interquartile range is narrower and the median gap is lower for the variant with the strategy, indicating more stable and reliable performance. Additionally, the maximum optimality gap is also reduced, suggesting that the conservative URT budget reservation rule helps prevent deteriorated performance in challenging instances. Henceforth, we adopt the column generation algorithm with two-phase diving and the conservative URT budget reservation rule for all subsequent experiments.

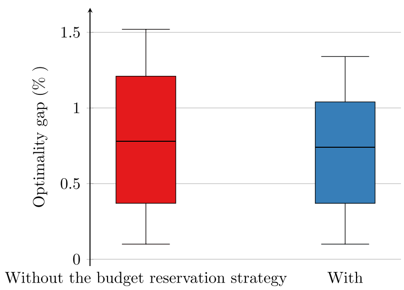


Fig. 8. Optimality gaps of the algorithms without and with the budget reservation strategy for the URT system, relative to the GUROBI optimal solutions.

Table 7
Comparison of our algorithm with benchmarks. Note: ↑ indicates higher values compared with benchmarks (worse performance), and ↓ indicates reduction compared with benchmarks (better performance).

Instance		Budget	GUROBI (PTN = 12)		Budget reservation strategy	Algorithm		Relative to GUROBI (%)	
(σ_p, σ_h)	$f_l^{\max}$		Optimal Obj.	CPU time (s)		Obj.	CPU time (s)	Obj. Gap	Gap of CPU time
(1.0, 0.8)	20	5,539	272,545	15,330	NO	276,683	891	1.52 ↑	94.19 ↓
					YES	275,918	865	1.24 ↑	94.36 ↓
		5,803	270,958	15,325	NO	273,067	751	0.78 ↑	95.10 ↓
					YES	272,961	732	0.74 ↑	95.22 ↓
		6,066	270,296	15,273	NO	271,613	602	0.49 ↑	96.06 ↓
					YES	271,613	605	0.49 ↑	96.04 ↓
	25	5,618	271,952	15,406	NO	275,816	702	1.42 ↑	95.44 ↓
					YES	275,586	723	1.34 ↑	95.31 ↓
		5,885	270,126	15,377	NO	272,992	581	1.06 ↑	96.22 ↓
					YES	272,942	668	1.04 ↑	95.66 ↓
		6,153	270,126	14,764	NO	270,400	552	0.10 ↑	96.26 ↓
					YES	270,400	533	0.10 ↑	96.39 ↓
(1.0, 0.6)	20	5,539	253,415	15,292	NO	256,840	980	1.35 ↑	93.59 ↓
					YES	256,043	939	1.04 ↑	93.86 ↓
		5,803	252,094	15,067	NO	253,684	839	0.63 ↑	94.43 ↓
					YES	253,421	737	0.53 ↑	95.11 ↓
		6,066	251,480	14,788	NO	252,418	707	0.37 ↑	95.22 ↓
					YES	252,418	667	0.37 ↑	95.49 ↓
	25	5,618	252,758	15,371	NO	255,814	735	1.21 ↑	95.22 ↓
					YES	255,570	582	1.11 ↑	96.21 ↓
		5,885	251,353	15,445	NO	253,964	614	1.04 ↑	96.02 ↓
					YES	253,964	561	1.04 ↑	96.37 ↓
		6,153	251,353	15,002	NO	251,842	627	0.19 ↑	95.82 ↓
					YES	251,842	551	0.19 ↑	96.33 ↓
Average					NO			0.85 ↑	95.30 ↓
					YES			0.77 ↑	95.53 ↓

Finding 3. The proposed column generation algorithm considerably outperforms Hybrid-LS on the tested instances. It solves all four representative instances within 1,000 seconds, with gaps no larger than 2.00% relative to the optimal solutions obtained by GUROBI under PTN = 12, whereas Hybrid-LS fails to find capacity-feasible solutions within 1,800 s for all instances. This indicates that column generation algorithm is better suited to the CLiPRPF problem than a hybrid method.

To further assess the effectiveness of the proposed column generation algorithm, we compare it with Hybrid-LS on four representative instances selected from the second set of experiments, covering different combinations of (σ_p, σ_h), $f_l^{\max}$, and budget levels. Hybrid-LS is terminated after 1,800 s. The results of Hybrid-LS are reported in Table 8. For each instance, we report the objective value, computational time, and the proportions of overloaded URT and truck travel arcs. The results show that Hybrid-LS performs poorly in both solution quality and computational efficiency, and fails to eliminate capacity violations in all four instances within the time limit. The proportion of overloaded travel arcs ranges from 1.50% to 11.62%.

This observation is consistent with the complexity results reported in the line planning literature. Bussieck (1998) showed that the basic line planning problem is already NP-hard, even in the special case where the minimum and maximum frequencies on each PTN edge are both equal to one. Schöbel and Scholl (2006) further proved that the line planning problem remains NP-hard even when the PTN is a linear graph and costs related lines are equal to one. Compared with these highly simplified settings, the CLiPRPF problem studied in this paper involves a considerably richer decision structure, including intermodal line planning, coupled passenger and freight routing, transfer-facility decisions, and capacity interactions across modes. These features make the problem computationally more challenging.

From the experimental results of Tables 7–8, we conclude that a hybrid method combining local search and GUROBI is not adequate for solving the CLiPRPF problem effectively. By contrast, the proposed column generation framework is able to exploit the mathematical structure of the formulation more directly. In particular, the dual information obtained from the RMP guides the pricing subproblems toward columns with the greatest potential to improve the current solution. This provides a much more informed search mechanism than purely neighborhood-based exploration. To summarize, we conclude that column generation outperforms Hybrid-LS on the tested instances and is better suited to the CLiPRPF problem.

6.2.3. *Benefits of the two-phase diving approach*

To demonstrate the benefits of the proposed two-phase diving approach, we conduct a set of experiments comparing it against the third benchmark introduced in Section 6.2.1. In this benchmark, the algorithm performs only a single diving phase and subsequently

Table 8
Computational performance of hybrid-LS.

