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Research Article

Two-Echelon Pickup and Delivery Problem Using Public Transport in City Logistics

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The rapid increase in e-commerce and the emergence of combined passenger/freight systems in urban areas have raised the question of how best to integrate public transport services into door-to-door deliveries. This paper develops a variant of the pickup and delivery problem, called the two-echelon pickup and delivery problem using public transport (2E-PDP-PT). In the 2E-PDP-PT, the transportation network is split into two echelons. Different vehicles are utilized across the first and second echelons to ensure distribution efficiency. Parcels are delivered by public transport with free capacity or via trucks between satellites in the first echelon, and logistics vehicles are operated in the second echelon. The satellites are located at the echelon borders to transfer commodities between echelons. The 2E-PDP-PT aims to minimize total delivery costs and improve public transport capacity utilization. We formulate a new mathematical model based on a space-time network and adopt an adaptive large neighborhood search (ALNS) algorithm for the 2E-PDP-PT. The effectiveness of the ALNS algorithm is validated using newly generated small-scale instances. Furthermore, we investigate large-scale instances based on the Beijing Yizhuang transportation network. The computations show that an average total delivery cost savings of 4.5% is feasible. In addition, we analyze the impact of demand distributions and compare the ALNS algorithm and the LNS algorithm. Finally, we conclude that dynamically integrating public transport into freight transport services can benefit both logistics companies and public transport operators.

1. Introduction

The substantial growth of e-commerce contributes to the huge demand for commodity deliveries, especially express delivery services in urban areas. In China, the express delivery market reached 111 billion orders in 2022, representing an increase of 2% over the previous year [1]. Massive express demand in a short period requires sufficient resources to ensure the timeliness of distribution. The external effects of this growth are significant and include congestion, emissions, noise pollution, and pavement damage [2]. To address these external effects and limit the movement of trucks, this paper studies the problem of two-echelon distribution by integrating freight and public transport.

In two-echelon systems, the transportation network is split into two echelons. Different vehicles are employed in the first and second echelons, and intermediate facilities called satellites facilitate the consolidation and transshipment of parcels between different vehicles [3]. Public transport and trucks deliver parcels in the first echelon. In the second echelon, pickup and delivery operations are carried out with small, low-emission vehicles, such as electric vehicles and cargo bikes. These vehicles in this paper are referred to as logistics vehicles. An illustration of the 2E-PDP-PT is provided in Figure 1. Public transport can be used as part of the freight service. The logistics vehicles pick up demands at the suppliers. Then, the demands are moved using public transport or via trucks from the origin satellite to the destination satellite. Finally, the demands are

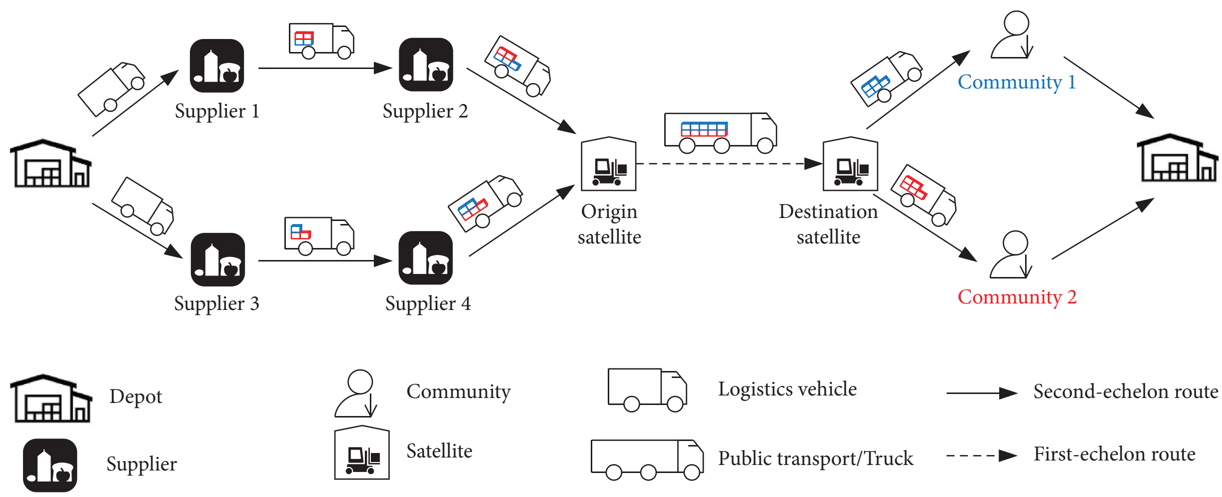

Figure 1: An illustration of the 2E-PDP-PT.

