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Operational Planning for Multi-modal Multi-stakeholder Transportation Systems with Shared Capacities

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Abstract. This paper investigates the operational planning of a multi-modal multi-stakeholder transportation system, where a platform facilitates a sequence of decision-making for dynamically received shipment requests and service offers. At each decision point, the platform optimizes the selection of shipment requests and service offers, along with shipment-to-service assignments, shipment itineraries, and service time schedules. Each shipment may be assigned to multiple services for a multimodal itinerary, while each service can accommodate multiple shipments. The operational plan must consider the consolidation of shipment flows from different shippers, as well as the synchronization of operations at consolidation and transshipment terminals. Due to resource limitations, we consider the time-varying handling and storage capacities at terminals. This paper develops a mixed integer linear programming model to formulate the operational planning problem. To handle dynamic events, a rolling horizon framework is employed, allowing for the re-optimization of shipment-to-service assignments and shipment itineraries. To generate high-quality solutions quickly at each decision time, a preprocessing-based adaptive large neighborhood search algorithm is designed. Shipments' feasible itineraries are preprocessed to avoid route generation in each iteration of the algorithm. Extensive numerical experiments are conducted to evaluate the proposed approaches. A sensitivity analysis based on a real case study is also conducted to provide managerial insights for relevant stakeholders.

Keywords: Freight transportation systems; Multi-stakeholder; Multi-modal; Operational planning; Capacity sharing; Consolidation; Synchronization

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1 Introduction

Transportation and Logistics (TL) systems play a pivotal role in societal and economic development by facilitating the movement of freight across regional, national, and international networks. The increasing integration of multi-modal networks is transforming TL systems, enabling diverse mobility solutions, including trains, barges, trucks, planes, etc. Typically, freight transport systems are managed by multiple stakeholders that organize the movement of goods over part of the TL chains independently without information and capacity sharing, which causes empty travel, low capacity utilization, high transportation costs, delays in deliveries, and heavy carbon emissions. With the advancement of information and communication technologies and the rise of intelligent transportation systems, innovative TL business models, such as City Logistics (Crainic et al., 2009; Taniguchi et al., 2016), Physical Internet (Crainic and Montreuil, 2016; Pan et al., 2021), and Synchromodality (Giusti et al., 2019; Sakti et al., 2023; Zhang et al., 2025), are increasingly proposed to tackle these challenges. The common feature of these systems is to provide efficient, effective, and sustainable services through the coordination and cooperation of multiple stakeholders, consolidating shipment flows, and synchronizing operations in integrated multi-modal networks driven by intelligent decision-making platforms. Given the complexity of interactions in such systems, comprehensive planning is required at the strategic, tactical, and operational levels. However, while existing literature extensively explores strategic and tactical planning, research on operational-level planning remains relatively limited (Crainic et al., 2021).

In this paper, we investigate the operational planning problem of a *multi-modal multi-stakeholder* transportation system, with Figure 1 illustrating its business, communication, and decision-making structure. On the one side of the system, many *shippers* (e.g., producers, wholesalers, and distributors) make *shipment requests* for cost and time-efficient transportation of their product loads. Each shipment needs to be transported from a given shipper location to a consignee location within given time windows. On the other side, many *carriers* (e.g., barge, train, and truck carriers) make *service offers* for transportation and request profitable loads. Each service provides a limited transport capacity on a specific route with or without time schedules. In the middle, an *Intelligent Decision Support Platform* (IDSP) delivers automated planning and operations optimization to profitably and simultaneously meet the needs of both categories of stakeholders. The recent developments in information technologies such as cloud computing and Internet of Things allow real-time monitoring of shipments' and vehicles' status and information sharing among stakeholders, which facilitates the adoption of such a platform in practice.

On the demand side, the transportation system operates under a dual mechanism of contract-based commitments and spot-market transactions. Contract shipment requests, governed by long-term agreements negotiated between shippers and the IDSP at the tactical planning level (Taherkhani et al., 2022), must be fully satisfied. In contrast, spot shipment requests arise dynamically due to fluctuating demand, urgent needs, or unexpected shortages. Selection decisions need to be made for spot requests depending

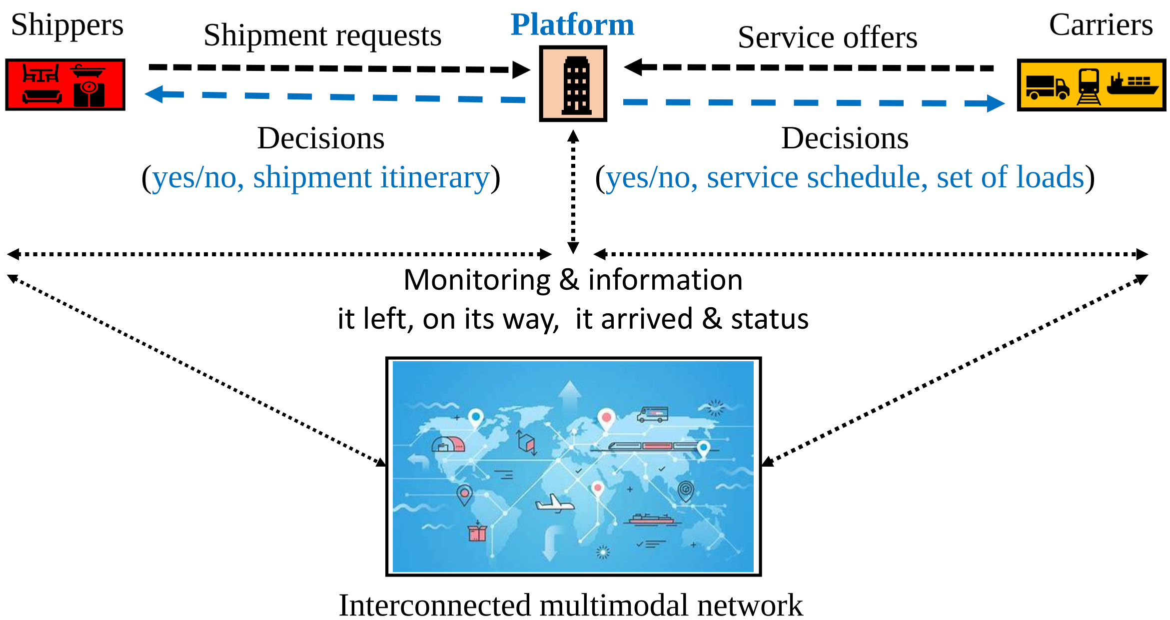


Figure 1: Business, communication, and decision structure of the transportation system.

on their profitability and the available service capacities. For contract and selected spot requests, the IDSP must determine shipment itineraries that specify the sequence of services used and the operations to be performed in time and space (i.e., when and where the shipments will be picked up, unloaded, temporally stored, loaded, and delivered). Shipments' itineraries are allowed to be adjusted until pickup, offering opportunities to optimize service capacity utilization and improve system performance. However, this flexibility also introduces operational planning complexities, as the IDSP must continuously optimize newly received requests and re-optimize active ones. Advanced technologies, such as real-time tracking, play a crucial role in enabling responsive decision-making under these dynamic conditions.

On the supply side, carriers offer both contract and spot services. Contract offers reflect long-term commitments, providing stability for both carriers and shippers. These contracts are often negotiated annually or quarterly for predictable freight volumes, and the IDSP accept them in full. Conversely, spot offers represent short-term capacity options. The IDSP selectively accepts spot offers based on their potential to efficiently fulfill shipment requests. For both contract and selected spot offers, the IDSP must determine the shipment-to-service assignments, indicating the loads to be transported on each segment of the service route. The services from both contract and spot carriers are categorized based on their time attributes: time-scheduled and time-flexible. Time-scheduled services have predefined timetables at origins, destinations, and intermediate stops. In contrast, time-flexible services are defined by departure time windows at origins. As such, the IDSP needs to determine the time schedules for time-flexible services.

While contract requests and offers arrive at the platform at planned time instants, spot requests and offers arise at any moment. In both cases, the information is kept until the next decision time of the platform. The IDSP responds to the streams of new information through a sequence of decisions. Decisions are made at application-specific time moments, e.g., when a new request or offer arrives, or according to a predefined schedule (e.g., every 15 minutes or once an hour), based on the available information at that time. At each decision point, the platform optimizes the selection of shipment requests and service offers, along with shipment-to-service assignments, shipment itineraries, and service time schedules. The operational transportation planning takes into account the collaboration among multiple stakeholders through capacity sharing, the consolidation of shipments from different shippers into the same vehicles for their complete or partial journeys, and the time and spatial synchronization of activities at consolidation and transshipment terminals. Due to resource limitations and the presence of dynamic tasks, the handling and storage capacities at terminals are limited and vary over time.

In the literature, there is a wide range of studies on tactical planning for multi-modal multi-stakeholder transportation systems (Crainic, 2008; Anand et al., 2015; Crainic et al., 2016; Dolati Neghabadi et al., 2018; Crainic et al., 2021; Taherkhani et al., 2022; Giusti et al., 2023; Crainic, 2024). Only a few studies in the field of synchromodality address the operational planning problem (Li et al., 2015; Qu et al., 2019; Guo et al., 2020; Rivera and Mes, 2022; Zhang et al., 2023; Larsen et al., 2023; Filom and Razavi, 2025). However, these studies focus mainly on dynamic shipment requests, assuming that all services are contracted and known in advance.

The main contributions of this paper are summarized as follows: (i) We develop a mathematical model that integrates decisions regarding the selection of shipment requests and service offers, along with decisions on shipment-to-service assignments, shipment itineraries, and service time schedules for multi-modal multi-stakeholder transportation systems at the operational level. (ii) We define a rolling horizon framework to study the model behavior and to control the implementation and re-optimization of decisions when new requests and offers are received. (iii) To generate high-quality solutions rapidly at each decision epoch, a preprocessing-based adaptive large neighborhood search (P-ALNS) algorithm is designed to address the optimization problem. (iv) We conduct extensive numerical experiments to evaluate the performance of the rolling horizon approach in comparison to a first-come-first-serve approach that does not consider re-optimization, and assess the efficiency of the P-ALNS algorithm in terms of computation time and solution quality in comparison to the CPLEX solver; (v) Finally, we design a real case study to evaluate the impact of scenario parameters, providing managerial insights for relevant stakeholders.

The remainder of this paper is organized as follows: Section 2 describes the operational planning problem. Section 3 reviews related works. Section 4 formulates the mathematical model. Section 5 presents the rolling horizon framework. Section 6 designs the heuristic algorithm. The experimental settings and results are provided in Section 7. Section 8 concludes and gives future research directions.

2 Problem Setting

In this section, we present the setting and main components of the multi-modal multi-stakeholder transportation system, including the physical network (Section 2.1), the shipment requests (Section 2.2), the service offers (Section 2.3), and the operational decisions of the IDSP (Section 2.4).

2.1 Physical network

The problem setting is defined on a transportation network as illustrated in Figure 2. Activities occur between several *service zones*, which are represented by the large circles in the figure. These zones can be urban areas or any other geographically, administratively or commercially relevant area. In this paper, we do not address the vehicle routing problem within zones; instead, we focus on interurban transport planning by aggregating demands in the same zone.

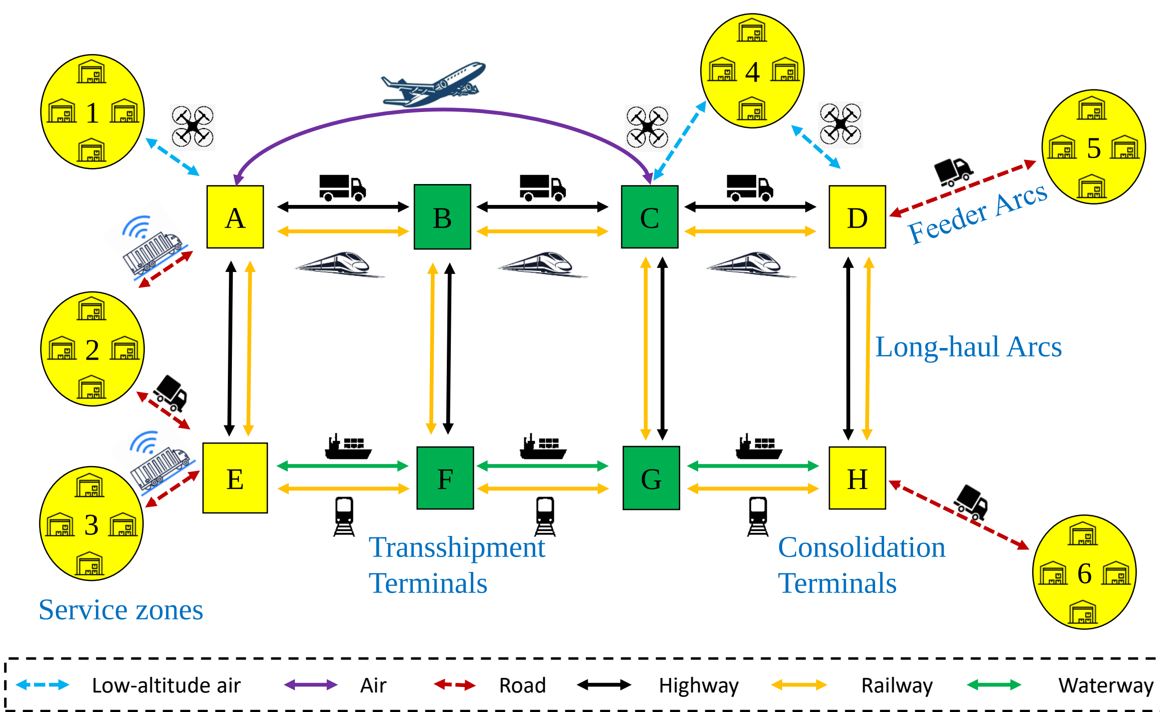


Figure 2: An illustrative example of an interconnected multi-modal network.

Terminals, squares in Figure 2, may be either owned, managed, or only used by the IDSP to perform required activities (e.g., warehousing or crossdock transferring). Two terminal types are considered in this paper: consolidation and transshipment. *Consolidation terminals*, the yellow (light) square in Figure 2, are generally "close" to at least a zone and performs the complete gamut of services, in particular, 1) first-mile service to the zones, receiving picked up shipments within the zones delivered by appropriate carriers and vehicles; 2) crossdock transfer of shipments between vehicles; 3) warehousing shipments temporarily, waiting for the next transportation; 4) last-mile service to the zones, preparing shipments for the distribution to the respective consignees. Transshipment terminals, green (dark) squares in Figure 2, perform services of types 2 and 3 only. The transfer and warehousing activities at both types of terminals are limited due to the limited number of available handling equipment and storage space. Notice that more than one terminal may service a single zone, particularly for large zones with important populations, industrial density, or access to several major modal infrastructures. A large city may thus have several terminals linking it to different geographical regions, or be serviced simultaneously by a maritime or river port, and one or several rail yards.

The nodes representing zones and terminals make up the nodes of the physical network. The arcs of the network represent physical or conceptual modal connections between these nodes. The former represent land-based infrastructure, e.g., roads, and railways, while the latter stand for maritime and air connections. Each mode is represented by a different arc in the physical network representation, the mode being an arc attribute. The physical network is thus made up of parallel modal arcs linking two nodes. In this paper, we consider two types of arcs: long-haul and feeder. The solid lines of Figure 2 represent the *long-haul arcs*. Dashed lines in the figure represent the *feeder arcs*, linking between terminals and zones.

2.2 Shipment requests

Shippers are the customers and hence the demand side of the transportation system. They make shipment requests to the IDSP for their loads. Each shipment request is defined by the following attributes:

- **Origin:** the service zone of the shipper's facility.
- **Destination:** the service zone of the consignee's facility.
- **Volume:** the number of packages. Shipments are assumed to be packaged in a "loading unit", which may be a container, a trailer, or a swap box. We assume a single product is transported in the system. The motivation for this choice comes from the Physical Internet idea of multi-usage smart boxes that can be assembled for grouped shipping even when holding different products; such boxes are referred to as π - containers (Montreuil et al., 2015).
- **Announce time:** the time when the platform receives the request. Contract requests arrive to the platform at planned time instants, spot requests arrive at any moment in time.
- **Pickup time window:** the interval when the shipment is available for pickup.

- **Target delivery time window:** the preferred time interval of delivery.
- **Early and late delivery time windows:** permissible delivery intervals outside of the target window, subject to penalty costs.
- **Fare:** the revenue earned by the IDSP to take care of the shipment, which is dependent on the delivery time, the volume, and the distance between origin and destination of the shipment.
- **Early and late delivery penalties:** the penalties the IDSP has to pay to the shipper for delivering the shipment outside of the target delivery time window.

2.3 Service offers

Carriers are the supply side of the multi-modal multi-stakeholder transportation system, operating vehicle fleets of various modes. We use a general definition of vehicle. It may be a physical vehicle, e.g., a truck, a plane, a rail car, etc, or be space on a ship or train. The IDSP does not manage the carrier fleets and operations. Carriers make service offers to the IDSP for providing transportation capacities of various modes under *multi-segment services* with intermediate stops (e.g., less-than truckload trucks, trains and barges) or *single segment services* without intermediate stops (e.g., full truckload trucks and drones). Each segment is an arc or a path of the physical network with an origin, a destination, mode and capacity limitations. These services can be further divided into two categories: *time-scheduled services* with predefined timetables, and *time-flexible services* with departure time windows, as illustrated in Figure 3.