(σ_p, σ_h)	$f^{\max}$	Budget	Obj. value	CPU time (s)	Ratio of overloaded travel arcs
(1.0, 0.8)	20	5,539	1.07×10^8	1,800.00	10.15%
	25	5,618	1.10×10^8	1,800.00	11.62%
(1.0, 0.6)	20	5,539	1.06×10^8	1,800.00	9.87%
	25	5,618	1.62×10^7	1,800.00	1.50%

uses GUROBI to obtain an integer solution for the **u** variables by fixing the route pool and the line concept. The weights in the objective function are set to $(\sigma_p, \sigma_h) = (1.0, 0.8)$.

Finding 4. The two-phase diving approach consistently ensures feasible and high-quality solutions by preserving flexibility in the route generation and allocation of resources within the intermodal network, while the benchmark approach with a single diving phase often leads to infeasibility under tight budgets.

Table 9 reports the results in terms of objective value and solution time. It can be observed that the benchmark algorithm, which applies a single-phase diving and then fixes both the line concept decisions for the URT system and the route pool before optimizing the transfer facility decisions using GUROBI, frequently results in infeasible solutions under constrained budget settings. In contrast, the two-phase approach consistently produces feasible solutions and achieves comparable or better objective values and computation times. The main reasons can be attributed to the following two-fold: (i) Fixing line concept of the URT system over-constrains the problem and removes the model's ability to flexibly allocate intermodal resources to accommodate demand bottlenecks during the second phase. (ii) The benchmark method fixes the route pool obtained during the first-phase diving and does not allow further route generation, which further limits the solution space and increases the risk of infeasibility.

However, our two-phase diving approach only fixes **w** for the URT system in the first phase, while keeping route generation flexible in the second phase through iteratively solving the RMP and PPs. This preserves modeling adaptability and enables the algorithm to maintain feasibility even under tight budgets. These results highlight that the proposed two-phase diving procedure is more reliable in practice, and should be preferred especially in realistically constrained cases.

Table 9
Comparison of the two-stage diving with the benchmark.

f_l^{max}	Budget	Benchmark		Two-phase diving	
		Obj.	CPU time (s)	Obj.	CPU time (s)
20	5,539	Infeasible	–	275,918	865
	5,803	Infeasible	–	272,961	732
	6,066	271,613	617	271,613	605
25	5,618	Infeasible	–	275,586	723
	5,885	Infeasible	–	272,942	668
	6,153	270,400	543	270,400	533

6.3. Managerial insights

This section offers insights into (i) the benefits of integrated planning in urban intermodal transport (Insight 1); (ii) the value of reserving budget for URT under limited budget conditions (Insight 2); (iii) the relationship between travel time and overall budget (Insight 3); and (iv) the impact of relaxing truck frequency limits (Insight 4) obtained from the 5×5-gird network. The practical insights from the real-life case studies will be discussed in Section 6.4.

Insight 1. Enhancing service quality does not necessarily require additional investment, but rather a more flexible and integrated design. Under equal budget, coordinating URT line planning with truck routing reduces the total travel time of passengers and freight by at least 0.92% and up to 1.87% compared to the solution obtained by optimizing URT line planning alone. When budgets become more constrained, using only the URT system fails to meet all passenger and freight demands. In contrast, the URT line planning approach with integrated truck routing maintains feasibility by flexibly reallocating resources across the two mode, achieving enhanced service quality through better coordination rather than additional investment.

Our CLiPRPF approach addresses the problem that jointly optimizes URT line planning and truck routing for passenger and freight co-modal mobility in an intermodal network. To assess the value of this integration, we compare our approach with a benchmark method that optimizes only the URT line planning, without incorporating truck routing. We perform the experiments by varying the budget settings.

Table 10 presents the performance comparison between the CLiPRPF model and the benchmark method that only optimizes the URT line planning. Under equal budget settings, our integrated approach consistently outperforms the benchmark in terms of total system cost. Specifically, the objective value is reduced by 0.92% when the budget is 5,803, and by 1.87% when the budget is 6,066. Moreover, when the budget is constrained to 5,539, the benchmark method fails to yield a feasible solution, while our proposed integrated optimization model remains feasible and provides a valid solution within reasonable computation time. These results demonstrate the effectiveness of jointly optimizing URT line planning and truck routing. The benchmark's reliance on the URT system alone limits its ability to serve all passenger and freight demands. In contrast, the integrated approach flexibly reallocates resources across both modes, improving efficiency and maintaining feasibility under tight budget conditions.

Table 10
Comparison of CLiPRPF and using URT services for passenger and freight co-modal mobility.

Budget	Obj. of using the URT system	Obj. of using the intermodal network	Obj. *Dev* (%)
5,539	Infeasible	275,918	–
5,803	275,494	272,961	0.92 ↓
6,066	276,778	271,613	1.87 ↓

Furthermore, Fig. 9 visualizes the optimized line plans and frequency assignments under equal budget settings. The integrated approach activates more low-frequency lines, offering broader coverage and greater flexibility in resource allocation. Intermodal coordination enables lower URT frequencies while maintaining connectivity, as part of the demand is served via truck routing. However, the benchmark solution concentrates budget on a few high-frequency lines to serve all demands, reducing adaptability when budgets tighten.