delivered from the destination satellite to the corresponding communities.

Urban freight journeys partially overlap with public transport routes, contributing to improving the utilization of public transport. Thus, this paper considers the use of public transport, such as bus and subway, to transport parcels. The lines of public transport as scheduled services can be called scheduled lines, and each scheduled line visits a sequence of several stations [4]. Integrating freight and passenger transport services is an effective approach to promoting urban sustainability and reducing the negative externalities of road-based transportation [5]. The satellites can be located at dedicated bus or subway stations. Collaborative logistics facilities are a reasonable alternative to utilizing limited resources and reducing total delivery costs.

In integrated services, passengers and freight are transported simultaneously on public transport. Passenger acceptance requires prioritizing passenger service over any freight activity. The freight service must not conflict with passenger service. During peak periods of public transport, such as commuting time and major events, there may be few or no demands for delivery by public transport. During off-peak periods, the free capacity of public transport can be fully utilized to deliver the demands. Periodic freight delivery using public transport is particularly suitable for instant deliveries and perishable freight [6].

Several barriers still prevent the integration of freight and passenger transport in short-haul transportation, in addition to passenger acceptance. Although handling freight at the passenger stations and coordinating deliveries are still technical obstacles, the main barriers preventing this integration are financing and stakeholder disagreement rather than the technical challenges of moving freight [2, 7]. The Amsterdam Cargo tram project has failed, but it is still considered a promising approach that provides social, economic, and environmental benefits [8]. Particularly, the integration improves operational and environmental efficiency by delivering the same demand with fewer vehicle-kilometers. In real cases, the application of this integration could be observed in specific case studies. As a revolutionary new city bus, the Freight ∗ Bus can transport both passengers and freight in urban areas [9]. Another example is that the Cargo-Tram and E-Tram have provided services for residents and bulky goods since 2003 in Stadt Zurich [10].

In this paper, we consider various routing characteristics including two-stage synchronization, free capacity of public transport, transfer time at satellites, and multiple goods delivery. Meanwhile, goods can be packed into standard-size boxes as recommended by physical Internet. To the best of our knowledge, a transportation scenario with all these characteristics has not been studied before. Specifically, the contributions of this paper include the following. First, the 2E-PDP-PT integrates two-echelon distribution with the integration of freight and public transport in the logistics distribution network. Second, we propose a new mathematical model for the 2E-PDP-PT based on a space-time network and adopt an ALNS algorithm to solve it. Third, we verify the effectiveness of the 2E-PDP-PT and the applicability of the ALNS algorithm based on newly generated instances.

The remainder of this paper is organized as follows. Section 2 provides the literature review. In Section 3, the problem statement and the mathematical formulation are provided. The ALNS algorithm for the 2E-PDP-PT is described in Section 4. Section 5 presents the results of computational experiments. Finally, the conclusions are stated in Section 6.

2. Literature Review

In this section, we review the literature on two-echelon distribution and vehicle routing problem with simultaneous pickup-delivery and time windows (VRPSPDTW). Subsequently, we focus on reviewing the literature related to the integration of freight and public transport.

Since the definition of two-echelon distribution was proposed by Crainic et al. [11] and a family of two-echelon vehicle routing problem (2E-VRP) was introduced by Perboli et al. [12], the number of literature studies dealing with 2E-VRP has continuously increased. Cuda et al. [13]

proposed an overview of two-echelon distribution systems and considered three classes of the 2E-VRP. Exact and heuristic solution methods for the 2E-VRP were reviewed and summarized by Sluijk et al. [3]. Recently, new variants of the two-echelon distribution have been studied, such as the 2E-VRP with drones [14], the 2E-VRP with time windows, intermediate facilities, and occasional drivers [15], and two-echelon multidepot multiperiod location-routing problem with pickup and delivery [16].