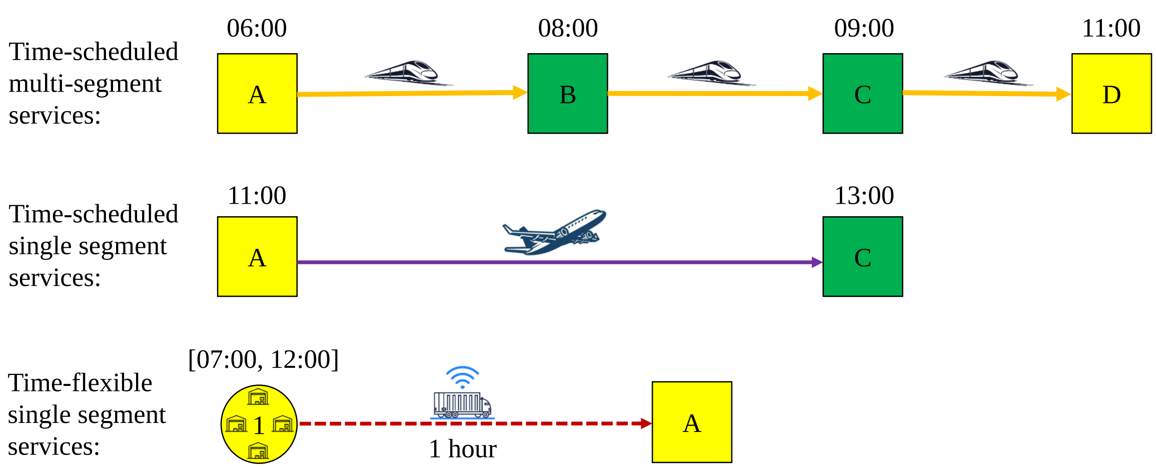


Figure 3: An illustration of different service types in multi-modal transportation.

We follow the pattern used for shipment requests, the time and economic attributes of each service offer are listed as follows:

- **Announce time:** the time when the platform receives the offer. Contract offers arrive to the platform at planned time instants, spot offers arise at any moment in time.
- **Time schedule:** each scheduled service has a timetable indicating the service departure and arrival times where it originates, stops, and terminates, i.e., each service segment has a departure time from the segment's origin and an arrival time at the segment's destination.
- **Departure time window:** the interval within which the time-flexible service is allowed to depart at its origin.
- **Travel time:** each service segment has a travel time, which is based either on general speed for the distance or corresponds to the given schedule.
- **Fixed cost:** the cost paid by the IDSP to select and use the service.
- **Variable transportation cost:** the unit cost of each segment for transportation.

2.4 Operational decisions of the IDSP

Orchestrator, the decision-maker of the platform, could be a third/fourth/fifth logistics service provider (3/4/5PL), or a neutral system manager that has an arm-length distance from all parties involved, enforcing the confidentiality of the information provided by the stakeholders involved, and coordinating, managing, and optimizing the system according to the collaboration principles. The operational planning goal of the IDSP is to optimize the selection of shipment requests and service offers as well as shipment-to-service assignments based on the known information at each decision point. At any moment in time, the known information encompasses: 1) contracted shipment requests and service offers; 2) spot shipment requests and service offers received in the past; 3) spot shipment requests and service offers received 'now'; and 4) decisions made in the past.

Spot shipment requests and service offers arrive at the platform dynamically. The platform responds to the streams of new information through a sequence of decisions. These decisions are made at *discrete* time points. In this case, time is represented by a sequence of *time instants*. Then, given a time instant t, the associated (time) period t represents the duration from instant $t-1$ to its successor instant t. At any given instant t, decisions are made based exclusively on the known information available "now", without taking into account what might happen afterwards.

At decision time t, the IDSP decides to:

- Accept or reject spot requests and offers received during time period t;
- Assign the shipments from contract and accepted spot requests that haven't been picked up to service segments of contract and selected spot offers;

- Schedule departure times for time-flexible services;
- Generate shipment itineraries for contract and accepted spot requests, which indicate the sequence of assigned service segments and the operations to be performed in time and space, as illustrated in Figure 4.

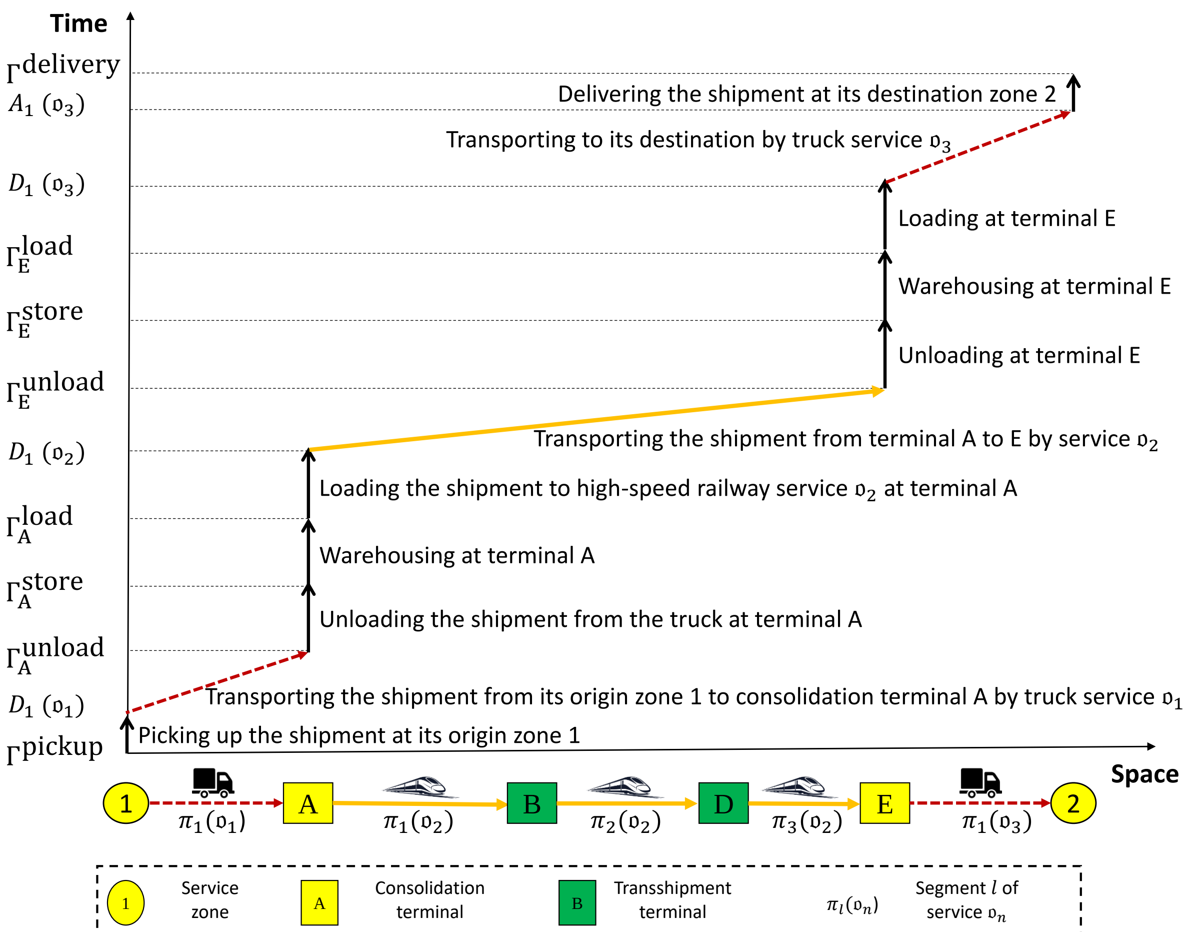


Figure 4: Example of a shipment itinerary in time and space.

3 Related Works

We review relevant literature to the multi-modal multi-stakeholder transportation systems. In particular, we focus on two themes: city logistics systems and synchromodal transportation systems.

3.1 City logistics systems

There are many definitions of city logistics, but common to all is that city logistics is about finding efficient and effective ways to transport freight in urban areas while taking into account the negative effects on congestion, safety, and environment (Crainic, 2008). It emphasizes the coordination and capacity sharing among stakeholders, consolidation of shipment flows, and synchronization of operations at satellite locations (Crainic et al., 2009). City logistics systems are complex TL systems with inherent interactions among multiple stakeholders. Advanced operations research methods are required to plan and manage such complex systems. Three planning levels are fund in city logistics systems: strategic, tactical, and operational(Crainic, 2024). Strategical planning addresses long-term design and deployment horizons (Anderluh et al., 2020). Tactical planning aims to select and schedule services, together with the itineraries used to move fright flows from origins to destinations in the resulting service network, to ensure the system is efficient and profitable (Savelsbergh and Woensel, 2016). Scheduled Service Network Design (SSND) is a widely adopted methodology to address tactical planning issues in city logistics systems (Crainic et al., 2009; Fontaine et al., 2021; Taherkhani et al., 2022). Operational planning shares similar considerations with tactical planning, yet focuses on a shorter time horizon with granular demand and supply data. At this level, the primary emphasis lies in dynamically optimizing vehicle routes and shipment schedules by incorporating real-time information (Marinelli et al., 2018; Firdausiyah et al., 2019).

Researchers have explored city logistics systems from various perspectives in the literature, including: (i) multi-modal transportation systems (Crainic et al., 2009; Savelsbergh and Woensel, 2016; Fontaine et al., 2021), where freight is transported using diverse vehicles that transfer at designated handover locations, considering the synchronization of activities in time and space; (ii) the integration of freight into public transportation (Masson et al., 2017; Ghilas et al., 2018; Fontaine et al., 2021; Elbert and Rentschler, 2022), which faces challenges such as predefined routes, time schedules and the capacity limitations of transportation services; and (iii) revenue management (Taherkhani et al., 2022), which involves shipper categories, demand classification, penalty costs for fulfilling demand outside specific time windows, and offering services in bundles.

3.2 Synchromodal transportation systems

Synchromodality is an emerging and attractive concept in intermodal transportation. It aims to reduce costs, emissions, and delivery times while maintaining the quality of supply chain service through smart utilization of available resources and synchronization of transport flows (Giusti et al., 2019; Sakti et al., 2023; Zhang et al., 2025). In synchromodal transportation, dynamic updating of transport plans in multimodal networks based on real-time information plays a key role in differentiating synchromodality from other paradigms. The most common dynamic events are the arrival of new shipment requests, but travel times and transfer capacities are possible dynamics as well.

In the literature, most of the studies address synchromodality at the operational planning level (Zhang et al., 2025). Li et al. (2015) presented a receding horizon intermodal container flow control approach to deal with the dynamic transport demands and dynamic traffic conditions in hinterland transportation. van Riessen et al. (2016) designed a decision tree to derive real-time decision rules for suitable allocation of shipment requests to services. Qu et al. (2019) proposed a re-planning framework to re-plan shipment routes and service schedules when uncertainties cause deviations from the original plan. Guo et al. (2020) developed a rolling horizon approach to handle shipment requests that arrive dynamically in a synchromodal matching platform for hinterland transportation. Rivera and Mes (2022) proposed an algorithm based on approximate dynamic programming to tackle the curse of dimensionality of a Markov decision process model for anticipatory freight selection in intermodal long-haul round-trips. Larsen et al. (2023) developed a real-time co-planning framework for decentralized synchromodal transport with two decision makers. Zhang et al. (2023) developed an online deep reinforcement learning approach to re-plan vehicle routes and shipment itineraries in response to service time uncertainties. Labarthe et al. (2024) proposed a model-based decision support approach for on-demand freight delivery services in urban areas enabled by synchromodality and synergy in passenger and freight mobility. Filom and Razavi (2025) presented a learning-based robust optimization framework for synchromodal freight transportation to drive data-driven explainable decisions.

3.3 Summary

Table 1 compares the formulation characteristics and methodologies of related literature. The analysis reveals that current research in transportation and logistics planning exhibits several limitations that hinder its applicability to real-world operational challenges. First, many existing models oversimplify temporal constraints by relying on fixed time points rather than more realistic pickup and delivery time windows, which are critical for practical logistics operations. Additionally, while some studies address either scheduled or flexible transportation services, few integrate both within a unified framework, despite their coexistence in actual supply chains. Besides, most prior work focuses on tactical planning, neglecting the need for real-time optimization in response to dynamically arriving shipment requests and service offers. This oversight limits the ability to account for time-varying system states, such as fluctuating transshipment capacities and storage constraints, which are essential for operational efficiency. Furthermore, the field lacks specialized algorithms that balance computational tractability with solution quality in dynamic settings.

This paper extends the literature by: (1) developing a comprehensive optimization model that integrates shipment request selection, service offer selection, shipment-to-service assignment, and service time scheduling under realistic temporal constraints at the operational level; (2) integrating heterogeneous transport services, including time-scheduled services (e.g., trains, barges) and time-flexible options (e.g., trucks, drones);

and (3) introducing tailored heuristic methods to ensure scalability and responsiveness in dynamic environments. These advances enhance the model's applicability to real logistics operations while bridging critical theoretical and practical gaps in the field.

Table 1: The formulation characteristics and methodologies of relevant literature.

Articles	Formulation characteristics							Methodologies	
	Network	Decisions[1]	Time windows	Service type	Time schedules	Transshipment capacity limitations	Dynamic events	Dynamic approach[2]	Optimization algorithm[3]
City logistics systems									
Crainic et al. (2009)	Urban	ASO, SSA	Delivery	Multi-segment	Scheduled	Time-constant			HDA
Ghilas et al. (2018)	Urban	VR, SR	Pickup, delivery	Single segment services, a fleet of vehicles	Scheduled, flexible	Unlimited			BP
Fontaine et al. (2021)	Urban	ASO, SSA	Time points	Multi-segment	Time-scheduled	Time-constant			BD
Taherkhani et al. (2022)	General	ASR, ASO, SSA, SR	Time points	Multi-segment	Time-scheduled	Time-varying			CPLEX solver
Synchromodal transportation systems									
Qu et al. (2019)	Inland	SR, SS	Time points	Multi-segment	Scheduled	Unlimited	Regular disturbances	RPF	CPLEX solver
Guo et al. (2020)	Inland	SSA, SR, SS	Time points	Single segment	Scheduled, flexible	Unlimited	Shipment requests	RHA	HA
Guo et al. (2021)	Global	ASR, SSA, SR, SS	Time points	Single segment	Scheduled, flexible	Unlimited	Shipment requests, travel times	RHA	HA
Rivera and Mes (2022)	Inland	SR	Time points	Single segment	Scheduled	Unlimited	Containers	MDP	ADP
Larsen et al. (2023)	Inland	SSA, SR, VR, SS	Time points	Single segment	Scheduled, flexible	Unlimited	Shipment requests	RHA	HA
Zhang et al. (2023)	Inland	SSA, SR, VR	Pickup, delivery	A fleet of vehicles	Time windows	Unlimited	Service times	DRL	ALNS
Labarthe et al. (2024)	Urban	SR	Time points	Multi-segment, single segment	Scheduled	Time-constant			HA
Filom and Razavi (2025)	Inland	ASR, SSA, SR	Time points	Single segment	Scheduled	Unlimited	Shipment requests	LROF	HA
This paper	General	ASR, ASO, SSA, SR, SS	Pickup, delivery	Multi-segment, single segment	Scheduled, flexible	Time-varying	Shipment requests, service offers	RHA	P-ALNS

[1] SR: Shipment routing; VR: Vehicle routing; SS: Service scheduling; SSA: Shipment-to-service assignment; ASR: Acceptance of shipment requests; ASO: Acceptance of service offers

[2] RPF: Re-planning framework; RHA: Rolling horizon approach; MDP: Markov decision process; DRL: Deep reinforcement learning; LROF: Learning-based robust optimization framework

[3] HDA: hierarchical Decomposition Approach; BP: Branch-and-price; BD: Benders decomposition; HA: Heuristic algorithm; ADP: Approximate dynamic programming; ALNS: Adaptive large neighborhood search; P-ALNS: Preprocessing-based adaptive large neighborhood search

4 Notation and Mathematical Formulations

We first define the notation and then present the mathematical formulation developed for the operational planning problem.

4.1 Notation

We first define the notation of service zones, consolidation and transshipment terminals, shipment requests, and service offers. We then define the system states and active events at any decision time.

Let $\mathcal{Z}$ stand for the set of service zones where to pick up or deliver shipments. For zone $z \in \mathcal{Z}$, define:

- t^{P}_{zm}: Pickup/delivery time with mode $m \in \mathcal{M}$;
- c^{P}_{zm}: Pickup/delivery cost per volume with mode $m \in \mathcal{M}$.

Let Θ be the set of consolidation and transshipment terminals. For terminal $i \in \Theta$, define:

- $t^{\mathtt{L}}_{im}$: Loading/unloading time for mode $m \in \mathcal{M}$;
- $c^{\mathtt{L}}_{im}$: Loading/unloading cost per volume for mode $m \in \mathcal{M}$;
- $c^{\mathtt{W}}_{i}$: Storage cost per volume per time unit;
- $u^{\mathtt{L}}_{i}$: Maximum loading and unloading capacity;
- $u^{\mathtt{W}}_{i}$: Maximum storage capacity.

Let $\mathfrak{R}$ be the set of shipment requests divided into two groups: contractual requests $\mathfrak{R}^{\text{contract}}$ and spot requests $\mathfrak{R}^{\text{spot}}$. For request $\mathfrak{r} \in \mathfrak{R}$, define:

- $o(\mathfrak{r})$: Origin, $o(\mathfrak{r}) \in \mathcal{Z}$, the shipper facility within a service zone;
- $d(\mathfrak{r})$: Destination, $d(\mathfrak{r}) \in \mathcal{Z}$, the consignee facility within a service zone;
- $u(\mathfrak{r})$: Shipment volume;
- $\alpha^{\mathtt{A}}(\mathfrak{r})$: Announce time, the time when the platform receives the request;
- $[\alpha^{\mathtt{R}}(\mathfrak{r}), \beta^{\mathtt{R}}(\mathfrak{r})]$: Pickup time window;
- $[\alpha^{\mathtt{E}}(\mathfrak{r}), \beta^{\mathtt{E}}(\mathfrak{r})]$: Early delivery time window;

- $[\alpha^{\mathtt{L}}(\mathfrak{r}), \beta^{\mathtt{L}}(\mathfrak{r})]$: Late delivery time window;
- $[\beta^{\mathtt{E}}(\mathfrak{r}), \alpha^{\mathtt{L}}(\mathfrak{r})]$: Target delivery time window;
- $\rho(\mathfrak{r})$: Fare, the revenue received from the shipper if request $\mathfrak{r}$ is accepted;
- $\psi^{\mathtt{E}}(\mathfrak{r})$: Early delivery penalty per time unit;
- $\psi^{\mathtt{L}}(\mathfrak{r})$: Late delivery penalty per time unit.