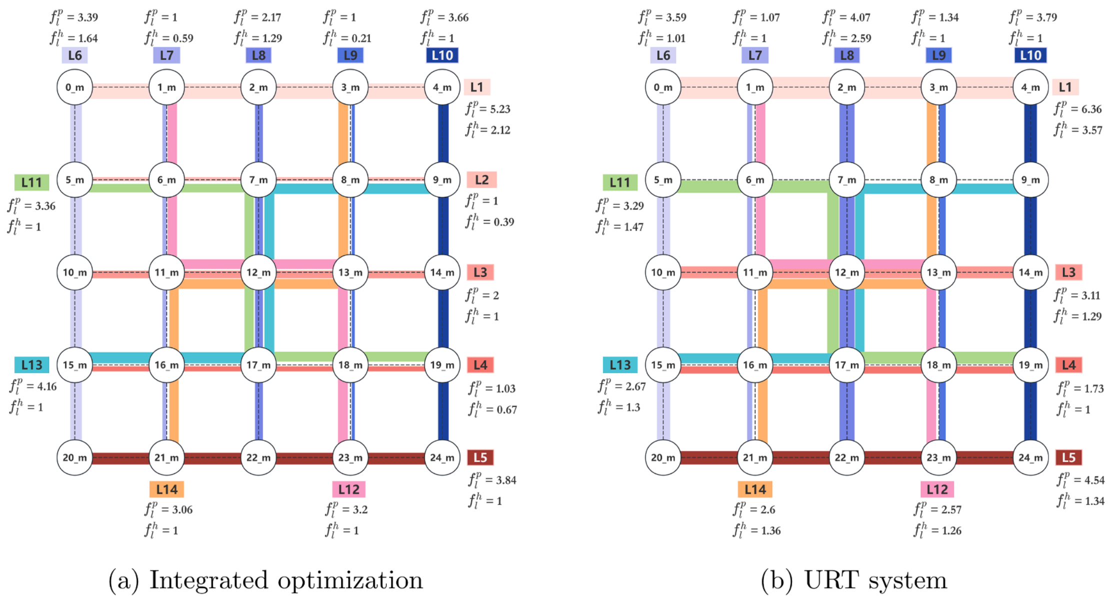


Fig. 9. Line plans and frequency assignments for the URT system with the budget of 5,803 under the integrared and URT-only optimization methods.

Insight 2. Prioritizing the URT system in budget allocation in the first-phase diving percedure improves overall solution quality under resource constraints.

When resources are limited, reserving budget for the URT system ensures improved service quality and reduces the risk of infeasibility. Trucks and freight transfer facility investments can then be flexibly adjusted based on residual capacity. Unless freight operations offer significantly higher marginal benefits, this strategy should be adopted.

This insight is supported by the results in Table 7 and Fig. 8, which compare the performance of two budget-handling strategies under fixed total budgets. The conservative URT budget reservation rule consistently outperforms the alternative without reservation. Specifically, it achieves a lower average optimality gap (0.77% vs. 0.85%) and improves computational efficiency. The difference is particularly evident when budget is tight, as relaxing the URT service floor often leads to longer waiting times, degraded passenger experience, and increased costs. In contrast, prioritizing the URT system stabilizes service quality on key corridors, allowing remaining resources to be used more effectively for freight and transfer components. As total budget increases, the performance gap narrows, but the reservation strategy remains more stable and reliable across budget levels.

Insight 3. Increasing the total budget reduces travel time of passengers and freight by enabling broader network expansion and higher service frequencies.

Within the tested budget range, total travel time decreases steadily as budget increases, regardless of parameter settings.

Fig. 10 presents the travel times of passengers and freight among various budget settings. It can be seen that the results of all instances exhibit a consistent inverse relationship between total travel time and budget. The main reason is that when the budget increases, more lines and intermodal transfer arcs are activated, improving network connectivity and reducing detours. Simultaneously, service frequencies on active lines increase, lowering waiting times and alleviating congestion. These two effects work jointly to shift passenger and freight flows into routes with lower travel times.

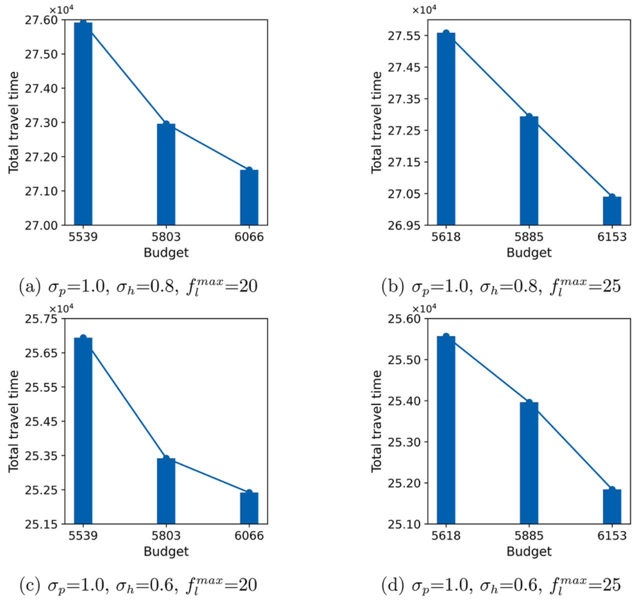


Fig. 10. Travel times of passengers and freight among various budget settings.

Insight 4. Relaxing the upper bound of truck frequency reduces travel time of passengers and freight, but at the expense of increased externalities such as road congestion and emissions.

Increasing the upper bound on truck service frequency lowers the travel time, even when the frequency of the URT system remains unchanged. This effect arises from more flexible routing and mode allocation for the freight demand. However, the resulting increase in truck departures raises road usage and vehicle-kilometers traveled, which may lead to congestion and emissions on the road. Frequency limits on trucks should therefore be treated as a tunable policy instrument, tightened or relaxed in accordance with road capacity and environmental goals in real-life operations.

We perform a set of experiments by fixing the frequency upper bound for the URT system at $f^{max}_{l\in\mathcal{L}_m} = 20$ and varying the upper bound for truck services $f^{max}_{l\in\mathcal{L}_u} \in \{15, 20, 25\}$. Fig. 11 shows the results. It can be observed that increasing the upper bound of frequency for truck services leads to a monotonic reduction in travel time of passengers and freight. This reduction stems from enhanced flexibility in freight assignment: a larger portion of freight demand is shifted onto faster truck routes, and existing truck lines operate at moderately higher frequencies. As set-up costs remain stable once the truck line set is determined, the marginal performance gain is primarily attributed to increased operating frequencies within the allocated budget. These findings highlight the role of truck frequency limits as a controllable policy lever that can significantly influence system efficiency, especially when URT expansion is constrained.

6.4. Practical insights from real-life case studies

To evaluate the practical effectiveness of the proposed model and the applicability of the solution approach in a real-world setting, we conduct a set of case studies on the city-wide Rotterdam intermodal network introduced in Section 6.1. Specifically, the experiments are based on the full candidate line pools summarized in Table 6, including 72 candidate URT lines, 66 candidate truck lines, 4,970 passenger OD pairs, and 3,422 freight OD pairs. We define the baseline budget B_{base} as the total set-up and operating cost of the current Rotterdam URT system, calculated according to constraint (1d).

To derive practical insights from the Rotterdam case studies, we next conduct three sets of experiments. The first set keeps the total budget fixed at B_{base} and compares different planning strategies, in order to evaluate the improvement under the current budget level. It is worth noting that the current Rotterdam system is a passenger-only URT network and does not include any truck services.