The vehicle routing with simultaneous pickup and delivery was rooted in Min [17], and a summary of VRPSPD was introduced by Koç et al. [18]. The VRPSPD with time windows, as a variant of the VRPSPD, was proposed by Angelelli and Mansini [19]. Recently, Liu et al. [20] developed a novel memetic algorithm to solve the VRPSPDTW and tested it in a real-world application of JD Logistics. Tang et al. [21] proposed a novel competitive coevolution scheme named coevolution of parameterized search (CEPS) to solve the VRPSPDTW and assessed its potential of CEPS using the date of JD Logistics.

The idea of integrating freight and public transport services was developed by Trentini and Mahléné [22]. Over the past two decades, an extensive literature study on the integration of freight and public transport services has emerged. Le Pira et al. [23] explored the possibility of integrating freight into Mobility as a Service (MaaS) and investigated the combination of freight and passenger trips. Bruzzone et al. [24] analyzed the potential of passenger and freight integration as a possible solution. Cavallaro and Nocera [25] reviewed the literature and defined future challenges, ranging from providing more reliable quantitative analysis to policy-related issues. Elbert and Rentschler [7] reviewed the literature for freight on public transit from a logistics and management perspective.

Integration is common for long-haul relations, such as in rail transport, air transport, and maritime shipping. Bollapragada et al. [26] developed an optimization algorithm-based software system to manage train dispatching. The system handles various types of traffic, including intermodal, automobile transport, manifest freight, and passengers. Vajdova et al. [27] discussed air transport for both passenger and freight transport. A regular sea link was established to transport goods and people in the Norwegian Hurtigruten [28]. In short-haul transportation, the integration is still uncommon in real cases. We refer the reader to Elbert and Rentschler [7] for more details and references. In Amsterdam, the Cargo Tram project started in 2007 but was closed due to a lack of funds in 2009. In Dresden, the Cargo Tram project adopted freight trains with five carriages to supply the Volkswagen factory. In Zurich, the tramway network was used to transport electrical waste and bulky goods. Several cities have started trying integration projects, but passengers and freight are still transported by different vehicles. There are instances where the same vehicle is used to deliver both passengers and freight. In the district of Heinsberg, MultiBus combined a door-to-door service for passengers and small goods [29]. The train service design (TSD) problem on the Union-Pearson Express Line with passenger and freight is proposed by Li et al. [30]. Passenger trains operate on a prescribed service frequency, and the timetable is allowed to be adjusted during the service period. Behiri et al. [31] focused on the freight-rail-transport-scheduling problem (FRTSP), which was formulated into a mixed-integer programming model.

There have been some recent studies on the modeling of the integration of freight and public transport. Li et al. [32] introduced the Share-a-Ride Problem (SARP) in which people and parcels share the same taxis and proposed a reduced problem based on the SARP. Masson et al. [33] proposed a two-tiered transportation problem in which goods are transported into the city core using the spare capacity of city buses. Cheng et al. [34] investigated the City-wide Package Distribution problem using Crowdsourced Public (CPDCP) transportation systems and proposed a genetic algorithm for solving this problem. Pternea et al. [35] explored a new operating scheme to integrate freight and public transport for last-mile parcel delivery. The operating scheme can determine the increase in bus frequency, if needed.

Some research studies have also shown that passengers and freight could be transported using scheduled lines. Ghilas et al. [36] described the pickup and delivery problem with time windows and scheduled lines (PDPTW-SL) as an arc-based mixed-integer program and analyzed the benefits of using SL for small instances. Ghilas et al. [37] proposed an ALNS algorithm to solve the PDPTW-SL and analyzed the cost savings using SL. Furthermore, Ghilas et al. [38] investigated the pickup and delivery problem with time windows, scheduled lines, and stochastic demands (PDPTW-SLSD) and adopted a heuristic method to deal with demand uncertainty. Ghilas [39] summarized the PDPTW-SL [36–38]. Mourad et al. [40] proposed that scheduled lines could be a part of the PD robot's journey and modeled the pickup and delivery problem as a two-stage stochastic problem. Schmidt et al. [4] introduced the last-mile delivery problem with scheduled lines (LMDPSL) and conducted an extensive computational study.