Let $\mathfrak{O}$ be the set of service offers, divided into two groups: contractual offers $\mathfrak{O}^{\text{contract}}$ and spot offers $\mathfrak{O}^{\text{spot}}$. For service offer $\mathfrak{o} \in \mathfrak{O}$, define:

- $\text{type}(\mathfrak{o})$: Service type, 1 if $\mathfrak{o}$ is a time-scheduled service, 0 otherwise;
- $\Pi(\mathfrak{o})$: Route of service $\mathfrak{o}$, i.e., the sequence of service segments, $\Pi(\mathfrak{o}) = \{\pi_l(\mathfrak{o}) \mid l = 1, \ldots, |\Pi(\mathfrak{o})|\}$; for multi-segment services, $|\Pi(\mathfrak{o})| \geq 2$; for single segment services, $|\Pi(\mathfrak{o})| = 1$;
- $o_l(\mathfrak{o})$: Origin of segment $\pi_l(\mathfrak{o})$, $l = 1, \ldots, |\Pi(\mathfrak{o})|$;
- $d_l(\mathfrak{o})$: Destination of segment $\pi_l(\mathfrak{o})$, $l = 1, \ldots, |\Pi(\mathfrak{o})|$;
- $m_l(\mathfrak{o})$: Mode of segment $\pi_l(\mathfrak{o})$, $l = 1, \ldots, |\Pi(\mathfrak{o})|$;
- $u_l(\mathfrak{o})$: Maximum capacity of segment $\pi_l(\mathfrak{o})$, $l = 1, \ldots, |\Pi(\mathfrak{o})|$;
- $\alpha^{\mathtt{A}}(\mathfrak{o})$: Announce time, the time when the platform receives the offer;
- $[\alpha_l^{\mathtt{R}}(\mathfrak{o}), \beta_l^{\mathtt{R}}(\mathfrak{o})]$: Departure time window of segment $\pi_l(\mathfrak{o})$ at its origin $o_l(\mathfrak{o})$; for time scheduled service offer $\mathfrak{o} \in \{\mathfrak{O} | \text{type}(\mathfrak{o}) = 1\}$, $\alpha_l^{\mathtt{R}}(\mathfrak{o}) = \beta_l^{\mathtt{R}}(\mathfrak{o})$;
- $\tau_l(\mathfrak{o})$: Travel time of segment $\pi_l(\mathfrak{o})$, $l = 1, \ldots, |\Pi(\mathfrak{o})|$;
- $f(\mathfrak{o})$: Fixed cost of service $\mathfrak{o}$;
- $c_l(\mathfrak{o})$: Variable transportation cost of segment $\pi_l(\mathfrak{o})$ per volume, $l = 1, \ldots, |\Pi(\mathfrak{o})|$.

The evolution of the platform is indexed by a discrete time variable t. We denote time period t as the duration from time $t-1$ to time t. Requests and offers received during time period t will be kept until decision time t. Notably, offers received 'now' involve departures and arrivals scheduled in future time periods. Requests received 'now' also specify pickup and delivery times in the future. We define T as the maximum allowable duration (e.g., one day or one week) for shipment delivery, which consequently determines the allowable storage and handling duration at terminals.

At any time t, decisions are made based on the current system state. The system state consists of the status of requests, offers, and terminals:

- Let binary parameter $\phi_{\mathfrak{r}}$ record request $\mathfrak{r}$'s decision status: 1 if request $\mathfrak{r} \in \mathfrak{R}$ is accepted, 0 otherwise; let binary parameter $\psi_{\mathfrak{r}}$ record request $\mathfrak{r}$'s operation status: 1 if request $\mathfrak{r} \in \mathfrak{R}$ is picked up from its origin zone, 0 otherwise.

- Let binary parameter $\phi_{\mathfrak{o}}$ record offer $\mathfrak{o}$'s decision status: 1 if offer $\mathfrak{o} \in \mathfrak{O}$ is accepted, 0 otherwise. We denote $u_l^t(\mathfrak{o})$ as the residual transport capacity of segment $\pi_l(\mathfrak{o})$ at decision time t, $\mathfrak{o} \in \mathfrak{O}, l \in \{1, ..., |\Pi(\mathfrak{o})|\}$.

- We denote $u_i^{\mathrm{L},t,p}$ the residual loading and unloading capacity at terminal $i \in \Theta$ during time period $p \in \{t+1, ..., t+T\}$ at decision time t; let $u_i^{\mathrm{W},t,p}$ be the residual storage capacity at terminal $i \in \Theta$ during time period p at decision time t.

At any time t, decisions are made for active requests and offers. The active request set consists of two groups: contract and accepted spot requests which haven't been picked up and new requests. Let $\dot{\mathfrak{R}}^t$ be the set of contract and accepted spot requests which haven't been picked up, $\dot{\mathfrak{R}}^t = \{\mathfrak{r} \in \mathfrak{R} : \alpha^{\mathtt{A}}(\mathfrak{r}) \leq t-1, \phi_{\mathfrak{r}} = 1, \psi_{\mathfrak{r}} = 0\}$; let $\tilde{\mathfrak{R}}^t$ be the set of new requests received during time period t, $\tilde{\mathfrak{R}}^t = \{\mathfrak{r} \in \mathfrak{R}^{\mathrm{spot}} : t-1 < \alpha^{\mathtt{A}}(\mathfrak{r}) \leq t, \phi_{\mathfrak{r}} = 0, \psi_{\mathfrak{r}} = 0\}$. We denote active requests $\mathfrak{R}^t = \dot{\mathfrak{R}}^t \cup \tilde{\mathfrak{R}}^t$.

At time t, the active offer set consists of two groups: contract and accepted spot offers and new offers. Let $\dot{\mathfrak{O}}^t$ represent the set of contract and accepted spot offers, $\dot{\mathfrak{O}}^t = \{\mathfrak{o} \in \mathfrak{O} : \alpha^{\mathtt{A}}(\mathfrak{o}) \leq t-1, \phi_{\mathfrak{o}} = 1\}$; let $\tilde{\mathfrak{O}}^t$ be the set of new offers received during time period t, $\tilde{\mathfrak{O}}^t = \{\mathfrak{o} \in \mathfrak{O}^{\mathrm{spot}} : t-1 < \alpha^{\mathtt{A}}(\mathfrak{o}) \leq t, \phi_{\mathfrak{o}} = 0\}$. We denote active offers $\mathfrak{O}^t = \dot{\mathfrak{O}}^t \cup \tilde{\mathfrak{O}}^t$.

4.2 Mathematical formulations

We propose a mixed integer linear programming model to formulate the operational planning problem at each decision time. At time t, the platform decides to accept or reject newly received shipment requests in $\tilde{\mathfrak{R}}^t$ and offers in $\tilde{\mathfrak{O}}^t$, and decides on shipment-to-service assignments, service schedules, and shipment itineraries for active requests in $\mathfrak{R}^t$ and offers in $\mathfrak{O}^t$:

- *Acceptance decisions.* Let $y_{\mathfrak{r}}^t$ be the binary variable, $y_{\mathfrak{r}}^t = 1$ if request $\mathfrak{r} \in \tilde{\mathfrak{R}}^t$ is accepted at time t, 0 otherwise; let $y_{\mathfrak{o}}^t$ be the binary variable, $y_{\mathfrak{o}}^t = 1$ if offer $\mathfrak{o} \in \tilde{\mathfrak{O}}^t$ is accepted at time t, 0 otherwise.

- *Assignment decisions.* Let $x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t$ be the binary variable, $x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t = 1$ if shipment $\mathfrak{r}$ is assigned to segment $\pi_l(\mathfrak{o})$ at time t, 0 otherwise, $\mathfrak{r} \in \mathfrak{R}^t$, $\mathfrak{o} \in \mathfrak{O}^t$, $l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}$; let $z_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')}^t$ be the binary variable, $z_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')}^t = 1$ if shipment $\mathfrak{r}$ will be transferred at terminal $i \in \Theta$ between segment $\pi_l(\mathfrak{o})$ and segment $\pi_{l'}(\mathfrak{o}')$ decided at time t, 0 otherwise.

- *Service schedules.* For service $\mathfrak{o} \in \{\mathfrak{O}^t|\text{type}(\mathfrak{o}) = 0\}, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o})$, let $D_l(\mathfrak{o})$ be the departure time of segment $\pi_l(\mathfrak{o})$ at its origin $o_l(\mathfrak{o})$; let $A_l(\mathfrak{o})$ be the arrival time of segment $\pi_l(\mathfrak{o})$ at its destination $d_l(\mathfrak{o})$.

- *Shipment itineraries.* Given the assigned service segments and service schedules, shipment itineraries can be calculated. Let $\Gamma_{\mathfrak{r}}^{\text{pickup}}$ represent the planned time that shipment $\mathfrak{r} \in \mathfrak{R}^t$ will be picked up at its origin; let $\Gamma_{\mathfrak{r}}^{\text{delivery}}$ be the planned time that shipment $\mathfrak{r}$ will be delivered at its destination; let $\Gamma_{\mathfrak{r}i}^{\text{unload}}$ be the planned time that shipment $\mathfrak{r}$ will start unloading at terminal $i \in \Theta$; let $\Gamma_{\mathfrak{r}i}^{\text{store}}$ be the planned time that shipment $\mathfrak{r}$ will start storage at terminal i; let $w_{\mathfrak{r}i}$ be the storage time of shipment $\mathfrak{r}$ at terminal i; let $\Gamma_{\mathfrak{r}i}^{\text{load}}$ be the planned time that shipment $\mathfrak{r}$ will start loading at terminal i;let $\Gamma_{\mathfrak{r}i}^{\text{depart}}$ be the planned time that shipment $\mathfrak{r}$ will depart from terminal i. Let $g_{\mathfrak{r}i}^{\text{unload},p}$ be the binary variable which equals 1 if shipment $\mathfrak{r}$ will be unloaded at terminal i during time period $p \in \{t+1, ..., t+T\}$; let $g_{\mathfrak{r}i}^{\text{store},p}$ be the binary variable which equals 1 if shipment $\mathfrak{r}$ will be stored at terminal i during time period $p \in \{t+1, ..., t+T\}$; let $g_{\mathfrak{r}i}^{\text{load},p}$ be the binary variable which equals 1 if shipment $\mathfrak{r}$ will be loaded at terminal i during time period $p \in \{t+1, ..., t+T\}$.

The objective function at each decision time aims to maximize the total profit for active requests and offers, including: the fare for accepted requests; the fixed costs for accepted offers; the transportation costs; the pickup costs at origin zones; the delivery costs at destination zones; the unloading and loading costs at consolidation and transshipment terminals; the storage costs at consolidation and transshipment terminals; the penalty costs for early delivery of shipments; the penalty costs for later delivery of shipments. The mixed integer linear programming model at time t is defined as follows:

$$
\begin{aligned}
\max \quad & \sum_{\mathfrak{r}\in\tilde{\mathfrak{R}}^t} \rho(\mathfrak{r}) y_{\mathfrak{r}}^t - \sum_{\mathfrak{o}\in\tilde{\mathfrak{O}}^t} f(\mathfrak{o}) y_{\mathfrak{o}}^t - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \sum_{\mathfrak{o}\in\mathfrak{O}^t} \sum_{l=1}^{|\Pi(\mathfrak{o})|} c_l(\mathfrak{o}) u(\mathfrak{r}) x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t \\
& - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \sum_{\mathfrak{o}\in\mathfrak{O}^t} \sum_{l:o_l(\mathfrak{o})=o(\mathfrak{r})} c^{\mathtt{P}}_{o(\mathfrak{r})m_l(\mathfrak{o})} u(\mathfrak{r}) x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \sum_{\mathfrak{o}\in\mathfrak{O}^t} \sum_{l:d_l(\mathfrak{o})=d(\mathfrak{r})} c^{\mathtt{P}}_{d(\mathfrak{r})m_l(\mathfrak{o})} u(\mathfrak{r}) x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t \\
& - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \sum_{i\in\Theta} \sum_{\mathfrak{o}\in\mathfrak{O}^t} \sum_{\mathfrak{o}'\in\mathfrak{O}^t} \sum_{l=1}^{|\Pi(\mathfrak{o})|} \sum_{l'=1}^{|\Pi(\mathfrak{o}')|} \left(c^{\mathtt{L}}_{im_l(\mathfrak{o})} + c^{\mathtt{L}}_{im_{l'}(\mathfrak{o}')} \right) u(\mathfrak{r}) z_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')}^t \\
& - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \sum_{i\in\Theta} c_i^{\mathtt{W}} u(\mathfrak{r}) w_{\mathfrak{r}i} - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \psi^{\mathtt{E}}(\mathfrak{r}) \check{\Gamma}_{\mathfrak{r}}^{\text{delivery}} - \sum_{\mathfrak{r}\in\mathfrak{R}^t} \psi^{\mathtt{L}}(\mathfrak{r}) \hat{\Gamma}_{\mathfrak{r}}^{\text{delivery}}
\end{aligned}
\tag{1}
$$

subject to

- Assignment constraints:

$$y^t_{\mathfrak{r}} \leq \sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),o_l(\mathfrak{o})=o(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} \leq 1, \quad \forall\mathfrak{r}\in\tilde{\mathfrak{R}}^t, \tag{2}$$

$$y^t_{\mathfrak{r}} \leq \sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),d_l(\mathfrak{o})=d(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} \leq 1, \quad \forall\mathfrak{r}\in\tilde{\mathfrak{R}}^t. \tag{3}$$

Constraints (2) ensure that new request $\mathfrak{r}\in\tilde{\mathfrak{R}}^t$ is assigned to a service that will depart from its origin $o(\mathfrak{r})$ if request $\mathfrak{r}$ is accepted by the platform at time t. Constraints (3) ensure that new request $\mathfrak{r}\in\tilde{\mathfrak{R}}^t$ is assigned to a service that will arrive at its destination $o(\mathfrak{r})$ if request $\mathfrak{r}$ is accepted by the platform at time t.

$$\sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),o_l(\mathfrak{o})=o(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = 1, \quad \forall\mathfrak{r}\in\dot{\mathfrak{R}}^t, \tag{4}$$

$$\sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),d_l(\mathfrak{o})=d(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = 1, \quad \forall\mathfrak{r}\in\dot{\mathfrak{R}}^t. \tag{5}$$

Constraints (4-5) ensure that contract or accepted spot request $\mathfrak{r}\in\dot{\mathfrak{R}}^t$ that hasn't been picked up is assigned to a service that will depart from its origin $o(\mathfrak{r})$ and a service that will arrive to its destination $d(\mathfrak{r})$.

$$\sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),d_l(\mathfrak{o})=o(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = 0, \quad \forall\mathfrak{r}\in\mathfrak{R}^t, \tag{6}$$

$$\sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),o_l(\mathfrak{o})=d(\mathfrak{r})} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = 0, \quad \forall\mathfrak{r}\in\mathfrak{R}^t. \tag{7}$$

Constraints (6) forbid a shipment enters its origin. Constraints (7) forbid a shipment leaves its destination.

$$\sum_{\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}),d_l(\mathfrak{o})=i} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = \sum_{\mathfrak{o}'\in\mathfrak{O}^t,\pi_{l'}(\mathfrak{o}')\in\Pi(\mathfrak{o}'),o_{l'}(\mathfrak{o}')=i} x^t_{\mathfrak{r}\pi_{l'}(\mathfrak{o}')}, \ \forall\mathfrak{r}\in\mathfrak{R}^t, i\in\Theta. \tag{8}$$

Constraints (8) ensure flow conservation of shipments at consolidation and transshipment terminals.

$$\begin{aligned} z^t_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')} \geq x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} + x^t_{\mathfrak{r}\pi_{l'}(\mathfrak{o}')} - 1, \ &\forall\mathfrak{r}\in\mathfrak{R}^t, i\in\Theta, \mathfrak{o},\mathfrak{o}'\in\mathfrak{O}^t, \mathfrak{o}\neq\mathfrak{o}', \pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}), \\ &\pi_{l'}(\mathfrak{o}')\in\Pi(\mathfrak{o}'), d_l(\mathfrak{o}) = o_{l'}(\mathfrak{o}') = i. \end{aligned} \tag{9}$$

$$\begin{aligned} z^t_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')} \leq x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}, \quad &\forall\mathfrak{r}\in\mathfrak{R}^t, i\in\Theta, \mathfrak{o},\mathfrak{o}'\in\mathfrak{O}^t, \mathfrak{o}\neq\mathfrak{o}', \pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}), \\ &\pi_{l'}(\mathfrak{o}')\in\Pi(\mathfrak{o}'), d_l(\mathfrak{o}) = o_{l'}(\mathfrak{o}') = i. \end{aligned} \tag{10}$$

$$\begin{aligned} z^t_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')} \leq x^t_{\mathfrak{r}\pi_{l'}(\mathfrak{o}')}, \quad &\forall\mathfrak{r}\in\mathfrak{R}^t, i\in\Theta, \mathfrak{o},\mathfrak{o}'\in\mathfrak{O}^t, \mathfrak{o}\neq\mathfrak{o}', \pi_l(\mathfrak{o})\in\Pi(\mathfrak{o}), \\ &\pi_{l'}(\mathfrak{o}')\in\Pi(\mathfrak{o}'), d_l(\mathfrak{o}) = o_{l'}(\mathfrak{o}') = i. \end{aligned} \tag{11}$$

Constraints (9-11) ensure shipment $\mathfrak{r}$ is transshipped at terminal $i\in\Theta$ between segment $\pi_l(\mathfrak{o})$ and segment $\pi_{l'}(\mathfrak{o}')$ if $x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} = 1$ and $x^t_{\mathfrak{r}\pi_{l'}(\mathfrak{o}')} = 1$.