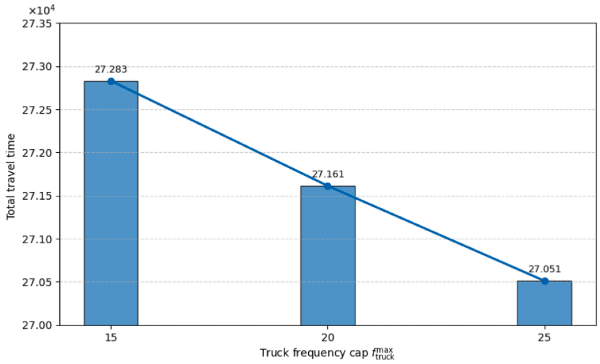


Fig. 11. The relationship between travel time and the upper bound of frequency for truck services.

Therefore, under the budget level B_{base}, any introduction of truck lines must be financed by reallocating part of the budget currently used by URT services. The second set varies the budget level to examine how the optimized line plan changes as the available budget increases or decreases. The third set varies the settings related to frequencies of URT and truck lines to explore structural insights.

In the first set of experiments, we compare three optimization strategies under the same budget level B_{base}. The purpose is to assess how much improvement can be achieved without increasing the current budget, and to distinguish the value of pure frequency adjustment, limited network expansion around the existing system, and full network redesign. Since truck services are absent in the current system but may be activated in the optimized solutions, we set the minimum and maximum service frequencies for both URT and truck lines to one and 20, respectively. Setting the minimum frequency to one ensures that, once an additional URT or truck line is activated, it provides an operationally meaningful service. More importantly, this setting allows the model to decide whether part of the baseline URT budget should be shifted to newly introduced truck services when such a reallocation improves the performance of the integrated passenger and freight co-mobility method in the intermodal network. The goal of these experiments is not to examine the effect of extra budget, but rather to identify the operational benefits that can be obtained through better resource allocation under the current expenditure level.

(i) Frequency optimization with the existing line plan for the current Rotterdam URT network. We fix the existing URT line plan and preserve the observed frequencies (denoted as f_l^{obs}) for each line. The optimization only determines the frequency allocation between passenger and freight flows on each existing line. To enforce this, we introduce the following constraints into the model:

$$f_l^p + f_l^h = f_l^{\text{obs}}, \quad \forall l \in \mathcal{L}_{\text{existing}}.$$

Given that the line plan is fully specified, the problem complexity is reduced. To obtain an optimal solution, we therefore solve the instance with this strategy to optimality using GUROBI.

(ii) Optimizing frequency and network expansion based on the existing URT network. This strategy reflects a realistic planning strategy in which the current Rotterdam URT network is preserved, while limited network expansion and frequency reallocation are allowed under the same budget as the current line plan, denoted by B_{base}. To do so, the five operated URT lines in the current Rotterdam URT network are fixed to be active by setting their corresponding binary decision variables to one (i.e., $w_l = 1$ for these five lines) in the optimization model. The remaining binary variables associated with other candidate lines in the URT and truck line pools are still treated as decision variables, so that additional URT and truck lines may be activated if beneficial. The optimization jointly determines which additional candidate URT and truck lines to activate, as well as the frequencies of all activated lines, including the five currently operated URT lines. The resulting model is solved using the proposed column generation algorithm with a two-phase diving procedure.

(iii) Complete optimization without pre-fixed lines. In this setting, no existing lines are pre-committed. The entire line plan is completely optimized using our proposed Formulation (1) under the baseline budget B_{base}. The instances under this strategy are also solved by employing our proposed algorithm.

Practical Insight 1. When new operational requirements arise, such as shifting from passenger-only to integrated passenger and freight services, the most effective solution under a fixed budget is to redesign the intermodal line plan from scratch. This full optimization (i.e., strategy iii) achieves the greatest service improvements. When such re-design is not feasible, expanding around the current URT backbone (i.e., strategy ii) still yields meaningful gains, while maintaining the existing network with only frequency adjustments (i.e., strategy i) offers limited benefits.

Table 11 summarizes the performance of the three strategies, reporting the objective value (Obj.), the total solution time from the construction of the two-layer CGN to the completion of optimization, and the relative reduction in the objective value. The results show considerable improvements in the travel time of passengers and freight as more flexibility is introduced. Strategy (ii) achieves a 3.84% reduction in the objective value compared to the baseline, while strategy (iii) yields the highest reduction of 6.50%, despite operating under the same total budget.

Table 11
Performance comparison among various strategies.

Strategy	Obj.	CPU time	Obj. Reduction (%)
(i) Frequency optimization with the existing line plan	1,898,653	10h 38m 41s	—
(ii) Optimizing frequency and network expansion	1,825,721	7h 35m 24s	3.84 ↓
(iii) Complete optimization without pre-fixed lines	1,775,268	8h 54m 34s	6.50 ↓

Next, in the second set of experiments, we investigate how the optimized URT line plan changes under different budget levels. The minimum and maximum service frequencies for both URT and truck lines are again set to 1 and 20, respectively, so as to keep the operational setting consistent with that in the first set of experiments. Unlike the first set, where the budget is fixed at the current budget B_{base} for the existing URT network, here we vary the budget from $95\% B_{\text{base}}$ to $180\% B_{\text{base}}$ to investigate how reduced or additional budget affects the structure of the optimized URT network.

Practical Insight 2. The Rotterdam case shows that introducing truck services into the current URT system changes how the existing URT budget should be used. Even under the current operating budget of the passenger-only URT system ($100\% B_{\text{base}}$), the optimized intermodal solution does not preserve the original URT structure. Instead, part of the budget is shifted to truck services, and the resulting URT network consists of more operated lines with a shorter average line length. This indicates that, once freight is incorporated, it may be inefficient to continue concentrating the budget on a small number of relatively long URT lines. A better use of the same budget is to let URT focus on its backbone function while using truck services as a complementary mode where URT-based service is less economical.