The relevant literature is summarized in Table 1. We review the relevant literature regarding the problems, modes, models, algorithms, and case studies. Existing literature has shown interesting perspectives on using public transport for freight transport, especially in last-mile delivery. Heuristic algorithms are often used to solve such routing problems. This paper considers a two-stage distribution problem in which public transport and trucks are used to transport goods in the first stage. In this context, various constraints are considered, such as two-stage synchronization constraint, free capacity of public transport, and transfer time at satellites. Furthermore, the goods to be transported are for different customers and can be packed into standard-size boxes. The literature review shows that no work has taken into account all these characteristics. Specifically, this paper contributes to the field of using public transport for freight transport in two aspects: (1) in the previous literature [30, 35], the prescribed service frequency of public transport can be adjusted to satisfy the demands. A new service could be acceptable to the public if it does not noticeably increase passenger travel time. Since passenger

Table 1: Summary of the related problems.

Reference	Problem	Mode	Model	Solution algorithm	Case study
Liu et al. [20]	VRPSPDTW	Freight vehicle	MIP	Memetic algorithm	JD Logistics, China
Tang et al. [21]	VRPSPDTW	Freight vehicle	—	Coevolution of parameterized search	JD Logistics, China
Li et al. [30]	TSD	Light rail	MILP	Train-based and shipment-based algorithms	Beijing, China
Behiri et al. [31]	FRTSP	Rail	MIP	Best dispatching rule and single-train-based algorithm	Paris, France
Masson et al. [33]	2E-VRP	Bus	MIP	ALNS algorithm	La Rochelle, France
Cheng et al. [34]	CPDCP	Bus	MILP	Heuristic based on genetic algorithm	Changsha, China
Pternea et al. [35]	VRPTW	Bus	MILP	Gurobi solver	Columbus, Ohio
Ghilas et al. [36]	PDPTW-SL	Public transport	MIP	CPLEX solver	Synthetical data
Ghilas et al. [37]	PDPTW-SL	Public transport	MIP	ALNS algorithm	Synthetical data
Ghilas et al. [38]	PDPTW-SLSD	Public transport	MIP	ALNS algorithm/SAA	Amsterdam, Netherlands
Mourad et al. [40]	PDPTW-SL	Public transport	MIP	ALNS algorithm/SAA	Synthetical data
Schmidt et al. [4]	LMDPSL	Public transport	MIP	Branch-price-and-cut algorithm	Synthetical data
This paper	2E-PDP-PT	Public transport or freight vehicle	MILP	ALNS algorithm	Beijing, China

MIP: mixed-integer program; MILP: mixed-integer linear program.

service must take priority over any freight service, this paper does not adjust the service frequency but uses a combination of public transport and dedicated trucks for delivery. (2) This paper formulates freight transport using public transport into a MILP based on a space-time network and efficiently solves it. Time window constraints can be integrated into the space-time network to simplify the model.

3. Methodology

3.1. Problem Statement. The problem statement of the 2E-PDP-PT is provided as follows. The logistics distribution consists of pickup, scheduled, and delivery stages. At the pickup stage, demands are collected using logistics vehicles from the origin depots to the original satellites. Then, the demands can be transported from the origin satellites to the destination satellites using the free capacity of public transport or via trucks at the scheduled stage. Finally, these demands are delivered to corresponding communities. The aim of the 2E-PDP-PT is to reduce the use of trucks in urban areas and minimize the total delivery costs. A realistic setting is that public transport, such as buses or subways, can operate on regular lines, allowing them to perform multiple circulations throughout the day. In addition, a more strategic phase of the system's design has identified potential stations suitable for transshipment of freight [4].