- Time constraints:

$$\alpha^{\mathtt{R}}(\mathfrak{r}) \leq \Gamma_{\mathfrak{r}}^{\text{pickup}} \leq \beta^{\mathtt{R}}(\mathfrak{r}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t. \tag{12}$$

Constraints (12) ensure that the pickup time of shipments at their origins is within their pickup time windows.

$$\alpha_l^{\mathtt{R}}(\mathfrak{o}) \leq D_l(\mathfrak{o}) \leq \beta_l^{\mathtt{R}}(\mathfrak{o}), \quad \forall \mathfrak{o} \in \mathfrak{O}^t, l \in \{1, \dots, |\Pi(\mathfrak{o})|\}, \tag{13}$$

$$A_l(\mathfrak{o}) = D_l(\mathfrak{o}) + \tau_1(\mathfrak{o}), \quad \forall \mathfrak{o} \in \mathfrak{O}^t, l \in \{1, \dots, |\Pi(\mathfrak{o})|\}. \tag{14}$$

Constraints (13) ensure that the departure time of time-flexible services at its origin is within its departure time window. Constraints (14) calculate the arrival time of segment l of service $\mathfrak{o} \in \mathfrak{O}^t$ at its destination node $d_l(\mathfrak{o})$.

$$\Gamma_{\mathfrak{r}}^{\text{pickup}} \leq D_l(\mathfrak{o}) - t^{\mathtt{P}}_{o_{\mathfrak{r}} m_l(\mathfrak{o})} + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = o(\mathfrak{r}), \tag{15}$$

$$\Gamma_{\mathfrak{r}}^{\text{pickup}} \geq D_l(\mathfrak{o}) - t^{\mathtt{P}}_{o_{\mathfrak{r}} m_l(\mathfrak{o})} + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = o(\mathfrak{r}), \tag{16}$$

Let B be a large enough value. Constraints (15-16) ensure that the pickup time of shipments at their origins equals the departure time of the assigned service segment minus the pickup time.

$$\Gamma_{\mathfrak{r}i}^{\text{unload}} \leq A_l(\mathfrak{o}) + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), d_l(\mathfrak{o}) = i, \tag{17}$$

$$\Gamma_{\mathfrak{r}i}^{\text{unload}} \geq A_l(\mathfrak{o}) + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), d_l(\mathfrak{o}) = i. \tag{18}$$

Constraints (17-18) ensure that the time that shipment $\mathfrak{r}$ starts unloading at terminal i equals the arrival time of the assigned service segment.

$$\Gamma_{\mathfrak{r}i}^{\text{store}} \leq A_l(\mathfrak{o}) + t^{\mathtt{L}}_{i m_l(\mathfrak{o})} + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), d_l(\mathfrak{o}) = i, \tag{19}$$

$$\Gamma_{\mathfrak{r}i}^{\text{store}} \geq A_l(\mathfrak{o}) + t^{\mathtt{L}}_{i m_l(\mathfrak{o})} + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), d_l(\mathfrak{o}) = i. \tag{20}$$

Constraints (19-20) ensure that the time that shipment $\mathfrak{r}$ starts storage at terminal i equals the arrival time of the assigned service segment plus the unloading time.

$$\Gamma_{\mathfrak{r}i}^{\text{load}} \leq D_l(\mathfrak{o}) - t^{\mathtt{L}}_{i m_l(\mathfrak{o})} + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = i, \tag{21}$$

$$\Gamma_{\mathfrak{r}i}^{\text{load}} \geq D_l(\mathfrak{o}^{'}) - t^{\mathtt{L}}_{i m_l(\mathfrak{o})} + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = i. \tag{22}$$

Constraints (21-22) ensure that the time that shipment $\mathfrak{r}$ starts loading at terminal i equals the departure time of the assigned service segment minus the loading time.

$$\Gamma^{\text{depart}}_{\mathfrak{r}i} \leq D_l(\mathfrak{o}) + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = i, \tag{23}$$

$$\Gamma^{\text{depart}}_{\mathfrak{r}i} \geq D_l(\mathfrak{o}) + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), o_l(\mathfrak{o}) = i. \tag{24}$$

Constraints (23-24) ensure that the time that shipment $\mathfrak{r}$ departs from terminal i equals the departure time of the assigned service segment.

$$w_{\mathfrak{r}i} = \Gamma^{\text{load}}_{\mathfrak{r}i} - \Gamma^{\text{store}}_{\mathfrak{r}i} \geq 0, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta. \tag{25}$$

Constraints (25) calculate the storage time of shipment $\mathfrak{r}$ at terminal i.

$$\Gamma^{\text{delivery}}_{\mathfrak{r}} \leq A_l(\mathfrak{o}) + t^{\mathtt{P}}_{d_\mathfrak{r} m_l(\mathfrak{o})} + B(1 - x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), \; d_l(\mathfrak{o}) = d(\mathfrak{r}), \tag{26}$$

$$\Gamma^{\text{delivery}}_{\mathfrak{r}} \geq A_l(\mathfrak{o}) + t^{\mathtt{P}}_{d_\mathfrak{r} m_l(\mathfrak{o})} + B(x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} - 1), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, \mathfrak{o} \in \mathfrak{O}^t, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), \; d_l(\mathfrak{o}) = d(\mathfrak{r}). \tag{27}$$

Constraints (26-27) ensure that the delivery time of shipments at their destinations equals the arrival time of the assigned service segment plus the delivery time.

$$\alpha^{\mathtt{E}}(\mathfrak{r}) \leq \Gamma^{\text{delivery}}_{\mathfrak{r}} \leq \beta^{\mathtt{L}}(\mathfrak{r}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t. \tag{28}$$

Constraints (28) ensure that the delivery time of shipments is within their delivery time windows.

$$\check{\Gamma}^{\text{delivery}}_{\mathfrak{r}} \geq \beta^{\mathtt{E}}(\mathfrak{r}) - \Gamma^{\text{delivery}}_{\mathfrak{r}}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, \tag{29}$$

$$\hat{\Gamma}^{\text{delivery}}_{\mathfrak{r}} \geq \Gamma^{\text{delivery}}_{\mathfrak{r}} - \alpha^{\mathtt{L}}(\mathfrak{r}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t. \tag{30}$$

Constraints (29-30) calculate shipments' early and late delivery time at destinations.

- Capacity limitations:

$$\sum_{\mathfrak{r} \in \mathfrak{R}^t} u(\mathfrak{r}) x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} \leq y^t_{\mathfrak{o}} u^t_l(\mathfrak{o}), \quad \forall \mathfrak{o} \in \tilde{\mathfrak{O}}^t, l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}, \tag{31}$$

$$\sum_{\mathfrak{r} \in \mathfrak{R}^t} u(\mathfrak{r}) x^h_{\mathfrak{r}\pi_l(\mathfrak{o})} \leq u^t_l(\mathfrak{o}), \quad \forall \mathfrak{o} \in \dot{\mathfrak{O}}^t, l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}. \tag{32}$$

Constraints (31) ensure that the total volumes of shipments assigned to segment l of new service offer $\mathfrak{o} \in \tilde{\mathfrak{O}}^t$ cannot exceed its residual capacity at time t if offer $\mathfrak{o}$ is accepted by the platform. Constraints (32) ensure that the total volumes of shipments assigned to segment l of accepted service $\mathfrak{o} \in \dot{\mathfrak{O}}^t$ cannot exceed its free capacity at time t.

$$\sum_{\mathfrak{r} \in \mathfrak{R}^t} u(\mathfrak{r}) \left(g^{\text{unload},p}_{\mathfrak{r}i} + g^{\text{load},p}_{\mathfrak{r}i} \right) \leq u^{\text{L},t,p}_i, \quad \forall i \in \Theta, p \in \{t+1, ..., t+T\}. \tag{33}$$

Constraints (33) ensure that the total volumes of shipments assigned to terminal i during time period p for loading and unloading operations cannot exceed its residual capacity during that period at decision time t.

$$\theta 1_{\mathfrak{r}i}^{\text{unload},p}, \theta 2_{\mathfrak{r}i}^{\text{unload},p} \in \{0,1\},\ \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{34}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{unload}} \leq B\theta 1_{\mathfrak{r}i}^{\text{unload},p}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{35}$$

$$\Gamma_{\mathfrak{r}i}^{\text{unload}} - p + 1 \leq B(1 - \theta 1_{\mathfrak{r}i}^{\text{unload},p}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{36}$$

$$\Gamma_{\mathfrak{r}i}^{\text{store}} + 1 - p \leq B\theta 2_{\mathfrak{r}i}^{\text{unload},p},\ \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{37}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{store}} \leq B(1 - \theta 2_{\mathfrak{r}i}^{\text{unload},p}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{38}$$

$$g_{\mathfrak{r}i}^{\text{unload},p} \geq \theta 1_{\mathfrak{r}i}^{\text{unload},p} + \theta 2_{\mathfrak{r}i}^{\text{unload},p} - 1, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{39}$$

$$g_{\mathfrak{r}i}^{\text{unload},p} \leq \theta 1_{\mathfrak{r}i}^{\text{unload},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{40}$$

$$g_{\mathfrak{r}i}^{\text{unload},p} \leq \theta 2_{\mathfrak{r}i}^{\text{unload},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}. \tag{41}$$

Constraints (34-41) ensure that binary variable $g_{\mathfrak{r}i}^{\text{unload},p} = 1$ if $\Gamma_{\mathfrak{r}i}^{\text{unload}} + 1 \leq p \leq \Gamma_{\mathfrak{r}i}^{\text{store}}$, which indicates the time periods that shipment $\mathfrak{r}$ is unloaded at terminal i.

$$\theta 1_{\mathfrak{r}i}^{\text{load},p}, \theta 2_{\mathfrak{r}i}^{\text{load},p} \in \{0,1\}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{42}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{load}} \leq B\theta 1_{\mathfrak{r}i}^{\text{load},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{43}$$

$$\Gamma_{\mathfrak{r}i}^{\text{load}} - p + 1 \leq B(1 - \theta 1_{\mathfrak{r}i}^{\text{load},p}), \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{44}$$

$$\Gamma_{\mathfrak{r}i}^{\text{depart}} + 1 - p \leq B\theta 2_{\mathfrak{r}i}^{\text{load},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{45}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{depart}} \leq B(1 - \theta 2_{\mathfrak{r}i}^{\text{load},p}), \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{46}$$

$$g_{\mathfrak{r}i}^{\text{load},p} \geq \theta 1_{\mathfrak{r}i}^{\text{load},p} + \theta 2_{\mathfrak{r}i}^{\text{load},p} - 1 \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{47}$$

$$g_{\mathfrak{r}i}^{\text{load},p} \leq \theta 1_{\mathfrak{r}i}^{\text{load},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}, \tag{48}$$

$$g_{\mathfrak{r}i}^{\text{load},p} \leq \theta 2_{\mathfrak{r}i}^{\text{load},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1,...,t+T\}. \tag{49}$$

Constraints (42-49) ensure that binary variable $g_{\mathfrak{r}i}^{\text{load},p} = 1$ if $\Gamma_{\mathfrak{r}i}^{\text{load}} + 1 \leq p \leq \Gamma_{\mathfrak{r}i}^{\text{depart}}$, which indicates the time periods shipment $\mathfrak{r}$ is loaded at terminal i.

$$\sum_{\mathfrak{r} \in \mathfrak{R}^t} u(\mathfrak{r}) g_{\mathfrak{r}i}^{\text{store},p} \leq u_i^{\text{W},t,p}, \quad \forall i \in \Theta, p \in \{t+1,...,t+T\}. \tag{50}$$

Constraints (50) ensure that the total volume of shipments assigned to terminal i during time period p for storage does not exceed its residual capacity.

$$\theta 1_{\mathfrak{r}i}^{\text{store},p}, \theta 2_{\mathfrak{r}i}^{\text{store},p} \in \{0,1\}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{51}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{store}} \leq B\theta 1_{\mathfrak{r}i}^{\text{store},p}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{52}$$

$$\Gamma_{\mathfrak{r}i}^{\text{store}} - p + 1 \leq B(1 - \theta 1_{\mathfrak{r}i}^{\text{store},p}), \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{53}$$

$$\Gamma_{\mathfrak{r}i}^{\text{load}} + 1 - p \leq B\theta 2_{\mathfrak{r}i}^{\text{store},p}, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{54}$$

$$p - \Gamma_{\mathfrak{r}i}^{\text{load}} \leq B(1 - \theta 2_{\mathfrak{r}i}^{\text{store},p}), \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{55}$$

$$g_{\mathfrak{r}i}^{\text{store},p} \geq \theta 1_{\mathfrak{r}i}^{\text{store},p} + \theta 2_{\mathfrak{r}i}^{\text{store},p} - 1, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{56}$$

$$g_{\mathfrak{r}i}^{\text{store},p} \leq \theta 1_{\mathfrak{r}i}^{\text{store},p}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}, \tag{57}$$

$$g_{\mathfrak{r}i}^{\text{store},p} \leq \theta 2_{\mathfrak{r}i}^{\text{store},p}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, p \in \{t+1, ..., t+T\}. \tag{58}$$

Constraints (51-58) ensure that binary variable $g_{\mathfrak{r}i}^{\text{store},p} = 1$ if $\Gamma_{\mathfrak{r}i}^{\text{store}} + 1 \leq p \leq \Gamma_{\mathfrak{r}i}^{\text{load}}$, which indicates the time periods that shipment $\mathfrak{r}$ is stored at terminal i.

- Decision domain:

$$y_{\mathfrak{r}}^t, y_{\mathfrak{o}}^t \in \{0,1\}, \quad \forall \mathfrak{r} \in \tilde{\mathfrak{R}}^t, \mathfrak{o} \in \tilde{\mathfrak{O}}^t, \tag{59}$$

$$\begin{aligned} x_{\mathfrak{r}\pi_l(\mathfrak{o})}^t, z_{\mathfrak{r}i\pi_l(\mathfrak{o})\pi_{l'}(\mathfrak{o}')}^t, g_{\mathfrak{r}i}^{\text{unload},p}, g_{\mathfrak{r}i}^{\text{load},p}, g_{\mathfrak{r}i}^{\text{store},p} \in \{0,1\}, \quad \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta, \mathfrak{o}, \mathfrak{o}' \in \mathfrak{O}^t, \\ \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o}), \pi_{l'}(\mathfrak{o}') \in \Pi(\mathfrak{o}'), p \in \{t+1, ..., t+T\}, \end{aligned} \tag{60}$$

$$D_l(\mathfrak{o}), A_l(\mathfrak{o}) \geq 0, \quad \forall \mathfrak{o} \in \mathfrak{O}^t, l \in \{1, ..., |\Pi(\mathfrak{o})|\}, \tag{61}$$

$$\Gamma_{\mathfrak{r}}^{\text{pickup}}, \Gamma_{\mathfrak{r}i}^{\text{unload}}, \Gamma_{\mathfrak{r}i}^{\text{store}}, \Gamma_{\mathfrak{r}i}^{\text{load}}, \Gamma_{\mathfrak{r}i}^{\text{depart}}, \Gamma_{\mathfrak{r}}^{\text{delivery}}, w_{\mathfrak{r}i} \geq 0, \forall \mathfrak{r} \in \mathfrak{R}^t, i \in \Theta. \tag{62}$$

5 Rolling Horizon Framework

To handle dynamic shipment requests and service offers, we need to design methodologies that can update the sequence of decisions based on dynamically revealed information. At any time t, decisions are made for active requests and offers. However, decisions suggested by the optimization model are not all to be implemented. The acceptance decisions made at time t are implemented, that is, they are not to be changed in the follow up periods, and are transmitted to the appropriate stakeholders and departments of the platform for execution; but the decisions regarding shipment-to-service assignments and shipment itineraries made at time t are changeable and re-optimized until the shipment is picked up at its origin. The optimization model is used repeatedly, as time advances and new information becomes available. This is called the rolling horizon procedure (Yang et al., 2004). The pseudocode of the rolling horizon framework is represented in Algorithm 1 in Appendix.

Based on the decisions made at time t, for accepted requests that will be picked up before the next decision time $t+1$, shipment itineraries are fixed, and the platform needs to book the transport, loading, unloading, and storage capacities required for these shipments; for time-flexible services that are assigned to shipments whose itineraries are fixed, their time schedules are also fixed, and the platform informs carriers the scheduled departure and arrival times. After implementing the fixed decisions made at time t, the platform reaches a new state at time $t+1$, including:

- Status updates:
  - $\phi_{\mathfrak{r}} \leftarrow 1$ if $y^t_{\mathfrak{r}} = 1$, $\forall \mathfrak{r} \in \tilde{\mathfrak{R}}^t$;
  - $\psi_{\mathfrak{r}} \leftarrow 1$ if $\Gamma^{\text{pickup}}_{\mathfrak{r}} \leq t+1, \forall \mathfrak{r} \in \mathfrak{R}^t$;
  - $\phi_{\mathfrak{o}} \leftarrow 1$ if $y^t_{\mathfrak{o}} = 1$, $\forall \mathfrak{o} \in \tilde{\mathfrak{O}}^t$.
- Service type updates:
  - For accepted time-flexible service $\mathfrak{o} \in \{\mathfrak{O}^t : \text{type}(\mathfrak{o}) = 0, \phi_{\mathfrak{o}} = 1\}$, the time schedules are fixed if any of the assigned shipments is to be picked up before the next decision time, i.e., if $\sum_{\mathfrak{r} \in \{\mathfrak{R}^t : \phi_{\mathfrak{r}}=1, \psi_{\mathfrak{r}}=1\}} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} \geq 1$, $\forall l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}$, update $\text{type}(\mathfrak{o}) \leftarrow 1$.
- Capacity updates:

$$u_i^{\mathrm{L},t+1,p} = u_i^{\mathrm{L},t,p} - \sum_{\mathfrak{r} \in \{\mathfrak{R}^t : \phi_{\mathfrak{r}}=1, \psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) \left(g^{\text{unload},p}_{\mathfrak{r}i} + g^{\text{load},p}_{\mathfrak{r}i} \right), \quad \forall i \in \Theta, \; p \in \{t+2, ..., t+T\}, \tag{63}$$

$$u_i^{\mathrm{L},t+1,t+1+T} = u_i^{\mathrm{L}}, \quad \forall i \in \Theta, \tag{64}$$

$$u_i^{\mathrm{W},t+1,p} = u_i^{\mathrm{W},t,p} - \sum_{\mathfrak{r} \in \{\mathfrak{R}^t : \phi_{\mathfrak{r}}=1, \psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) g^{\text{store},p}_{\mathfrak{r}i}, \quad \forall i \in \Theta, \; p \in \{t+1, ..., t+T\}, \tag{65}$$

$$u_i^{\mathrm{W},t+1,t+1+T} = u_i^{\mathrm{W}}, \quad \forall i \in \Theta, \tag{66}$$

$$u_l^{t+1}(\mathfrak{o}) = u_l^t(\mathfrak{o}) - \sum_{\mathfrak{r} \in \{\mathfrak{R}^t : \phi_{\mathfrak{r}}=1, \psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}, \quad \forall \mathfrak{o} \in \mathfrak{O}^t, \; l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}. \tag{67}$$

Equations (63,65) indicate that the loading and unloading, and storage capacity at terminal i during time period p at the next decision time $t+1$ equals the loading and unloading, and storage capacity at terminal i during time period p at the time t minus the booked loading and unloading, and storage capacity at time t, $p \in \{t+1, ..., t+T\}$, respectively. Equations (64,66) indicate that the loading and unloading, and storage capacity at terminal i during time period $t+1+T$ at decision time $t+1$ equals the maximum loading and unloading, and storage capacity at terminal i, respectively. Equations (67) indicate that the transport capacity of segment l of service $\mathfrak{o}$ at the next decision time $t+1$ equals the capacity of segment l of service $\mathfrak{o}$ at the time t minus the booked capacity at time t.