Table 12 reports the structural characteristics of both the optimized URT line plans under different budget levels and those of the current Rotterdam URT network. Although truck services are jointly optimized in these experiments, the present analysis focuses on the structural changes in the URT network, whereas the role of truck services is discussed separately later. Relative to the existing line plan, the optimized solution under $100\% B_{\text{base}}$ operates more URT lines (9 instead of 5) while reducing the average line length from 24.40 to 20.78 stations. Meanwhile, the share of long lines with more than 30 stations decreases from 20% to 0, whereas the share of short lines with fewer than 15 stations increases from 0 to 22.22%. This indicates that, once the freight demand is incorporated and part of the budget is allocated to truck services, the optimized URT network tends to shift away from a structure dominated by a few relatively long lines toward a more targeted backbone network with shorter services. Across budget levels, the number of operated URT lines increases steadily from 8 under $95\% B_{\text{base}}$ to 17 under $180\% B_{\text{base}}$, whereas the average line length remains relatively stable at around 21 stations. When the budget exceeds the baseline level of 100% B_{base}, both short and long lines become more prevalent, suggesting that the added budget is used to diversify the portfolio of operated lines rather than to uniformly increase their lengths.

Table 12
Comparison between existing URT line plan and optimized URT line plans under different budget levels in real-life case studies.

Solution	# of operated lines	Average line length (# of stations)	Maximum line length	Minimum line length	Share of short lines (<15 stations)	Share of long lines (>30 stations)
Existing (100% B_{base})	5	24.40	32	17	0	20%
95% B_{base}	8	20.50	29	14	25%	0
100% B_{base}	9	20.78	29	14	22.22%	0
130% B_{base}	13	21.15	33	8	30.77%	23.08%
180% B_{base}	17	20.94	33	8	29.41%	23.53%

Practical Insight 3. As the available budget increases, the optimized URT network in Rotterdam expands primarily through a larger number of operated lines rather than through a uniform increase in line lengths. In particular, the number of operated URT lines rises steadily, while the average line length remains broadly stable. At the same time, higher budget levels are associated with the emergence of both more short lines and some long lines, suggesting that the additional budget is mainly used to support a more diversified line structure that combines backbone services with shorter complementary lines. From a practical viewpoint, this indicates that added budget is used to enrich the network structure and improve coverage across different parts of the city, rather than simply to make all operated lines longer.

Lastly, in contrast to the previous sets of experiments, the third set of experiments investigates how the optimized URT and truck line plans change across budget levels when different frequency settings are imposed. Specifically, the minimum frequency of URT lines is increased to three, the maximum frequencies of both URT and truck lines are reduced to 10, while the minimum frequency of truck lines remains one.

Figs. 12 and 13 visualize the optimized intermodal line plans under $90\% B_{\text{base}}$ and $150\% B_{\text{base}}$, respectively. It can be observed that under $90\% B_{\text{base}}$, the optimized solution consists of a relatively compact network with seven URT lines and one truck line. Under $150\% B_{\text{base}}$, the optimized solution expands to 14 URT lines and six truck lines. This change is not merely a frequency enhancement of the lower-budget solution, but a redesign of the intermodal network. More URT lines are introduced to reinforce the backbone structure, while truck lines are deployed to provide supplementary freight connections across different parts of the network.

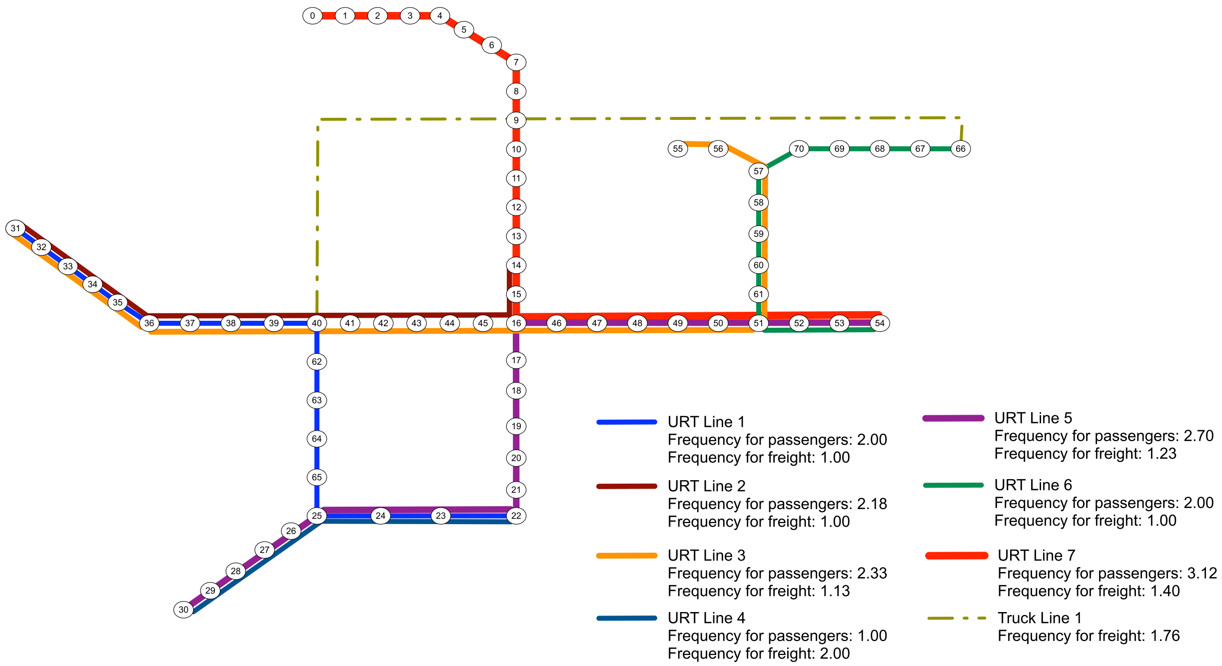


Fig. 12. The optimized intermodal line plan under budget 90% B_{base}.

Practical Insight 4. In the Rotterdam intermodal system, the value of the budget increase lies not only in enhancing the supply of services to both passengers and freight, but more importantly in the ability to build a more comprehensive structure of the intermodal network. From a planning perspective, budget expansion is most useful when it allows a more complete passenger and freight co-modal network, rather than merely increasing the frequency of the same set of operated lines. In addition, the Rotterdam case studies suggest that truck services should be viewed as a complementary mode to URT, rather than as a substitute for it. In the optimized intermodal solutions, URT serves as the dominant backbone of the system, and truck services provide additional flexibility and support freight movements that are less suitable for URT-based transport.