The logistics vehicles are homogeneous and sufficient, and the depots of logistics vehicles can be in the same or different locations. In the planning horizon, demands are not split to pick up but can be picked up across periods. Satellites are positioned at the passenger stations, where the original satellites refer to those that collect and transfer demands to the scheduled stage, and the destination satellites are those where demands are transferred from the scheduled stage to the delivery stage. The transfer time at the satellites depends on the number of goods delivered by public transport. Meanwhile, the goods can be packed into standard-size boxes with the same volume and maximum weight [30]. The standard-size boxes have been found in some instances, such as in the studies by Barrow [41] and Danard and Janin [42]. Since public transport gives priority to passengers, the transfer time required for goods must not violate capacity constraints or the predetermined schedule of public transport. For simplicity, at the scheduled stage, both trucks and public transport, referred to as first echelon vehicles (FE vehicles), are considered to travel on the scheduled links in the transportation network. The strategy adopted in this paper is to first use public transport for delivery and then use trucks when the free capacity of public transport is insufficient to meet the demands. Whether public transport can be used to transport demands depends on the relationship between the free capacity of public transport and the demands.

Formally, the 2E-PDP-PT is defined on a graph $G = (N, A)$. The node set N consists of node set N^P at the pickup stage, node set N^D at the delivery stage, and node set N^S at the scheduled stage. The link set A is composed of the link sets A^P, A^D, and A^S at three stages, respectively. For all links $(i, j) \in A$, d_{ij} represents the distance of the link (i, j). A planning horizon is set to T. At the pickup and delivery stages, the set of logistics vehicles is defined as K^P/K^D, and the capacity of logistics vehicle $k \in K^P \cup K^D$ is set to Q^{PD}. The travel cost at link (i, j), fixed cost, and average velocity of logistics vehicle k are $c^p_{i,j}/c^d_{i,j}$, $\mathrm{fc}^p_k/\mathrm{fc}^d_k$, and v^p_k/v^d_k. At the scheduled stage, the set of FE vehicles is defined as K^S including public transport K^{S1} and truck K^{S2}. The capacity, the travel cost at link (i, j), fixed cost, and average velocity of the vehicle of public transport K^{S1} and truck K^{S2} are Q^{S1}/Q^{S2}, $c^{s1}_{i,j}/c^{s2}_{i,j}$, $\mathrm{fc}^{s1}_k/\mathrm{fc}^{s2}_k$, and v^{s1}_k/v^{s2}_k.

The demands $q_{\tau l} = [q^0_{\tau l}, q^1_{\tau l}, \ldots, q^u_{\tau l}]$ are picked up at the loading node l and delivered to the unloading node u at period τ. Each loading node l has a specific time window $[e_l, l_l]$, and the unloading node u has the latest service time l_u. The loading and unloading nodes have a service time st. The transfer time wt for satellites depends on the number of goods delivered by public transport. In addition, we assume that public transport timetables are known, and public transport can be fully utilized to deliver the demands.

The notations and definitions used are summarized in Table 2.

A simple 11-node transportation network of the 2E-PDP-PT is provided in Figure 2. The network includes four suppliers and two communities. Four periods are set, each lasting 60 minutes. Public transport operates once during each period. The demand for each period is generated randomly. The fixed cost of each logistics vehicle is 2 units, and the transportation cost and time of logistics vehicles are interpreted as the number in the link. The free capacity of public transport is determined to be sufficient. We assume that the capacity of one standard-size box is 10 and the transfer time of one box is 1 min. The service time is zero. The case with randomly generated demands can be solved using the formulation of the 2E-PDP-PT, as provided in Section 3.2. The total delivery costs are 240, and the latest delivery time of all vehicles is 58 min at each period ensuring the requirement of on-time delivery.