6 Meta-heuristic Algorithm

Due to the computational complexity of the MILP model proposed in Section 4, this section proposes a preprocessing-based adaptive large neighborhood search algorithm (P-ALNS) to generate timely and high quality solutions. The algorithm consists of three steps: the preprocessing of feasible itineraries, the generation of an initial solution, and the improvements by ALNS. Considering that service offers with either flexible or scheduled services have fixed routes, this paper proposes to generate feasible itineraries for shipment requests before the remove and repair process. In this way, the computation time for constructing feasible itineraries during the repair process can be largely reduced.

6.1 Preprocessing of feasible itineraries

The pseudocode for preprocessing of feasible itineraries is presented in Algorithm 2 in Appendix. The preprocessing of feasible itineraries consists of two steps:

- **The generation of feasible paths.** The feasible paths consist of service segments from active offers between all the nodes of the physical network are generated. A path is feasible, if it satisfies time and spatial constraints among service segments. For example, for a path $p = [\pi_l(\mathfrak{o}), \pi_{l'}(\mathfrak{o}^{'})]$, the earliest arrival time of service segment $\pi_l(\mathfrak{o})$ should be earlier than the latest departure time of service segment $\pi_{l'}(\mathfrak{o}^{'})$, and the destination of service segment $\pi_l(\mathfrak{o})$ should be the same as the origin of service segment $\pi_{l'}(\mathfrak{o}^{'})$.
- **The generation of feasible itineraries.** The feasible itineraries for active requests are generated. An itinerary is feasible if the shipment and the selected path have time and spatial compatibility. For example, for request $\mathfrak{r}$ and path $p = [\pi_l(\mathfrak{o}), ..., \pi_{l'}(\mathfrak{o}^{'})]$, path p is feasible for request $\mathfrak{r}$ if the origin of service segment $\pi_l(\mathfrak{o})$ is the same as request $\mathfrak{r}$, the destination of service segment $\pi_{l'}(\mathfrak{o}^{'})$ is the same as the destination of request $\mathfrak{r}$, and the departure time window of service segment $\pi_l(\mathfrak{o})$ has overlap with the pickup time window of request $\mathfrak{r}$. Since the departure and arrival times of flexible-service segments are not fixed and within given time windows, we use the earliest arrival time of service segment $\pi_{l'}(\mathfrak{o}^{'})$ to estimate the delivery time of request $\mathfrak{r}$. The total cost associated with selecting path p for request $\mathfrak{r}$ is thus an estimated value, comprising fixed transit and transshipment costs, along with estimated penalty cost for early or late delivery.

6.2 Initial solution

To generate an initial solution, we use the best insertion idea in which requests are accepted sequentially based on estimated profits. The pseudocode for generating initial solution is presented in Algorithm 3 in Appendix. For each request, if its best itinerary (i.e. the feasible path with the highest estimated profit) is infeasible in time schedules or capacity constraints, then the second best is checked, until find a feasible itinerary. The pseudocode for feasible schedules and capacity check is presented in Section 6.3.3. For new request $\mathfrak{r} \in \tilde{\mathfrak{R}}^t$, if a feasible itinerary exists, then the request will be accepted; for new offer $\mathfrak{o} \in \tilde{\mathfrak{O}}^t$, if any of its service segments are assigned to shipment requests, then the offer will be accepted.

6.3 Adaptive Large Neighborhood Search

We propose an adaptive large neighborhood search algorithm (ALNS) to improve the solution quality. The ALNS applies removal and insertion operators to a given solution, as shown in Algorithm 4 in Appendix. The basic idea is to search for a better solution at each iteration by removing some requests from the current solution and inserting them in a different way. The removal and insertion operators are selected dynamically according to the performance achieved during the search. A weight is associated with each operator and the selection probability of an operator is related to its weight, which is adjusted during the search based on its past success. The main components of the ALNS are presented in the following subsections.

6.3.1 Removal operators

The removal stage aims to remove n requests from the current solution and add them to the removal list $\mathfrak{L}$. For requests in the removal list, their itineraries are reset to empty. The capacities of service segments and terminals assigned to these requests are released. At each iteration, n is randomly selected from an interval $[\alpha * |\mathfrak{R}^t|, \beta * |\mathfrak{R}^t|]$.

- *Random removal.* Randomly removes n requests from the current solution.
- *Worst removal.* Remove n requests with the lowest profits.
- *Related removal.* Randomly select a request to remove, then remove the $n-1$ requests according to distance between requests' origins and destinations, the difference between pickup time windows and delivery time windows, and the difference in volume of the two requests. Note that each component needs to be normalized by dividing the largest value of all requests.

$$\begin{aligned} Relate(I_{\mathfrak{r}_1}, I_{\mathfrak{r}_2}) = \theta_1 \left(dis_{o(\mathfrak{r}_1),o(\mathfrak{r}_2)} + dis_{d(\mathfrak{r}_1),d(\mathfrak{r}_2)} \right) + \theta_2 \big(|\alpha^{\mathrm{R}}(\mathfrak{r}_1) - \alpha^{\mathrm{R}}(\mathfrak{r}_2)| \\ + |\beta^{\mathrm{L}}(\mathfrak{r}_1) - \beta^{\mathrm{L}}(\mathfrak{r}_2)| \big) + \theta_3 \left(|u(\mathfrak{r}_1) - u(\mathfrak{r}_2)| \right) \end{aligned} \tag{68}$$

6.3.2 Insertion operators

All insertion operators iteratively reinsert the removed requests into the solution. They stop when all requests are inserted. Here, we generate the insertion list by randomly sorting the removal list.

- *Random insertion.* For each request in the insertion list, a randomly selected itinerary will be inserted. If the selected itinerary is infeasible in time schedules or capacity constraints, then the request will be rejected.
- *Best insertion.* For each request in the insertion list, inserting the best itinerary, if its infeasible, then insert the second best, until find a feasible insertion or all the itineraries are checked.
- *Regret-2 insertion.* Insert requests based on regret values. Let $\Delta f_{\mathfrak{r}}^2$ be the insertion cost (i.e., the estimated total cost consisting of transit and transshipment costs along with projected early or late delivery penalties) of request $\mathfrak{r} \in \mathfrak{L}$ with the second best itinerary. At each iteration, the operator select the request $\mathfrak{r}^*$ for insertion with the best itinerary such that $\mathfrak{r}^* = argmax_{\mathfrak{r}\in\mathfrak{L}}\,(\Delta f_{\mathfrak{r}}^2 - \Delta f_{\mathfrak{r}}^1)$.
- *Most constrained insertion.* The idea is to insert the request that is most difficult to insert according to distance, time windows, and volume. Specifically, requests with longer transit distance or shorter lead times or heavier volumes are inserted first. Equation (69) calculates the difficult value of request $\mathfrak{r}$. Note that each component needs to be normalized by dividing the largest value of all requests.

$$Constrain(\mathfrak{r}) = \gamma_1 dis_{o(\mathfrak{r}_1),d(\mathfrak{r}_1)} + \gamma_2 \left(\beta^{\mathrm{L}}(\mathfrak{r}_1) - \alpha^{\mathrm{R}}(\mathfrak{r}_1)\right) + \gamma_3 u(\mathfrak{r}_1) \tag{69}$$

6.3.3 Feasibility check and service scheduling

The pseudocode for feasibility check in time and capacities is presented in Algorithm 5 in Appendix. An itinerary is feasible only if the request and the assigned service segments satisfy time and capacity compatibility:

- *Time compatibility.* The pickup time of shipment $\mathfrak{r}$ at its origin should be within its pickup time window $[\alpha^{\mathtt{R}}(\mathfrak{r}), \beta^{\mathtt{R}}(\mathfrak{r})]$; the delivery time of shipment $\mathfrak{r}$ at its destination should be within its delivery time window $[\alpha^{\mathtt{E}}(\mathfrak{r}), \beta^{\mathtt{L}}(\mathfrak{r})]$; if shipment $\mathfrak{r}$ is transferred at terminal $i \in \Theta(\mathfrak{r})$ between service segment $\pi_l(\mathfrak{o})$ and $\pi_{l'}(\mathfrak{o}^{'})$, the arrival time of service segment $\pi_l(\mathfrak{o})$ plus unloading and loading time should be the earlier than the departure time of service segment $\pi_{l'}(\mathfrak{o}^{'})$. For time-flexible services $\{\mathfrak{o}|\pi_l(\mathfrak{o}) \in I_{\mathfrak{r}}, \mathrm{type}(\mathfrak{o}) = 0\}$, the departure time of service segment $\pi_l(\mathfrak{o})$ must be with its departure time window, and we select the earliest departure times that satisfy shipments' time windows, and changes the service type to time scheduled.

- *Capacity compatibility.* For service segment $\pi_l(\mathfrak{o}) \in I_{\mathfrak{r}}$, the volume of request $\mathfrak{r}$ cannot exceed the available capacity of service segment $\pi_l(\mathfrak{o})$; if shipment $\mathfrak{r}$ is transferred at terminal $i \in \Theta(\mathfrak{r})$ during time period p, the volume of request $\mathfrak{r}$ cannot exceed the transshipment capacity within that period; if shipment $\mathfrak{r}$ is stored at terminal $i \in \Theta(\mathfrak{r})$ during time period p, the volume of request $\mathfrak{r}$ cannot exceed the storage capacity within that period.

7 Numerical Experiments

We use an interurban multi-modal network in China to evaluate the performance of the proposed approaches. All approaches are implemented in MATLAB, and all experiments are executed on 3.70 GHz Intel Xeon processors with 32 GB of RAM. The optimization problems are solved with CPLEX 12.6.3. The topology of the network is shown in Figure 5, which includes 10 urban areas, 14 high-speed railway stations, 4 river/maritime ports, and 7 airports. Let instance $I - n_1 - n_2 - n_3 - n_4$ represent the instance with n_1 zones, n_2 terminals, n_3 shipment requests, and n_4 service offers.

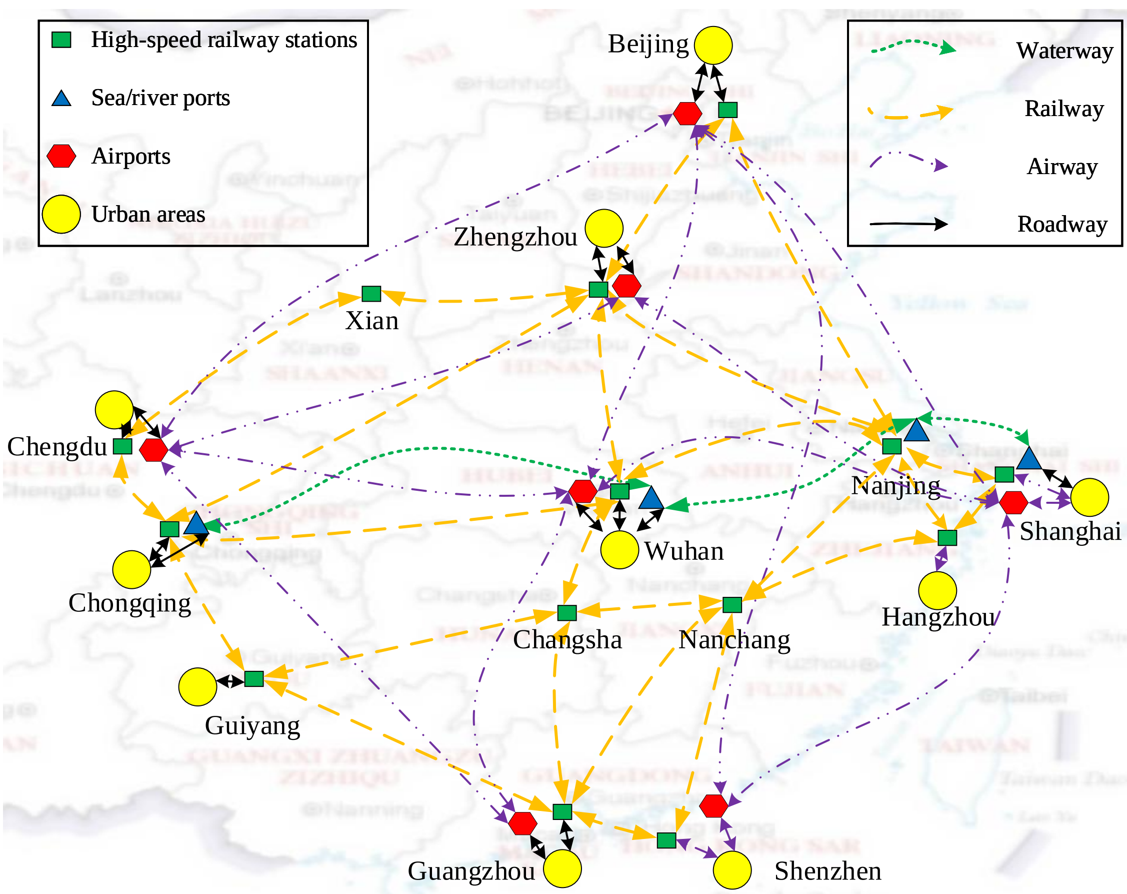


Figure 5: The topology of an interurban multi-modal network in China.

7.1 Parameter tuning

To tune the algorithm parameters of the P-ALNS, we vary the values of the simulation length (i.e., the number of iterations that ALNS runs), the removal fraction rate, σ_1, σ_2, σ_3, θ_1, θ_2, θ_3, γ_1, γ_2, and γ_3 for a given instance $I - 10 - 10 - 150 - 50$. For each case, we run 10 times to obtain the average and best values. Table 2 shows that the larger the simulation length, the better solution quality the P-ALNS algorithm and the heavier the computation time. Increasing the removal fraction rate from 1% to 40%, the solution quality increases dramatically. When further increasing the fraction rate to 60%, the performance of P-ALNS becomes worse. Also, the higher the removal fraction rate, the longer the CPU. Another interesting finding is that the P-ALNS can find the best solution when the score for worse but new solutions σ_3 is higher than the score for the best solutions σ_1 and the score for a better and new solution σ_2. It turns out to be an effective way for diversifying the search. The P-ALNS performs best when $\theta_1 > \theta_3 > \theta_2$, which means that in related removal process, the requests with similar distances are more likely to select the same service segments. Interestingly, the P-ALNS performs best when $\gamma_2 > \gamma_3 > \gamma_1$, which means that in most constrained insertion process, the requests with larger distances are not that important. Instead, requests with tighter time windows become more difficult to insert, and therefore must be considered first.

The algorithm parameters in the following experiments are designed concerning a trade-off between solution quality and CPU time, as shown in Table 3.

7.2 Comparison results between CPLEX and P-ALNS

To evaluate the performance of the P-ALNS algorithm, we compare it with the lower bounds, which represent the best feasible objective values, found by the CPLEX solver for 14 instances. Each instance is executed 10 times by the P-ALNS algorithm. For clarity, the abbreviations of the performance indicators along with their definition are provided in Table 4. Table 5 shows that the P-ALNS outperforms CPLEX in finding superior feasible solutions in 10 out of 13 instances. For example, in instance $I-4-6-45-15$, CPLEX takes 1199 seconds, while P-ALNS achieves near-optimal solutions with an average gap of just 0.47% in 34 seconds. In instance $I-10-10-240-80$, the P-ALNS improves solution quality by an average of 55.38%. Additionally, in instance $I-10-10-270-90$, CPLEX encounters an out of memory error. Moreover, for instances with 10 terminals, P-ALNS consistently finds better solutions than CPLEX in significantly shorter computation time.

7.3 Comparison results between FCFS and RHA

To investigate the effectiveness of the Rolling Horizon Approach (RHA) in handling dynamic shipment requests and dynamic service offers, we compare it to a First-Come-

Table 2: Sensitivity analysis of algorithm parameters.