The results from Figs. 12 and 13 suggest that, when freight demand is incorporated into the current passenger-only URT system, part of the available budget must then be used for serving freight, including truck operations and transfer-related connections. As a result, the optimized URT network becomes more selective in its role. Rather than serving all demand through long lines, it concentrates on corridors where URT can create the greatest system-wide value for both passengers and freight, while complementary truck services are used to support freight movements. In this sense, the Rotterdam results suggest that intermodal planning is not simply a question of adding freight onto the existing URT system, but of redesigning the intermodal network so that each mode performs the duties for which it is most structurally efficient.

A second observation is that a higher budget does not restore the current passenger-only URT line plan. Instead, the optimized intermodal solutions selectively retain and reorganize URT services in a way that better matches the passenger and freight co-modal mobility. For example, under 90% B_{base}, none of the five existing lines in the current URT system is operated, whereas under 150% B_{base}, only two of them are retained. From the perspective of Rotterdam, this suggests that when incorporating freight demand, some existing lines may continue to serve as structurally valuable corridors, while the rest of the network should be adapted to work jointly with truck services.

The third observation from the visualized line plans is that the two modes have a functional division. In both budget settings, URT services remain concentrated on the major corridors and continue to form the backbone of the network. Truck services, by contrast, are introduced to provide supplementary freight connections for movements that would be inefficient to serve through URT alone. Even when the budget increases, the optimized solution does not replace the URT backbone with trucks. Instead, it reinforces intermodal coordination by jointly expanding the URT services and the set of complementary truck services.

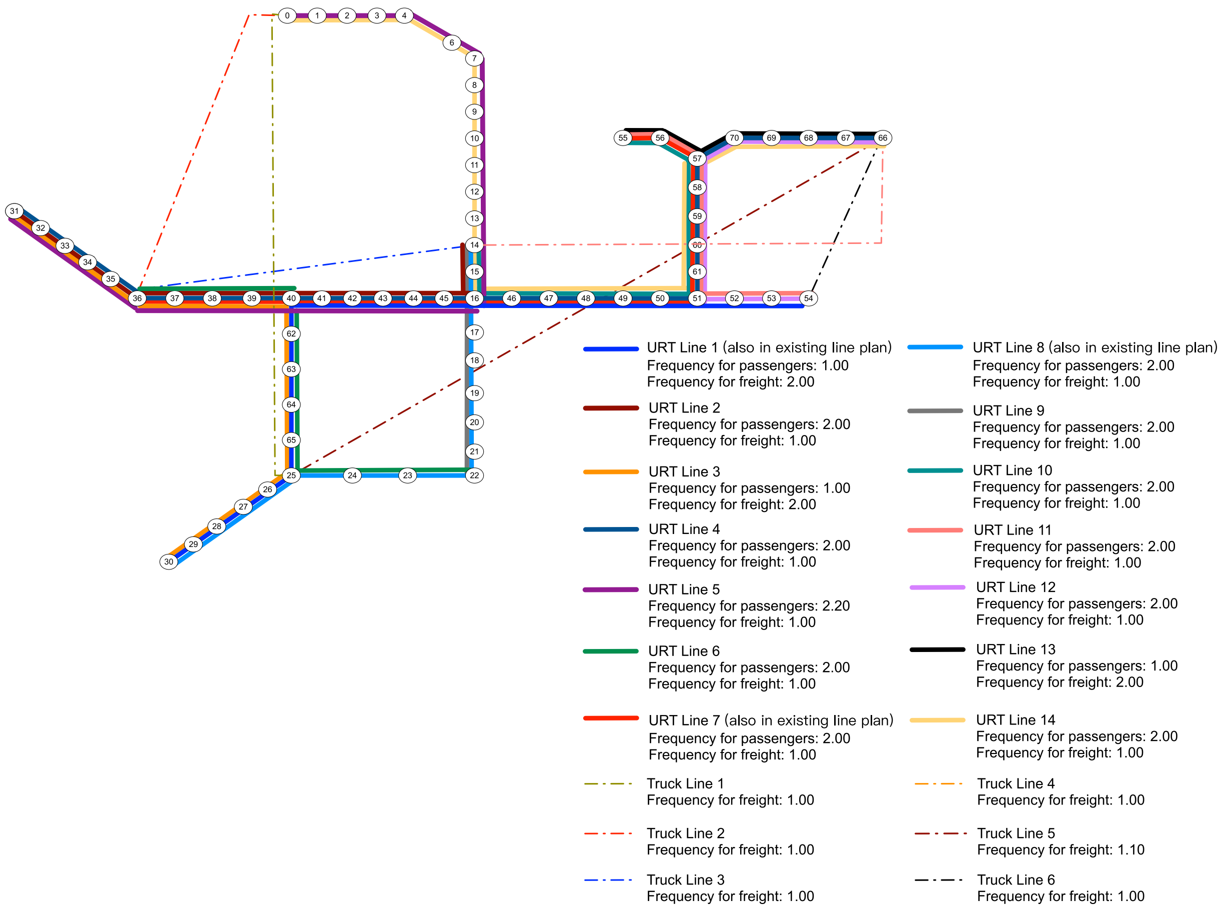


Fig. 13. The optimized intermodal line plan under budget 150% B_{base}.

7. Conclusion

This paper addressed a capacitated line planning problem with integrated truck routing for passenger and freight co-modal mobility. We extend traditional passenger-oriented line planning in several key dimensions: (i) by jointly optimizing URT line planning and truck routing to serve both passenger and freight demands; (ii) by explicitly modeling intermodal routing decisions for freight and path choices for both passengers and freight; and (iii) by allocating resources across URT and truck services within a unified budget-constrained framework. The problem is formulated as a mixed-integer linear program that incorporates realistic operational and routing constraints. In particular, the model distinguishes between passengers' and freight's transfer penalties, accounts for heterogeneous transfer costs across modes (e.g., between URT lines and between URT and trucks), and explicitly models the facility requirements for freight intermodal transfers.

To solve this complex problem involving a vast number of potential passenger and freight routes, we developed a column generation algorithm combined with a novel two-phase diving procedure. The column generation framework iteratively identifies promising columns, while the two-phase diving algorithm ensures efficient convergence to integer solutions. A key innovation is the incorporation of a budget reservation strategy for the URT system, designed based on the structural properties of our model and integrated into the first-phase diving process. Notably, the proposed two-phase diving procedure is generalizable and can be readily applied to other problems involving two sets of binary or integer decision variables.