The logistics distribution is further constructed in a space-time network. In the space-time network, the planning horizon is discretized into a set of time slots, denoted by $T = \{t_o, t_o + \Delta t, t_o + 2\Delta t, \ldots, t_o + M\Delta t\}$. t_0 represents the given departure time of the vehicles, and Δt is a time interval. M is a sufficiently large positive integer so that the time from t_o to $t_o + M\Delta t$ can cover the planning horizon. The network consists of the vertices (i, t) and the arcs (i, j, t, t'). (i, t) indicates the state of node i at time t, and (i, j, t, t') represents the vehicle runs from node i at time t to node j at time t', where $(t' - t)$ indicates the travel time of the link (i, j) plus the service time at node j. The time windows $[e_l, l_l]$ and l_u can be integrated into the space-time network. In more detail, vehicle v is only allowed to pick up demands $q_{\tau l}$ at loading node l between the time e_l and l_l and deliver to unloading node u before the time l_u. Interested readers are referred to Mahmoudi and Zhou [43]. A space-time network of the above illustrated case at a period is shown in Figure 3.

Table 2: Mathematical notations and definitions in our model.

Notation	Definition
Set and parameters	
N	Set of nodes in the transportation network, $N = N^P \cup N^D \cup N^S$
N^P	Set of nodes at the pickup stage, where $N^L \subseteq N^P$ is the set of loading nodes
N^D	Set of nodes at the delivery stage, where $N^U \subseteq N^D$ is the set of unloading nodes
N^S	Set of nodes at the scheduled stage
A	Set of links in the transportation network, $A = A^P \cup A^D \cup A^S$
$\delta^+(i,t)$	Set of links in A whose tail is node i at time t
$\delta^-(i,t)$	Set of links in A whose head is node i at time t
T	Set of time intervals, $T = \{t_o, t_o + \Delta t, t_o + 2\Delta t, \ldots, t_o + M\Delta t\}$
K	Set of vehicles, $K = K^P \cup K^D \cup K^S$
Q^{PD}	The capacity of logistics vehicles, $k \in K^P \cup K^D$
Q^S	The capacity of FE vehicles k, including Q^{S1} of public transport $k \in K^{S1}$ and Q^{S2} of trucks $k \in K^{S2}$
i, j	Index of nodes, $i, j \in N$
(i, j)	Index of links, $(i, j) \in A$
t, t'	Index of time intervals, $t, t' \in \{t_o, t_o + \Delta t, t_o + 2\Delta t, \ldots, t_o + M\Delta t\}$
τ	Index of time periods, $\tau \in T$
k, k'	Index of vehicles, $k, k' \in K$
$q_{\tau l}$	Demands of loading node $l \in N^L$ at period τ
$q_{\tau l}^u$	Demands of loading node l to unloading node $u \in N^U$ at period τ
$q_{\tau a}$	Demand across period τ
$c_{i,j}^p$, $c_{i,j}^d$	Travel cost of logistics vehicles at link (i, j)
$c_{i,j}^s$	Travel cost of FE vehicle k at link (i, j), including $c_{i,j}^{s1}$ of public transport $k \in K^{S1}$ and $c_{i,j}^{s2}$ of trucks $k \in K^{S2}$
fc_k^p, fc_k^d	The fixed cost of logistics vehicle k, $k \in K^P \cup K^D$
fc_k^s	The fixed cost of FE vehicle k, including fc_k^{s1} of public transport $k \in K^{S1}$ and fc_k^{s2} of trucks $k \in K^{S2}$
fc_q	The penalty cost of each demand across periods
v_k^p, v_k^d	The average velocity of logistics vehicles
v_k^s	The average velocity of FE vehicle k, including v_k^{s1} of public transport $k \in K^{S1}$ and v_k^{s2} of trucks $k \in K^{S2}$
o	The origin depot of logistics vehicles
d	The destination depot of logistics vehicles
d_{ij}	The distance of link (i, j)
st	The service time of the loading and unloading nodes
wt	The transfer time at satellites
(i, t), (j, t')	Index of space-time vertices
(i, j, t, t')	Index of space-time arcs
$[e_l, l_l]$	Time window of the loading node l, where e_l is the earliest service time and l_l is the latest service time
l_u	The latest service time of the unloading node u
M	A sufficiently large positive integer
Decision variables	
$x_{i,j,t,t',k}^{\tau p}$	= 1 if logistics vehicle k traverses arc (i, j, t, t') at period τ at the pickup stage, $(i, j, t, t') \in A^P$; = 0 otherwise
$x_{i,j,t,t',k}^{\tau d}$	= 1 if logistics vehicle k traverses arc (i, j, t, t') at period τ at the delivery stage, $(i, j, t, t') \in A^D$; = 0 otherwise
$x_{i,j,t,t',k}^{\tau s}$	= 1 if FE vehicle $k \in K^{S1} \cup K^{S2}$ traverses arc (i, j, t, t') at period τ at the scheduled stage, $(i, j, t, t') \in A^S$; = 0 otherwise
$y_k^{\tau p}$	= 1 if logistics vehicle k serves loading node p at period τ at the pickup stage, $k \in K^P$; = 0 otherwise
$y_k^{\tau d}$	= 1 if logistics vehicle k is used at period τ at the delivery stage, $k \in K^D$; = 0 otherwise
$y_k^{\tau s}$	= 1 if FE vehicle $k \in K^{S1} \cup K^{S2}$ is used at period τ at the scheduled stage; = 0 otherwise
$f_{i,j,t,t',k}^{\tau u}$	Total load to the unloading node $u, u \in N^U$ that is carried along arc (i, j, t, t') by vehicle $k \in K$ at period τ