ID	Simulation length	Removal fraction	σ_1	σ_2	σ_3	θ_1	θ_2	θ_3	γ_1	γ_2	γ_3	P-ALNS$_{best}$	P-ALNS$_{average}$	CPU
1	1000	20%	33	9	13	9	3	2	9	3	2	19292	18954	15
2	3000	20%	33	9	13	9	3	2	9	3	2	19787	19411	46
3	5000	20%	33	9	13	9	3	2	9	3	2	20037	19700	74
4	**7000**	20%	33	9	13	9	3	2	9	3	2	**20065**	**19919**	110
5	5000	1%	33	9	13	9	3	2	9	3	2	18837	18220	7
6	5000	5%	33	9	13	9	3	2	9	3	2	19881	19341	23
7	5000	10%	33	9	13	9	3	2	9	3	2	19802	19530	44
8	5000	20%	33	9	13	9	3	2	9	3	2	20037	19700	74
9	5000	**40%**	33	9	13	9	3	2	9	3	2	**20085**	**19750**	151
10	5000	60%	33	9	13	9	3	2	9	3	2	19652	19215	173
11	5000	20%	9	13	33	9	3	2	9	3	2	20110	19676	74
12	5000	20%	9	33	13	9	3	2	9	3	2	20121	**19789**	68
13	5000	20%	**13**	**9**	**33**	9	3	2	9	3	2	**20381**	19737	79
14	5000	20%	13	33	9	9	3	2	9	3	2	19981	19783	67
15	5000	20%	33	9	13	9	3	2	9	3	2	20037	19700	74
16	5000	20%	33	13	9	9	3	2	9	3	2	20041	19784	70
17	5000	20%	33	9	13	2	3	9	9	3	2	19739	19417	82
18	5000	20%	33	9	13	2	9	3	9	3	2	19656	19423	72
19	5000	20%	33	9	13	3	2	9	9	3	2	19778	19304	71
20	5000	20%	33	9	13	3	9	2	9	3	2	19916	19445	74
21	5000	20%	33	9	13	**9**	**2**	**3**	9	3	2	**20070**	**19847**	73
22	5000	20%	33	9	13	9	3	2	9	3	2	20037	19700	74
23	5000	20%	33	9	13	9	3	2	2	3	9	19983	19672	75
24	5000	20%	33	9	13	9	3	2	**2**	**9**	**3**	**20300**	**19796**	72
25	5000	20%	33	9	13	9	3	2	3	2	9	20059	19715	75
26	5000	20%	33	9	13	9	3	2	3	9	2	20176	19778	73
27	5000	20%	33	9	13	9	3	2	9	2	3	20241	19628	73
28	5000	20%	33	9	13	9	3	2	9	3	2	20037	19700	74

First-Serve (FCFS) approach. In the FCFS method, shipment-to-service assignments, shipment itineraries, and service schedules cannot be reoptimized. We vary the number of spot requests and offers under instance $I-4-6-50-50$. Table 6 indicates that RHA outperforms FCFS in 9 out of 10 cases regarding total profits and the number of accepted requests and offers. This is because under the FCFS method, the platform allocates service capacities to shipment requests based on their arrival order. In contrast, RHA allows for the reassignment of service capacities to late-arriving, high-valued shipments, optimizing resource allocation dynamically. In case 6, all shipment requests and service offers are contracted, and their information are known. Since no new requests or offers arrive in this case, reoptimization under RHA is unnecessary. Comparing cases 1 and 6, we can observe that the higher the ratio of contracted request, the better the performance of FCFS, which benefits from 'global' optimization. Interestingly, under RHA, the total profit increases from cases 1 to 4, then declines from cases 4 to 6. This decline can be attributed to the necessity of accepting non-profitable contracted requests in cases 5 and 6. When comparing cases 4, 7, 8, we see that both FCFS and RHA benefit from the ability

Table 3: Default settings.

Parameters	Value
Number of runs per instance	10
Simulation length per run	5000
Number of route-wheel iterations	100
Reaction factor	0.1
Score for new best solution	13
Score for better solution	9
Score for worse but new solution	33
Start temperature control parameter	0.05
Cooling rate	0.9998
Lower limit of removal fraction	10%
Upper limit of removal fraction	40%
First Shaw parameter of distance	9
Second Shaw parameter of time	2
Third Shaw parameter of volume	3
First MCI parameter of distance	2
Second MCI parameter of time	9
Third MCI parameter of volume	3
Initial weights for removal operators	1,1,1
Initial weights for repair operators	1,1,1,1
CPLEX time limitation in seconds	3600

Table 4: Abbreviation of performance indicators and definition.

Abbreviations	Definition
UB_{MILP}	The upper bound of the MILP model obtained by CPLEX within 3600 seconds
LB_{MILP}	The best feasible objective value found by CPLEX solver within 3600 seconds
P-ALNS$_{best}$	The best feasible objective value obtained by the P-ALNS under default settings
P-ALNS$_{average}$	The average feasible objective value obtained by the P-ALNS under default settings
IMP_{best}	The improvement of P-ALNS$_{best}$ over LB_{MILP}: $\frac{P-ALNS_{best}-LB_{MILP}}{LB_{MILP}}$
$IMP_{average}$	The improvement of P-ALNS$_{average}$ over LB_{MILP}: $\frac{P-ALNS_{average}-LB_{MILP}}{LB_{MILP}}$
CPU_{MILP}	CPU time for solving the MILP model by CPLEX, unit: seconds
CPU_{P-ALNS}	The average computing duration of the P-ALNS algorithm, unit: seconds

to reject non-profitable service offers. This underscores the importance of incorporating decision-making flexibility to enhance profitability. Finally, when comparing cases 9 and 10, it becomes clear that some profitable spot service offers may be rejected because they arrive before the spot requests that could be matched to them. This highlights the need for predictive mechanisms to temporarily hold or prioritize service offers that could be matched to future high-value shipment requests.

Table 5: Comparison results between CPLEX and P-ALNS.

Instances	UB_{MILP}	LB_{MILP}	P-ALNS$_{best}$	P-ALNS$_{average}$	IMP_{best}	$IMP_{average}$	CPU_{MILP}	CPU_{P-ALNS}
I-4-6-15-5	3113	3113	3113	3113	0.00%	0.00%	19	5
I-4-6-30-10	5164	5164	5164	5164	0.00%	0.00%	136	11
I-4-6-45-15	8850	8850	8818	8808	-0.36%	-0.47%	1199	34
I-4-6-60-20	12079	11075	11130	11049	0.50%	-0.23%	3600	74
I-4-6-75-25	17742	15692	15974	15799	1.80%	0.68%	3600	167
I-4-6-90-30	20880	18832	18508	18270	-1.72%	-2.98%	3600	204
I-4-6-105-35	23784	19465	20776	20484	6.73%	5.23%	3600	274
I-4-6-120-40	31824	21271	26923	26510	26.57%	24.63%	3600	377
I-10-10-120-40	20803	17795	18450	18199	3.68%	2.27%	3600	69
I-10-10-150-50	24434	19617	19991	19815	1.90%	1.01%	3600	99
I-10-10-180-60	31923	22088	26022	25787	17.81%	16.75%	3600	136
I-10-10-210-70	37590	23764	29022	28754	22.12%	21.00%	3600	178
I-10-10-240-80	42066	20099	31708	31230	57.76%	55.38%	3600	222
I-10-10-270-90	Out of memory		33039	31990	-	-	3600	231
Average					**10.52%**	**9.48%**		

Table 6: Comparison results between FCFS and RHA.

Cases	$\lvert\mathfrak{R}^{\text{contract}}\rvert$	$\lvert\mathfrak{R}^{\text{spot}}\rvert$	$\lvert\mathfrak{O}^{\text{contract}}\rvert$	$\lvert\mathfrak{O}^{\text{spot}}\rvert$	FCFS			RHA		
					Total profit	Number of accepted requests	Number of accepted offers	Total profit	Number of accepted requests	Number of accepted offers
1	0	50	50	0	5687	18	50	11976	48	50
2	10	40	50	0	5432	19	50	12218	48	50
3	20	30	50	0	5796	20	50	12366	48	50
4	30	20	50	0	8958	31	50	12474	49	50
5	40	10	50	0	10418	41	50	12326	49	50
6	50	0	50	0	12327	50	50	12245	50	50
7	30	20	40	10	9175	31	40	12515	48	40
8	30	20	30	20	9487	32	30	12679	48	30
9	30	20	20	30	9596	33	20	11816	42	28
10	30	20	10	40	8134	36	14	11153	34	21

7.4 Sensitivity analysis of scenario parameters

We use instance $I-7-13-12-22$ to perform a sensitivity analysis of scenario parameters. Detailed information on time-scheduled and time-flexible service offers are presented in Table 7 and Table 8, respectively. Based on the real operations of various carriers, we set the speeds as follows: high-speed rail (HSR) at 250 km/h, airplane at 800 km/h, truck at 80 km/h, barge at 28 km/h, intelligent vehicles at 60 km/h, and drones at 98 km/h, respectively. The travel time for each segment is calculated using the Euclidean distance. We designate HSR, airplane, and barge as long-haul transport modalities that connect consolidation and transshipment terminals, while intelligent vehicles and drones are allocated for feeder connections between service zones and consolidation terminals. The loading/unloading costs for HSR, airplane, truck, barge, intelligent vehicles, and drones are set as 0.3, 0.3, 0.3, 0.6, 0.3, 0.1 per unit, respectively. The loading/unloading times of HSR, airplane, truck, barge, intelligent vehicles, and drones are established at 0.25, 0.5, 0.5, 1, 0.25, 0.1 hours, respectively. The storage cost at terminals is set to 0.01

Table 7: Detailed information of time-scheduled service offers.

Offer ID	Type	Route	Offer fixed cost	Segment origin	Segment destination	Segment mode	Segment capacity	Segment departure time	Segment arrival time	Segment travel time	Segment travel cost	Segment distance
1	1	Chengdu-Chongqing-Wuhan-Shanghai	100	Chengdu	Chongqing	HSR	150	Mon 05:30	Mon 07:30	2	2	504
				Chongqing	Wuhan	HSR	150	Mon 08:00	Mon 11:30	3.5	4	876
				Wuhan	Shanghai	HSR	150	Mon 12:00	Mon 15:30	3.5	4	807
2	1	Shenzhen-Guangzhou-Wuhan-Beijing	100	Shenzhen	Guangzhou	HSR	150	Mon 06:30	Mon 07:00	0.5	1	147
				Guangzhou	Wuhan	HSR	150	Mon 07:30	Mon 11:30	4	4.5	920
				Wuhan	Beijing	HSR	150	Mon 12:00	Mon 16:00	4	4.5	1013
3	1	Chongqing-Wuhan-Shanghai	10	Chongqing	Wuhan	Barge	150	Mon 05:00	Wed 02:30	45.5	0.25	1274
				Wuhan	Shanghai	Barge	150	Wed 04:30	Thu 20:30	40	0.25	1125
4	1	Shenzhen-Shanghai	120	Shenzhen	Shanghai	Airplane	150	Mon 08:00	Mon 10:00	2	30	1600
5	1	Chengdu-Beijing	120	Chengdu	Beijing	Airplane	150	Mon 08:00	Mon 10:00	2	30	1503

per unit per hour. Under the benchmark scenario, the maximum storage and handling capacities at terminals are set to 150 units. Detailed information of shipment requests is presented in Table 9. For all shipment requests, we have established differentiated fare classes. Requests (1, 2, 4, 5, 7, 8, 10, 11) with shorter lead times feature higher fares and early/later delivery penalties, while requests (3, 6, 9) with longer lead times have lower fares and penalties.

Table 8: Detailed information of time-flexible service offers.

Offer ID	Type	Route	Offer fixed cost	Segment origin	Segment destination	Segment mode	Segment capacity	Segment time	departure window	Segment travel time	Segment travel cost	Segment distance
6	0	Guangzhou-Guangzhou	20	Guangzhou service zone	Guangzhou railway station	Intelligent vehicle	150	Mon 00:00	Mon 08:00	0.5	1	30
7	0	Guangzhou-Shenzhen	20	Guangzhou service zone	Shenzhen airport	Truck	150	Mon 00:00	Mon 08:00	2	4	160
8	0	Shenzhen-Shenzhen	20	Shenzhen service zone	Shenzhen railway station	Drone	150	Mon 00:00	Mon 08:00	0.2	0.8	20
9	0	Shenzhen-Shenzhen	20	Shenzhen service zone	Shenzhen airport	Drone	150	Mon 00:00	Mon 08:00	0.2	0.8	20
10	0	Chongqing-Chongqing	20	Chongqing service zone	Chongqing railway station	Intelligent vehicle	150	Mon 00:00	Mon 08:00	0.5	1	30
11	0	Chongqing-Chongqing	20	Chongqing service zone	Chongqing riverport	Intelligent vehicle	150	Mon 00:00	Mon 08:00	1	2	60
12	0	Chongqing-Chengdu	20	Chongqing service zone	Chengdu airport	Truck	150	Mon 00:00	Mon 08:00	7	14	560
13	0	Chengdu-Chengdu	20	Chengdu service zone	Chengdu railway station	Intelligent vehicle	150	Mon 00:00	Mon 08:00	0.5	1	30
14	0	Chengdu-Chengdu	20	Chengdu service zone	Chengdu airport	Intelligent vehicles	150	Mon 00:00	Mon 08:00	1	2	60
15	0	Chengdu-Chongqing	20	Chengdu service zone	Chongqing river port	Truck	150	Mon 00:00	Mon 08:00	7	14	560
16	0	Beijing-Beijing	20	Beijing railway station	Beijing service zone	Intelligent vehicle	150	Mon 10:00	Mon 24:00	0.5	1	30
17	0	Beijing-Beijing	20	Beijing airport	Beijing service zone	Intelligent vehicle	150	Mon 10:00	Mon 24:00	0.5	1	30
18	0	Shanghai-Shanghai	20	Shanghai railway station	Shanghai service zone	Drone	150	Mon 10:00	Mon 24:00	0.2	0.8	20
19	0	Shanghai-Shanghai	20	Shanghai airport	Shanghai service zone	Drone	150	Mon 10:00	Mon 24:00	0.2	0.8	20
20	0	Shanghai-Shanghai	20	Shanghai seaport	Shanghai service zone	Intelligent vehicle	150	Mon 10:00	Mon 24:00	1	2	60
21	0	Shanghai-Shanghai	20	Shanghai seaport	Shanghai service zone	Intelligent vehicle	150	Thu 10:00	Thu 24:00	1	2	60
22	0	Wuhan-Wuhan	20	Wuhan railway station	Wuhan river port	Intelligent vehicle	150	Mon 24:00	Wed 04:30	1	2	60

Table 9: Detailed information of shipment requests.

ID	Origin	Destination	Volume	Release time window		Early delivery time window		Target delivery time window		Late delivery time window		Fare	Early delivery penalty	Late delivery penalty
1	Guangzhou	Beijing	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	400	1	4
2	Guangzhou	Shanghai	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	450	1	4.5
3	Guangzhou	Shanghai	15	Mon 00:00	Mon 08:00	Mon 08:00	Tue 24:00	Wed 00:00	Thu 24:00	Fri 00:00	Fri 24:00	300	1	0.3
4	Shenzhen	Beijing	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	450	1	4.5
5	Shenzhen	Shanghai	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	500	1	5
6	Shenzhen	Shanghai	15	Mon 00:00	Mon 08:00	Mon 08:00	Tue 24:00	Wed 00:00	Thu 24:00	Fri 00:00	Fri 24:00	350	1	0.35
7	Chengdu	Beijing	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	500	1	5
8	Chendu	Shanghai	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	450	1	4.5
9	Chendu	Shanghai	15	Mon 00:00	Mon 08:00	Mon 08:00	Tue 24:00	Wed 00:00	Thu 24:00	Fri 00:00	Fri 24:00	300	1	0.3
10	Chongqing	Beijing	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	500	1	5
11	Chongqing	Shanghai	10	Mon 00:00	Mon 08:00	Mon 08:00	Mon 12:00	Mon 12:00	Mon 20:00	Mon 20:00	Mon 24:00	400	1	4
12	Chongqing	Shanghai	15	Mon 00:00	Mon 08:00	Mon 08:00	Tue 24:00	Wed 00:00	Thu 24:00	Fri 00:00	Fri 24:00	250	1	0.25

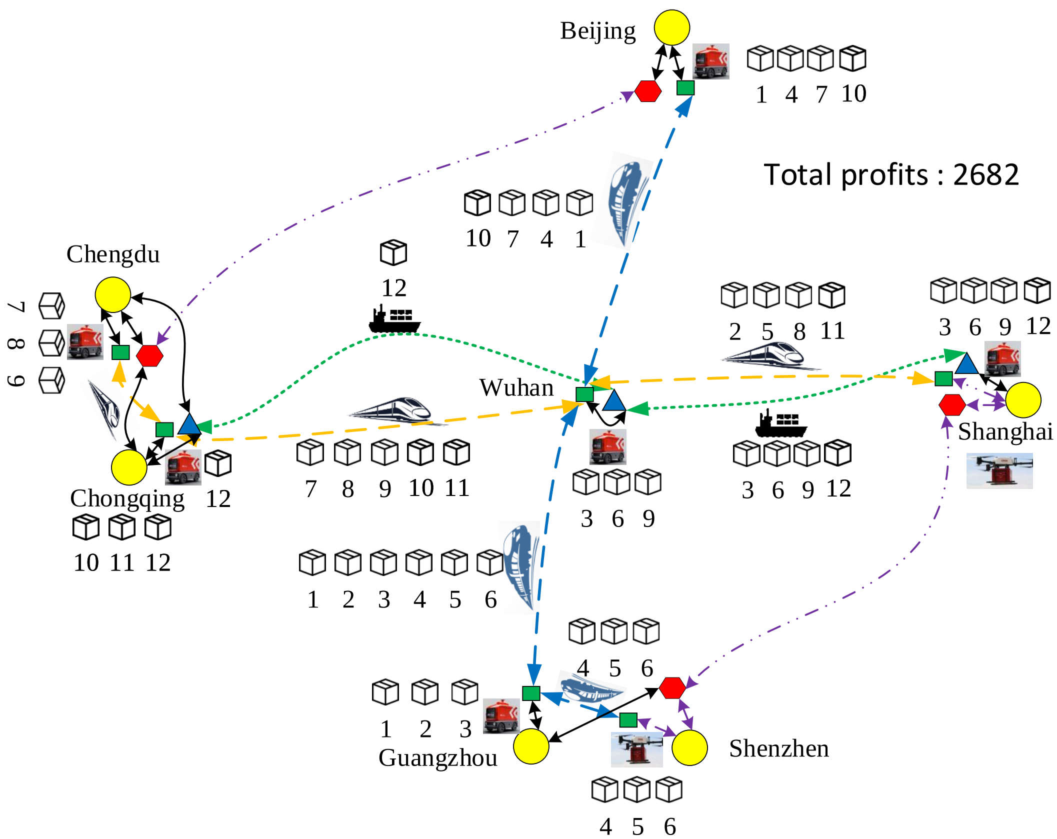


Figure 6: Shipment itineraries under the benchmark scenario.