Extensive computational experiments yield several key takeaways. First, on the 5×5-grid network, our algorithm achieves high-quality solutions with an average optimality gap of 0.77%, while reducing computation time by 95.53% compared to GUROBI. Second, the approach also scales effectively to real-life instances, finding line plans that outperform the current operational one in terms of travel time of passengers and freight without requiring any increase in total operating cost. These results highlight the potential of our approach as a practical planning tool for urban intermodal transit systems.

From a practical standpoint, the findings from Rotterdam case studies highlight the value of integrated intermodal planning when adapting URT systems to new service requirements, such as the inclusion of freight alongside passenger transport. Among the evaluated strategies, a full redesign of the line plan shows the highest potential for reducing travel time of passengers and freight without requiring additional operational budget. Even when a complete redesign is not feasible, selectively expanding the network leads to considerable gains. The results further show that effective freight integration relies on reallocating budget across modes and redesigning the usage of existing infrastructure resources, with URT serving as the backbone of the intermodal system and truck services acting as a complementary mode. These findings suggest that a coordinated line planning approach is critical for ensuring both efficiency and adaptability in future urban intermodal transport systems.

Future research can focus on the following aspects. First, this paper provides a first proof-of-concept study by assuming that passenger and freight routing is jointly optimized with capacitated line planning in an intermodal transportation network from a system-optimal perspective. This assumption allows us to develop an integrated modeling framework and to capture the system-level interactions between capacitated line planning and passengers' and freight's routing decisions in this intermodal transportation network. It also enables us to quantify the potential benefits of coordinated intermodal line planning and co-modal mobility of passenger and freight under a system-optimal setting with the consideration of in-vehicle capacity. In practice, passengers' and/or freight's route choices may depend on their own travel costs under the realized line plan and/or train timetable. As a result, the realized flow distribution may differ from the system-optimal assignment assumed in the model, and the performance of the optimized line plans may deviate from the obtained objective values. A natural next step is therefore to incorporate route choice behavior into the proposed modeling framework.

In the literature, route choice behavior is typically modeled using approaches such as the logit model, the Wardrop user equilibrium model, and the shortest-path model. Van Lieshout and Dalmeijer (2025) recently showed that, although the logit model is the preferred choice for accurately capturing traveler behavior, its advantage over the shortest-path model diminishes as the planning focus shifts from route sets to line plans. This suggests that, for strategic planning problems such as line planning, relatively simple behavioral assumptions may already be sufficient to support good decisions. Nevertheless, once route choice behavior is explicitly considered together with capacity limitations, the interaction between line planning decisions and flow distribution becomes fundamentally different from that in the current system-optimal formulation. Extending the current framework to a bi-level optimization model would therefore be a meaningful direction for future research, where the upper-level model determines the line plan and service frequencies, and the lower-level model captures route choice behavior under the realized line plan.

A second interesting direction is to develop dedicated solution algorithms for the bi-level optimization model. This would not merely be an algorithmic extension of the current study, but a new methodological problem in its own right, since the introduction of route choice behavior would fundamentally change the structure of the model. Future work may focus on new heuristic or hybrid solution approaches tailored to this extended model.

A third promising direction is to explore how the Direct Link Network (DLN) proposed in Vermeir et al. (2021) and Aktaş et al. (2024) can be extended and adapted to the intermodal capacitated line planning problem studied in this paper. These studies have demonstrated the computational advantage of formulating models based on DLN for solving shortest-path problems, which is particularly relevant here because the lower-level problem in the above bi-level extension is expected to rely heavily on shortest-path-based route choice behavior. Therefore, it would be worthwhile to investigate whether a customized two-layer DLN can be constructed to replace the current two-layer CGN from the network representation level. Based on a tailored two-layer DLN, a new bi-level optimization model could then be developed, in which both the upper-level line planning decisions and the lower-level routing problem are built upon the new network structure. In this way, the computational benefits of DLN could be exploited more fundamentally, by accelerating the lower-level problem from the modeling level itself.

Lastly, line planning decisions are typically made for the long term. However, future demand may vary substantially over time. The evolution of passenger and freight demand over a long-term planning horizon is a highly complex stochastic process affected by many uncertain factors. Future research could therefore address the line planning problem in an intermodal network while explicitly accounting for such uncertainty.

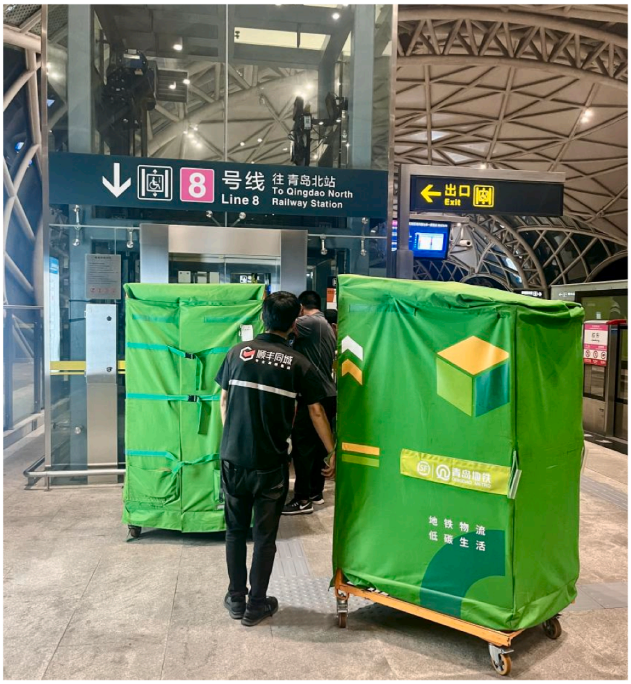
CRediT authorship contribution statement

Yahan Lu: Conceptualization, Methodology, Software, Formal analysis, Visualization, Writing – original draft, Writing – review & editing ; **Yuwen Peng:** Investigation, Methodology, Software, Writing – original draft; **Dongyang Xia:** Validation, Methodology, Formal analysis, Writing – review & editing, Supervision; **Patrick Stokkink:** Investigation, Writing – review & editing, Supervision; **Shadi Sharif Azadeh:** Investigation, Writing – review & editing, Supervision.