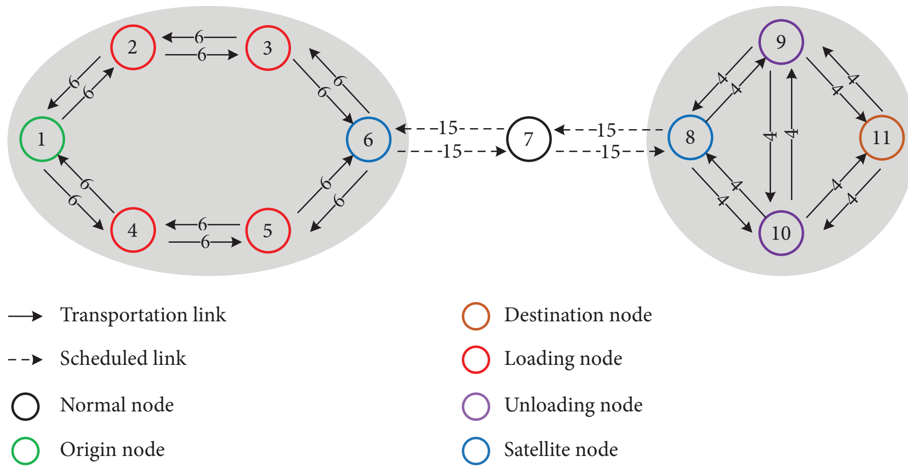

FIGURE 2: A transportation network of the 2E-PDP-PT.

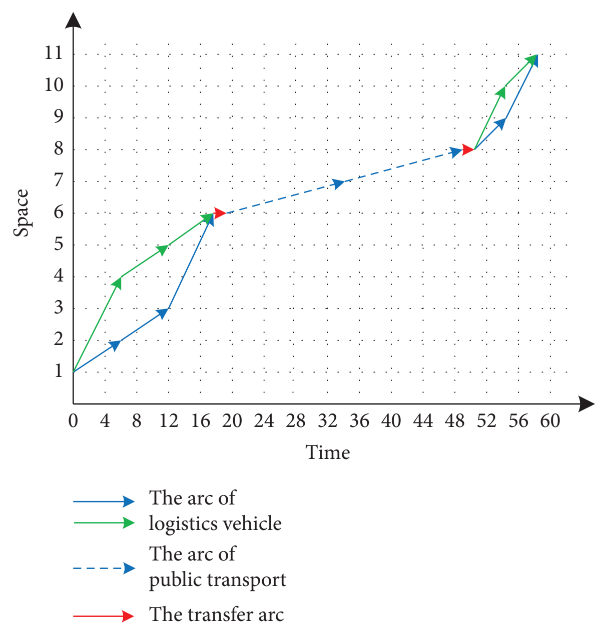

FIGURE 3: Illustration of a space-time network.