Figure 6 illustrates shipment itineraries under the benchmark scenario. Shipments 1, 2, 3 will be transported by intelligent vehicles from Guangzhou service zone to Guangzhou railway station. From there, they will take high-speed rail (HSR) to Wuhan railway station. Shipment 2 will then transfer to another HSR, heading to Shanghai railway station, while shipment 3 will switch to a barge service from Wuhan port to Shanghai port. Shipments 4, 5, 6 will be transported by drones from Shenzhen service zone to Shenzhen railway station. After this, they will be transported via HSR from Shenzhen railway station to Wuhan railway station. Shipment 5 will switch to another HSR service, while shipment 6 will transfer to a barge service. Shipments 7, 8, 9 will be transported by intelligent vehicles from Chengdu service zone to Chengdu railway station, where they will then transfer to a HSR bound for Wuhan railway station. Shipment 7 will continue on another HSR from Wuhan railway station to Beijing railway station, and shipment 9 will be transferred to a barge service from Wuhan port to Shanghai port. Lastly, shipments 10, 11, 12 will be initially transported from Chongqing service zone to Chongqing railway station. They will then board a HSR service from Chongqing railway station to Wuhan railway station. Afterward, shipment 10 will transfer to another HSR service from Wuhan railway station to Beijing railway station, while shipment 12 will switch to a barge service from Wuhan port to Shanghai port.

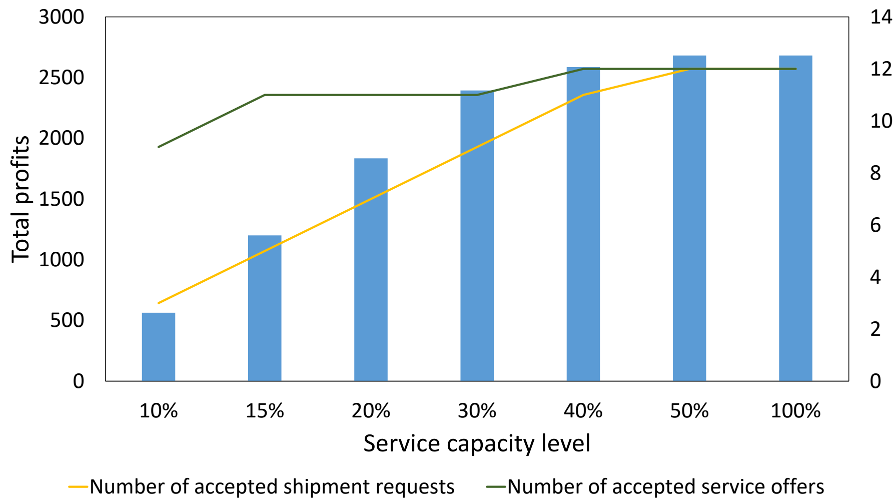


Figure 7: Impact of service capacity limitations.

7.4.1 Impact of service and terminal capacity limitations

In the benchmark scenario, the capacity of all services and terminals is set at 150 units, which exceeds the total volumes of all shipments. To evaluate the impact of service capacity limitations, we reduce gradually the service capacity to 10%. Figure 7 shows that both the total profit and the number of accepted shipment requests and service offers decline as the service capacity level decreases. At a service capacity level of 30%, each service segment capacity is reduced to 45 units, allowing a maximum of 4 shipments per segment. Consequently, the original transport plan under the benchmark scenario becomes infeasible at this capacity level. As a result, shipments 3, 6, 9, which have lower fares and profits, are rejected by the platform since there are no profitable itineraries available to replace them.

The experiment highlights the critical role of service capacity in maintaining profitability and operational feasibility. When service capacity is significantly reduced, the system becomes constrained, leading to a decline in both total profits and the number of accepted shipment requests. This is particularly evident for lower-fare shipments, which are more likely to be rejected when capacity is limited, as they do not provide sufficient profitability to justify their inclusion in the transport plan.

To evaluate the impact of terminal capacity limitations, we reduce gradually the terminal capacity to 10%. Figure 8 illustrates that the total profits decreases as the terminal capacity decreases. At a terminal capacity level of 20%, each terminal can only handle and storage 30 units at each time period. Shipments 1, 6, and 9 are thus rejected due to terminal handling capacity limitations.

The experiment shows that terminal capacity constraints directly impact operational efficiency and profitability. When terminal capacity is reduced, the system's ability to

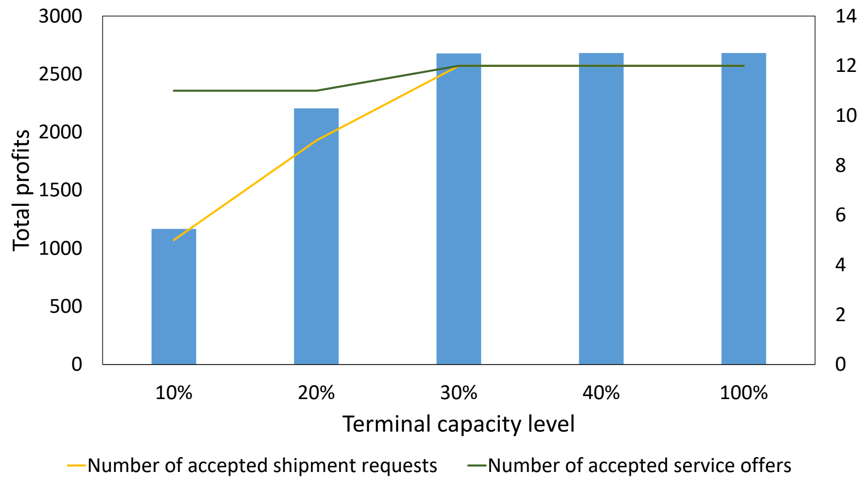


Figure 8: Impact of terminal capacity limitations.

handle and store shipments is significantly limited, leading to the rejection of certain shipments and a decline in total profits. This underscores the importance of terminal capacity as a critical bottleneck in the logistics network.

7.4.2 Impact of shipment time windows

To evaluate the impact of shipment time windows, we adjusted the length of the delivery time windows to 50% and 75% of the benchmark scenario. When shipments' time windows reduces to 75% of the benchmark scenario, the latest delivery time of shipments 3, 6, 9, and 12 changes to Thursday 18:00. Barge service 3 becomes infeasible for these shipments since its arrival time is Thursday 20:30. As a result, these shipments' itineraries from Wuhan to Shanghai switch from barge service 3 to HSR service 1, as shown in Figure 9. This change results in total profits decreasing from 2682 to 2607. When we further decrease shipments' time windows to 50% of the benchmark scenario, the latest delivery time of shipments 1, 2, 4, 5, 7, 8, 10, 11 changes to Monday 12:00. In this scenario, only airplane services 4 and 5 are feasible for these shipments. The platform rejects non-profitable requests 1, 4, 8, 10, and 11, and assigns shipments 2, 5, 7 to the airplane services. As a result, total profits drop to 180.

The experiment reveals that tighter shipment time windows significantly impact the feasibility of transportation modes and overall profitability. When delivery time windows are reduced, certain services become infeasible due to misaligned time schedules, forcing a shift to more expensive alternatives (e.g., high-speed rail or airplane services). This not only increases operational costs but also leads to the rejection of less profitable shipments, further reducing total profits.

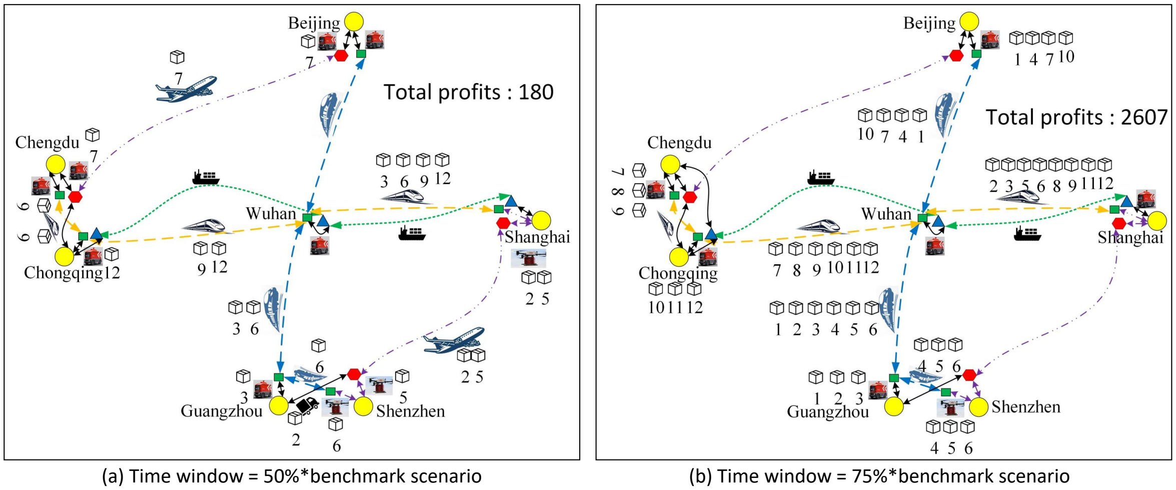


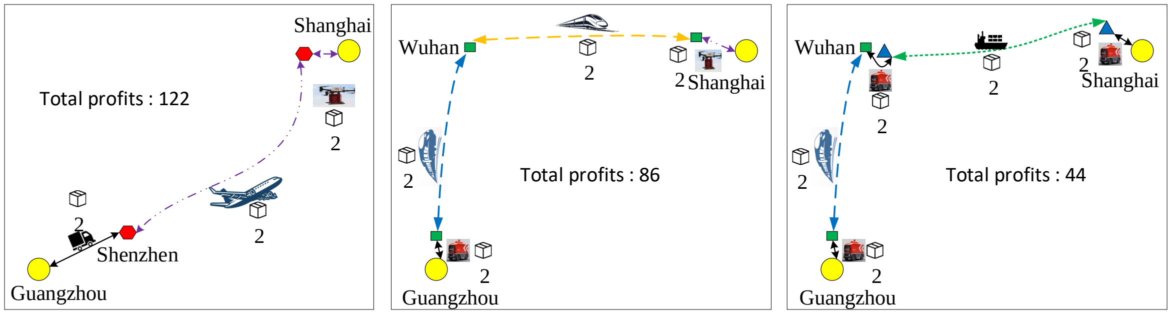
Figure 9: Impact of shipment time windows.

7.4.3 Impact of differentiated fare classes

To assess the impact of differentiated fare classes, we design three fare categories for shipment request 2 from Guangzhou to Shanghai:

- *High fare class:* this option guarantees delivery before Monday 12:00, with a fare of 650 and a delay penalty of 6.5 per unit per hour;
- *Medium fare class:* this option ensures delivery before Monday 24:00, with a fare of 450 and a delay penalty of 4.5 per unit per hour;
- *Low fare class:* this option provides delivery before Friday 24:00, with a fare of 350 and a delay penalty of 0.35 per unit per hour.

Figure 10 illustrates the transport modes used under each fare class scenario. Under the high fare class, the shipment is transported by airplane for long-haul transportation. In the medium fare class scenario, the shipment is moved using two high-speed rail lines. For the low fare class, the shipment utilizes a combination of HSR and barge services for the long-haul transportation. The experiment highlights the importance of aligning transportation modes with fare classes and customer preferences. High fare classes, typically associated with high-value products and strict time windows, justify the use of faster but more expensive transportation modes like airplanes. In contrast, low fare classes, often linked to low-value products and flexible time windows, allow for the use of cost-effective but slower multimodal options, such as a combination of high-speed rail and barge services. This emphasizes that fare class segmentation enables the optimization of transportation costs while meeting diverse customer needs.



(a) High fare class (b) Medium fare class (c) Low fare class

Figure 10: Impact of differentiated fare classes.

Table 10: Impact of resource sharing among different carriers.

Carriers	Requests	Without resource sharing	With resource sharing
HSR	1	$Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$	$Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$
	3	$Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$	$Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{barge} Shanghai$
	4	$Shenzhen \xrightarrow{HSR} Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$	$Shenzhen \xrightarrow{HSR} Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$
	6	$Shenzhen \xrightarrow{HSR} Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$	$Shenzhen \xrightarrow{HSR} Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{barge} Shanghai$
	8	$Chengdu \xrightarrow{HSR} Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$	$Chengdu \xrightarrow{HSR} Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$
	11	$Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$	$Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$
Barge	9	reject	$Chengdu \xrightarrow{HSR} Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{barge} Shanghai$
	12	$Chongqing \xrightarrow{barge} Wuhan \xrightarrow{barge} Shanghai$	$Chongqing \xrightarrow{barge} Wuhan \xrightarrow{barge} Shanghai$
Air	2	$Guangzhou \xrightarrow{truck} Shenzhen \xrightarrow{air} Shanghai$	$Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$
	5	$Shenzhen \xrightarrow{air} Shanghai$	$Shenzhen \xrightarrow{HSR} Guangzhou \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Shanghai$
	7	reject	$Chengdu \xrightarrow{HSR} Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$
	10	reject	$Chongqing \xrightarrow{HSR} Wuhan \xrightarrow{HSR} Beijing$
Total profits		1262	2682

7.4.4 Impact of resource sharing among different carriers

To evaluate the benefits of resource sharing among different carriers, we design a scenario involving three carriers that operate in long-haul transportation: a HSR carrier, a barge carrier, and an air carrier. The HSR carrier operates HSR services 1 and 2 and receives shipment requests 1, 3, 4, 6, 8, and 11. The barge carrier operates barge service 3 and receives shipment requests 9, and 12. The air carrier operates air services 4 and 5 and receives shipment requests 2, 5, 7, and 10. Table 10 indicates that without resource sharing, shipment requests 7, 9, 10 are rejected. Furthermore, shipments 3 and 6 switch from barge to HSR service, while shipments 2 and 5 switch from HSR to air service, which incurs higher costs. Consequently, total profits decrease from 2682 to 1262.

The experiment underscores the significant benefits of resource sharing among carriers in enhancing operational efficiency and profitability. Without resource sharing, carriers are constrained by their individual capacities and service offerings, leading to the rejection of certain shipments and suboptimal routing decisions (e.g., switching to more expensive transportation modes). This results in a substantial decline in total profits. Resource sharing, however, enables carriers to leverage synergies, optimize capacity utilization, and provide more flexible and cost-effective transportation solutions, ultimately supporting synchromodality in interurban transportation.

8 Conclusions and Future Research

This paper investigated the operational planning problem of a multi-modal multi-stakeholder transportation system. We formulated a mixed-integer linear programming model that integrates the acceptance decisions of shipment requests and service offers, shipment-to-service assignments, shipment itineraries and service time schedules. To accommodate dynamic shipment requests and service offers, we developed a rolling horizon approach (RHA) that controls the implementation and re-optimization of decisions. Given the computational complexity, we proposed a preprocessing-based adaptive large neighborhood search algorithm (P-ALNS) to address the optimization problem. We validated these approaches using an interurban multimodal network in China. The experimental results emphasize that the P-ALNS outperforms the CPLEX solver for large-scale instances. Furthermore, the RHA surpasses the first-come-first-serve approach in all scenarios except when there are no dynamic requests and offers. Additionally, we conducted a sensitivity analysis to assess the effects of service and terminal capacity limitations, shipment time windows, differentiated fare classes, and resource sharing among various carriers. The analysis provides valuable managerial insights based on the results obtained:

- **Balance capacity and demand**: Platform managers should align service capacity with demand to optimize profitability and efficiency, avoiding costs from overcapacity and revenue loss from undercapacity.
- **Improve transportation schedules**: To address tight time windows of shipment requests, platform managers should focus on optimizing transportation schedules and improving service flexibility.
- **Tailor service offerings**: Platform managers should develop differentiated services for various fare classes. High fare shippers should receive fast and reliable options, while low fare shippers benefit from cost-effective multimodal solutions.
- **Promote collaboration**: Carriers should actively pursue collaboration and resource-sharing agreements with other carriers to improve system-wide efficiency and profitability. By pooling resources and coordinating operations, carriers can reduce inefficiencies, accommodate more shipments, and offer competitive transportation options. Investing in platforms or technologies that facilitate real-time resource sharing and coordination among carriers can further enhance the benefits of the system.

While this study provides valuable insights into the operational planning of multi-modal multi-stakeholder systems, several avenues for future research remain unexplored. First, in real transportation, many factors, such as weather condition, traffic congestion, terminal congestion, demand and capacity fluctuation, and dynamic pricing, can significantly impact the feasibility and efficiency of transport plans. Future research could focus on the integration of advanced predictive analytics and machine learning techniques to enhance the responsiveness and resilience of the rolling horizon approach by building a look-ahead model in such uncertain environments. Second, the current model could be extended to incorporate first-mile and last-mile logistics, including intelligent vehicle and drone routing. This extension would address the critical challenge of synchronizing operations at consolidation terminals, ensuring seamless transitions between long-haul transportation and local delivery. Exploring collaboration between intelligent vehicles and drones, could further optimize the efficiency of the entire logistics chain.

Acknowledgments

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Appendix

Algorithm 1 Rolling horizon framework.

Input: Terminals Θ; shipment requests $\mathfrak{R}$; service offers $\mathfrak{O}$; maximum duration T.