Data availability

The authors do not have permission to share data.

Appendix A. Examples of freight transfer operations within the urban rail transit system



(a) Qingdao (China Transportation News 2025)

(b) Hangzhou (China News Network 2024)

(c) Shenzhen (Vanke 2025)

Fig. A.1. Examples of freight transfer operations in urban rail transit systems. Figures (a) and (b) illustrate freight handling by logistics staff in the Qingdao metro (China Transportation News, 2025) and Hangzhou metro (China News Network, 2024), respectively, while Figure (c) illustrates freight transfer using an autonomous robot in the Shenzhen metro (Vanke, 2025).

Appendix B. A hybrid algorithm combining local search with GUROBI

In this section, we describe the Hybrid-LS benchmark used in the numerical experiments. We first introduce the initial solution generation, neighborhood structure, evaluation of the candidate solution, and stopping criteria. The overall framework is then summarized in Algorithm 2.

Initial solution. An initial solution is generated by a randomized greedy procedure that selects line-activation variables w_l under the budget constraint.

Neighborhood structure. Starting from the current solution, the local search heuristic explores three basic neighborhood moves: dropping a selected line, adding an unselected line, and swapping a selected line with an unselected one. To limit the computational effort, only a randomly sampled subset of neighboring solutions is evaluated at each iteration.

Evaluation of a candidate solution. In the computational experiments, the capacity constraints in (1f) and (1g) are often difficult to satisfy. Therefore, we relax these constraints by introducing nonnegative violation variables ξ_a and η_a, and penalize them in the objective function through large coefficients M_1 and M_2 for capacity violations. For each candidate solution, the line-activation decisions are fixed to the corresponding values $\hat{w}_l$, and Problem (B.1) is solved. The resulting penalized objective value is then used to evaluate the candidate solution.

$$\min \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^c} \sigma_p c_a x_a + \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u} \sigma_h c_a y_a + M_1 \sum_{a\in\mathcal{A}^t} \xi_a + M_2 \sum_{a\in\mathcal{A}^t\cup\mathcal{A}^u} \eta_a \tag{B.1a}$$

$$f_l^{min}\hat{w}_l \le f_l^p + f_l^h \le f_l^{max}\hat{w}_l \quad \forall l\in\mathcal{L}_m\cup\mathcal{L}_u, \tag{B.1b}$$

$$\sum_{l\in\mathcal{L}_m\cup\mathcal{L}_u} \left[b_l(f_l^p + f_l^h) + e_l\hat{w}_l\right] + \sum_{a\in\mathcal{A}^{ct}} e_a u_a \le B, \tag{B.1c}$$

$$y_a \le M_a u_a \quad \forall a\in\mathcal{A}^{ct}, \tag{B.1d}$$

$$x_a \le \sum_{l\in\mathcal{L}(a)} Q_l^p f_l^p + \xi_a \quad \forall a\in\mathcal{A}^t, \tag{B.1e}$$

$$y_a \le \sum_{l\in\mathcal{L}(a)} Q_l^h f_l^h + \eta_a \quad \forall a\in\mathcal{A}^t\cup\mathcal{A}^u, \tag{B.1f}$$

$$x_a = \sum_{r\in\mathcal{R}_a} z_r \quad a\in\mathcal{A}^t\cup\mathcal{A}^c, \tag{B.1g}$$

$$y_a = \sum_{r\in\mathcal{R}_a} m_r \quad \forall a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u, \tag{B.1h}$$

$$\sum_{r\in\mathcal{R}_a^p} z_r \le d_p f_{l(a)}^p \quad \forall a\in\mathcal{A}^t\cup\mathcal{A}^c, p\in\mathcal{P}, \tag{B.1i}$$

$$\sum_{r\in\mathcal{R}_a^h} m_r \le d_h f_{l(a)}^h \quad \forall a\in\mathcal{A}^t\cup\mathcal{A}^{cr}\cup\mathcal{A}^{ct}\cup\mathcal{A}^u, h\in\mathcal{H}, \tag{B.1j}$$

$$\sum_{r\in\mathcal{R}^p} z_r = d_p \quad \forall p\in P, \tag{B.1k}$$

$$\sum_{r\in\mathcal{R}^h} m_r = d_h \quad \forall h\in\mathcal{H}, \tag{B.1l}$$

$$u_a \in \{0,1\} \quad \forall a\in\mathcal{A}^{ct}, \tag{B.1m}$$

$$f_l^p, f_l^h \ge 0 \quad \forall l\in\mathcal{L}_m\cup\mathcal{L}_u \tag{B.1n}$$

$$x_a, y_a \ge 0 \quad \forall a\in\mathcal{A}, \tag{B.1o}$$

$$z_r, m_r \ge 0 \quad \forall r\in\mathcal{R}, \tag{B.1p}$$

$$\xi_a \ge 0 \quad \forall a\in\mathcal{A}^t, \tag{B.1q}$$

$$\eta_a \ge 0 \quad \forall a\in\mathcal{A}^t\cup\mathcal{A}^u. \tag{B.1r}$$

Stopping criteria. The hybrid algorithm updates the current best solution whenever an improving sampled neighbor is found. The search terminates when the total computation time exceeds a pre-given limit.

Algorithm 2 Hybrid algorithm combining local search and GUROBI.

Require: Line pool, model (1), model (B.1) passengers' candidate routes, freight's candidate routes, stopping criteria
Ensure: Best-found line plan

Generate an initial line-activation solution $\hat{w}_l$
Evaluate the initial solution by solving Problem (B.1) with fixed line-activation decisions $\hat{w}_l$
Set the initial solution as the current incumbent solution
while the stopping criteria are not met **do**
    Generate neighboring solutions using drop, add, and swap moves
    Randomly sample a subset of neighboring solutions
    Initialize the best sampled neighbor as null
    for each sampled neighbor **do**
        Fix its line-activation decisions $\hat{w}_l$
        Solve Problem (B.1) and compute its penalized objective value
        if the sampled neighbor is better than the current best sampled neighbor **then**
            Update the current best sampled neighbor
        end if
    end for
    if the best sampled neighbor improves upon the current incumbent solution **then**
        Update the current incumbent solution with the best sampled neighbor
    else
        break
    end if
end while
return the current incumbent solution

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