Output: Acceptance decision $\left[y^t_{\mathfrak{r}}\right]_{\forall \mathfrak{r}\in\tilde{\mathfrak{R}}^t}$ and $\left[y^t_{\mathfrak{o}}\right]_{\forall \mathfrak{o}\in\tilde{\mathfrak{O}}^t}$; assignment decision $\left[x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}\right]_{\forall \mathfrak{r}\in\mathfrak{R}^t,\mathfrak{o}\in\mathfrak{O}^t,\pi_l(\mathfrak{o})\in\Pi(\mathfrak{o})}$; service schedules $\left[D_l(\mathfrak{o})\right],\left[A_l(\mathfrak{o})\right],\forall \mathfrak{o} \in \{\mathfrak{O}^t : \text{type}(\mathfrak{o}) = 0\}, \pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o})$; shipment schedules $\left[\Gamma^{\text{pickup}}_{\mathfrak{r}}\right]$, $\left[\Gamma^{\text{delivery}}_{\mathfrak{r}}\right]$, $\left[\Gamma^{\text{unload}}_{\mathfrak{r}i}\right]$, $\left[\Gamma^{\text{store}}_{\mathfrak{r}i}\right]$, $\left[\Gamma^{\text{load}}_{\mathfrak{r}i}\right]$, $\left[\Gamma^{\text{depart}}_{\mathfrak{r}i}\right]$, $\forall \mathfrak{r}\in\mathfrak{R}^t, i\in\Theta$.

Initialize: Let $\mathfrak{R}^t \leftarrow \emptyset$, $\dot{\mathfrak{R}}^t \leftarrow \emptyset$, $\tilde{\mathfrak{R}}^t \leftarrow \emptyset$, $\mathfrak{O}^t \leftarrow \emptyset$, $\dot{\mathfrak{O}}^t \leftarrow \emptyset$, $\tilde{\mathfrak{O}}^t \leftarrow \emptyset$.

for decision time t **do**
 update set of accepted requests not yet picked up $\dot{\mathfrak{R}}^t \leftarrow \{\mathfrak{R} : \alpha^{\mathtt{A}}(\mathfrak{r}) \le t-1, \phi_{\mathfrak{r}} = 1, \psi_{\mathfrak{r}} = 0\}$
 update set of new requests $\tilde{\mathfrak{R}}^t \leftarrow \{\mathfrak{r} \in \mathfrak{R}^{\text{spot}} : t-1 < \alpha^{\mathtt{A}}(\mathfrak{r}) \le t, \phi_{\mathfrak{r}} = 0, \psi_{\mathfrak{r}} = 0\}$
 update set of active requests $\mathfrak{R}^t \leftarrow \dot{\mathfrak{R}}^t \cup \tilde{\mathfrak{R}}^t$
 update set of accepted offers $\dot{\mathfrak{O}}^t \leftarrow \{\mathfrak{o} \in \mathfrak{O} : \alpha^{\mathtt{A}}(\mathfrak{o}) \le t-1, \phi_{\mathfrak{o}} = 1\}$
 update set of new offers $\tilde{\mathfrak{O}}^t \leftarrow \{\mathfrak{o} \in \mathfrak{O}^{\text{spot}} : t-1 < \alpha^{\mathtt{A}}(\mathfrak{o}) \le t, \phi_{\mathfrak{o}} = 0\}$
 update set of active offers $\mathfrak{O}^t \leftarrow \dot{\mathfrak{O}}^t \cup \tilde{\mathfrak{O}}^t$
 generate acceptance decisions, assignment decisions, service schedules, shipment itineraries
 for request $\mathfrak{r} \in \tilde{\mathfrak{R}}^t$ **do**
  if $y^t_{\mathfrak{r}} = 1$ **then**
   update decision status $\phi_{\mathfrak{r}} \leftarrow 1$
   inform shippers that request $\mathfrak{r}$ is accepted
 for request $\mathfrak{r} \in \mathfrak{R}^t$ **do**
  if $\phi_{\mathfrak{r}} = 1$ and $\Gamma^{\text{pickup}}_{\mathfrak{r}} \le t+1$ **then**
   update operation status $\psi_{\mathfrak{r}} \leftarrow 1$
   inform shippers the shipment's itinerary
 for offer $\mathfrak{o} \in \tilde{\mathfrak{O}}^t$ **do**
  if $y^t_{\mathfrak{o}} = 1$ **then**
   update decision status $\phi_{\mathfrak{o}} \leftarrow 1$
   inform carriers that offer $\mathfrak{o}$ is accepted
 for offer $\mathfrak{o} \in \mathfrak{O}^t$, **do**
  for $\pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o})$ **do**
   update capacity $u^{t+1}_l(\mathfrak{o}) = u^t_l(\mathfrak{o}) - \sum_{\mathfrak{r}\in\{\mathfrak{R}^t:\phi_{\mathfrak{r}}=1,\psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) x^t_{\mathfrak{r}\pi_l(\mathfrak{o})}$
  inform carriers the booked transport capacity
  if type$(\mathfrak{o}) = 0$ and $\phi_{\mathfrak{o}} = 1$ **then**
   for $\pi_l(\mathfrak{o}) \in \Pi(\mathfrak{o})$ **do**
    if $\sum_{\mathfrak{r}\in\{\mathfrak{R}^t:\phi_{\mathfrak{r}}=1,\psi_{\mathfrak{r}}=1\}} x^t_{\mathfrak{r}\pi_l(\mathfrak{o})} \ge 1$ **then**
     update type$(\mathfrak{o}) \leftarrow 1$
     inform carriers the service schedules
 for terminal $i \in \Theta, p \in \{t+1, ..., t+T\}$ **do**
  update loading and unloading capacity $u^{\text{L},t+1,p}_i = u^{\text{L},t,p}_i - \sum_{\{\mathfrak{R}^t:\phi_{\mathfrak{r}}=1,\psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) \left(g^{\text{unload},p}_{\mathfrak{r}i} + g^{\text{load},p}_{\mathfrak{r}i}\right)$
  update storage capacity $u^{\text{W},t+1,p}_i = u^{\text{W},t,p}_i - \sum_{\mathfrak{r}\in\{\mathfrak{R}^t:\phi_{\mathfrak{r}}=1,\psi_{\mathfrak{r}}=1\}} u(\mathfrak{r}) g^{\text{store},p}_{\mathfrak{r}i}$

Algorithm 2 Feasible itinerary generation.

Input: zones $\mathcal{Z}$, terminals Θ, requests $\mathfrak{R}^t$, service offers $\mathfrak{O}^t$, the largest number of service segments in an itinerary $N^{\max}$.
Output: feasible paths $\{P^l_{ij}\}_{i\in\Theta,j\in\Theta,l\in\{1,\ldots,N^{\max}\}}$, feasible itineraries $\{I_{\mathfrak{r}}\}_{\forall\mathfrak{r}\in\mathfrak{R}^t}$, estimated costs $[c_{\mathfrak{r}p}]_{\forall\mathfrak{r}\in\mathfrak{R},p\in I_r}$
Initialize: Let $P \leftarrow \emptyset, I \leftarrow \emptyset, e \leftarrow 2$.

generate feasible paths:
for node $i \in \mathcal{Z} \cup \Theta$, node $j \in \mathcal{Z} \cup \Theta$ **do**
  for service offer $\mathfrak{o} \in \mathfrak{O}^t$ **do**
    for service segment $l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}$ **do**
      if origin $o_l(\mathfrak{o}) = i$ and destination $d_l(\mathfrak{o}) = j$ **then**
        feasible path $p \leftarrow [\pi_l(\mathfrak{o})]$
while $e \leq N^{\max}$ **do**
  for node $i \in \mathcal{Z} \cup \Theta$, node $j \in \mathcal{Z} \cup \Theta$ **do**
    for service offer $\mathfrak{o} \in \mathfrak{O}^t$ **do**
      for service segment $l \in \{1, \ldots, |\Pi(\mathfrak{o})|\}$ **do**
        if origin $o_l(\mathfrak{o}) \neq i$ and destination $d_l(\mathfrak{o}) = j$ **then**
          for feasible path $p \in P^{e-1}_{io_l(\mathfrak{o})}$ **do**
            if earliest arrival time of path $p \leq$ latest departure time of service segment $\pi_l(\mathfrak{o})$ **then**
              $P^e_{ij} \leftarrow P^e_{ij} \cup \{[p, \pi_l(\mathfrak{o})]\}$
  $e \leftarrow e + 1$
generate feasible itineraries:
for request $\mathfrak{r} \in \mathfrak{R}^t$ **do**
  for $e \in \{1, 2, ..., N^{\max}\}$ **do**
    for feasible path $p = [\pi_{l_1}(\mathfrak{o}_1), ..., \pi_{l_e}(\mathfrak{o}_e)] \in P^e_{o_r d_r}$ **do**
      if departure time window of path p has overlap with pickup time window of request $\mathfrak{r}$ **then**
        $\tilde{c}_{\mathfrak{r}p} \leftarrow$ Transit cost + Transshipment cost+ estimated penalty cost for early and late delivery
        if $\tilde{c}_{\mathfrak{r}p} \leq \rho(\mathfrak{r})$ **then**
          $I_{\mathfrak{r}} \leftarrow I_{\mathfrak{r}} \cup \{p\}$
  sort $I_{\mathfrak{r}}$ in descending order based on $\tilde{c}_{\mathfrak{r}p}$

Algorithm 3 Initial solution generation.

Input: requests $\mathfrak{R}^t$, service offers $\mathfrak{O}^t$, feasible itineraries $\{I_\mathfrak{r}\}_{\forall \mathfrak{r} \in \mathfrak{R}^t}$, estimated costs $[c_{\mathfrak{r}p}]_{\forall \mathfrak{r} \in \mathfrak{R}, p \in I_\mathfrak{r}}$.
Output: initial itineraries I^{initial}, initial service schedules $[D^{\text{initial}}, A^{\text{initial}}]$, initial shipment schedules Γ^{initial}.
Initialize: let $List \leftarrow \emptyset$.

for $\mathfrak{r} \in \mathfrak{R}^t$ **do**
    estimated profit when best itinerary is selected $\leftarrow \rho(\mathfrak{r}) - \tilde{c}_{\mathfrak{r}p_1}$
$List \leftarrow$ sort requests in descending order based on estimated profits
for $\mathfrak{r} \in List$ **do**
    $index = 1$
    while $index \leq$ the length of feasible itineraries $I_\mathfrak{r}$ **do**
        itinerary $p = I_{\mathfrak{r},index}$
        feasibility$(\mathfrak{r}, p) \leftarrow FEASIBLESCHEDULESANDCAPACITY$
        if feasibility$(\mathfrak{r}, p) = 1$ **then**
            $I_\mathfrak{r}^{\text{initial}} \leftarrow p$
            for service segment $\pi_l(\mathfrak{o}) \in p$ **do**
                service schedules $[D_l^{\text{initial}}(\mathfrak{o}), A_l^{\text{initial}}(\mathfrak{o})] \leftarrow FEASIBLESCHEDULESANDCAPACITY(\mathfrak{r}, p)$
            $\Gamma_\mathfrak{r}^{\text{initial}} \leftarrow FEASIBLESCHEDULESANDCAPACITY(\mathfrak{r}, p)$
        else
            $index = index + 1$
for $\mathfrak{r} \in \tilde{\mathfrak{R}}^t$ **do**
    if $I_\mathfrak{r}^{\text{initial}} \neq \emptyset$ **then**
        $y_\mathfrak{r}^t = 1$
for $\mathfrak{r} \in \mathfrak{R}^t$ **do**
    if $I_\mathfrak{r}^{\text{initial}} \neq \emptyset$ **then**
        for $\pi_l(\mathfrak{o}) \in I_\mathfrak{r}^{\text{initial}}$ **do**
            if $\mathfrak{o} \in \tilde{\mathfrak{O}}^t$ **then**
                $y_\mathfrak{o}^t = 1$

Algorithm 4 Adaptive large neighborhood search algorithm.

Input: initial solution $\mathbf{x}^{\text{initial}} = [I^{\text{initial}}, D^{\text{initial}}, A^{\text{initial}}, \Gamma^{\text{initial}}]$
Output: best solution $[\mathbf{x}^{\text{best}}]$

$\mathbf{x}^{\text{current}} \leftarrow \mathbf{x}^{\text{initial}}$, $\mathbf{x}^{\text{best}} \leftarrow \mathbf{x}^{\text{initial}}$
while stopping criterion not met **do**
    select a remove operator and a repair operator based on roulette-wheel mechanism
    $\mathbf{x} \leftarrow \mathbf{x}^{\text{current}}$;
    $\mathbf{x} \leftarrow \text{Remove}(\mathbf{x})$;
    $\mathbf{x} \leftarrow \text{Insert}(\mathbf{x})$;
    if total profit$(\mathbf{x}) >$ total profit$(\mathbf{x}^{\text{current}})$ **then**
        $\mathbf{x}^{\text{current}} \leftarrow \mathbf{x}$
    else
        $\mathbf{x}^{\text{current}} \leftarrow \mathbf{x}$ with probability $p = e^{\frac{\text{totalprofit}(\mathbf{x}) - \text{totalprofit}(\mathbf{x}^{\text{current}})}{T^{\text{temp}}}}$
    if total profit$(\mathbf{x}) >$ total profit$(\mathbf{x}^{\text{best}})$ **then**
        $\mathbf{x}^{\text{best}} \leftarrow \mathbf{x}$
    $T^{\text{temp}} \leftarrow T^{\text{temp}}.c$ (c is the cooling rate)

Algorithm 5 FEASILESCHEDULESANDCAPACITY.

Input: request $\mathfrak{r}$, itinerary p, terminal Θ.
Output: feasibility$(\mathfrak{r}, p)$, service schedules $[D_l(\mathfrak{o}), A_l(\mathfrak{o})]_{\forall \pi_l(\mathfrak{o}) \in p}$, shipment schedules $\Gamma_{\mathfrak{r}}$.
Initialize: let feasibility$(\mathfrak{r}, p) \leftarrow 1$.

for $\pi_l(\mathfrak{o}) \in p$ **do**
  if $u(\mathfrak{r}) > u_l^t(\mathfrak{o})$ **then**
    feasibility$(\mathfrak{r}, p) \leftarrow 0$
  else
    $u_l^t(\mathfrak{o}) \leftarrow u_l^t(\mathfrak{o}) - u(\mathfrak{r})$
$\pi_{l_1}(\mathfrak{o}_1) \leftarrow$ the first service segment in itinerary p
if the departure time window of $\pi_{l_1}(\mathfrak{o}_1)$ has overlap with the pickup time window of request $\mathfrak{r}$ **then**
  if $\pi_{l_1}(\mathfrak{o}_1)$is time-flexible: type$(\pi_{l_1}(\mathfrak{o}_1)) = 0$ **then**
    select the earliest feasible time to depart: $D_{l_1}(\mathfrak{o}_1) \leftarrow \min\{\alpha^{\mathtt{R}}(\mathfrak{r}), \alpha_{l_1}^{\mathtt{R}}(\mathfrak{o}_1)\}$
    update service segment's arrival time: $A_{l_1}(\mathfrak{o}_1) \leftarrow D_{l_1}(\mathfrak{o}_1) + \tau_{l_1}(\mathfrak{o}_1)$
    update service segment's type: type$(\pi_{l_1}(\mathfrak{o}_1)) \leftarrow 1$
  else
    feasibility$(\mathfrak{r}, p) \leftarrow 0$
for $\pi_{l_i}(\mathfrak{o}_i) \in p : i > 1$ **do**
  if the earliest arrival time of $\pi_{l_{i-1}}(\mathfrak{o}_{i-1}) \leq$ the latest departure time of $\pi_{l_{i-1}}(\mathfrak{o}_{i-1})$ **then**
    if $\pi_{l_{i-1}}(\mathfrak{o}_{i-1})$is time-flexible: type$(\pi_{l_{i-1}}(\mathfrak{o}_{i-1})) = 0$ **then**
      select the earliest feasible time to depart: $D_{l_i}(\mathfrak{o}_i) \leftarrow \min\{A_{l_{i-1}}(\mathfrak{o}_{i-1}) +$ unloading and loadingtime$, \alpha_{l_i}^{\mathtt{R}}(\mathfrak{o}_i)\}$
      update service segment's type: type$(\pi_{l_i}(\mathfrak{o}_i)) \leftarrow 1$
  else
    feasibility$(\mathfrak{r}, p) \leftarrow 0$
if feasibility$(\mathfrak{r}, p) = 1$ **then**
  calculate shipment schedules $\Gamma_{\mathfrak{r}}$ based on the service segments' schedules in the itinerary
  for terminal $i \in \Theta$, $\Gamma_{\mathfrak{r}}^{\text{unload}} + 1 \leq p \leq \Gamma_{\mathfrak{r}}^{\text{store}}$ **do**
    if $u(\mathfrak{r}) > u_i^{\text{L},t,p}$ **then**
      feasibility$(\mathfrak{r}, p) \leftarrow 0$
    else
      $u_i^{\text{L},t,p} \leftarrow u_i^{\text{L},t,p} - u(\mathfrak{r})$
  for terminal $i \in \Theta$, $\Gamma_{\mathfrak{r}}^{\text{store}} + 1 \leq p \leq \Gamma_{\mathfrak{r}}^{\text{load}}$ **do**
    if $u(\mathfrak{r}) > u_i^{\text{W},t,p}$ **then**
      feasibility$(\mathfrak{r}, p) \leftarrow 0$
    else
      $u_i^{\text{W},t,p} \leftarrow u_i^{\text{W},t,p} - u(\mathfrak{r})$
  for terminal $i \in \Theta$, $\Gamma_{\mathfrak{r}}^{\text{load}} + 1 \leq p \leq \Gamma_{\mathfrak{r}}^{\text{depart}}$ **do**
    if $u(\mathfrak{r}) > u_i^{\text{L},t,p}$ **then**
      feasibility$(\mathfrak{r}, p) \leftarrow 0$
    else
      $u_i^{\text{L},t,p} \leftarrow u_i^{\text{L},t,p} - u(\mathfrak{r})$