3.2. Mathematical Formulation

3.2.1. Objective Function. The objective function (1) is to minimize total delivery costs, including six parts: variable and fixed costs of logistics vehicles at the pickup stage; variable and fixed costs of FE vehicles; variable and fixed costs of logistics vehicles at the delivery stage.

$$\min Z = \sum_{\tau\in T}\sum_{k\in K^P}\sum_{(i,j,t,t')\in A^P} c^p_{i,j,t,t'}\cdot x^{\tau p}_{i,j,t,t',k} + \sum_{\tau\in T}\sum_{k\in K^P} fc^p_k\cdot y^{\tau p}_k + \sum_{\tau\in T}\sum_{k\in K^S}\sum_{(i,j,t,t')\in A^S} c^s_{i,j,t,t'}\cdot x^{\tau s}_{i,j,t,t'k} + \sum_{\tau\in T}\sum_{k\in K^S} fc^s_k\cdot y^{\tau s}_k$$
$$+ \sum_{\tau\in T}\sum_{k\in K^D}\sum_{(i,j,t,t')\in A^D} c^d_{i,j,t,t'}\cdot x^{\tau d}_{i,j,t,t',k} + \sum_{\tau\in T}\sum_{k\in K^D} fc^d_k\cdot y^{\tau d}_k. \quad (1)$$

3.2.2. Constraints. The constraints include the following four categories: constraints at the pickup stage; constraints at the delivery stage; constraints at the scheduled stage; and synchronization constraints.

(1) Constraints at the Pickup Stage

$$\sum_{(o,j,t,t')\in\delta^-(o,t)} x^{\tau p}_{o,j,t,t',k} = 1 \quad \forall\tau\in T, k\in K^P, (o,j,t,t')\in A^P, \tag{2}$$

$$\sum_{(j,so,t,t')\in\delta^+(so,t')} x^{\tau p}_{j,so,t,t',k} = 1 \quad \forall\tau\in T, k\in K^P, (j,so,t,t')\in A^P, \tag{3}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau p}_{i,j,t,t',k} - \sum_{(j,j',t',t'')\in\delta^-(j,t')} x^{\tau p}_{j,j',t',t'',k} = 0 \quad \forall\tau\in T, k\in K^P, j\in N^P, j\neq o, \mathrm{so}, \tag{4}$$

$$\sum_{k\in K^P}\sum_{(j,j',t',t'')\in\delta^-(j,t')} f^{\tau u}_{j,j',t',t'',k} - \sum_{k\in K^P}\sum_{(i,j,t,t')\in\delta^+(j,t')} f^{\tau u}_{i,j,t,t',k} = q^u_{\tau j} \quad \forall\tau\in T, j\in N^L, u\in N^U, \tag{5}$$

$$0\leq \sum_{u\in N^U} f^{\tau u}_{i,j,t,t',k} \leq Q^{PD}\cdot x^{\tau p}_{i,j,t,t',k} \quad \forall k\in K^P, \forall\tau\in T, (i,j,t,t')\in A^P, \tag{6}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau p}_{i,j,t,t',k} \leq y^{\tau p}_k \quad \forall\tau\in T, k\in K^P, j\in N^L. \tag{7}$$

Constraints (2)–(4) are flow balance constraints at the pickup stage. Constraints (2) and (3) guarantee that each logistics vehicle starts from the origin $o, o\in N^P$ and ends at the destination $\mathrm{so}, \mathrm{so}\in N^S$, respectively. Constraint (4) denotes that input flow is the same as output flow on other intermediate nodes. Constraint (5) ensures that all pickup requests are satisfied. Constraint (6) respects the capacity of each logistics vehicle for demand pickup. Constraint (7) indicates that logistics vehicle k can serve loading nodes no more than once.

(2) Constraints at the Delivery Stage

$$\sum_{(\mathrm{sd},j,t,t')\in\delta^-(\mathrm{sd},t)} x^{\tau d}_{\mathrm{sd},j,t,t',k'} = 1 \quad \forall\tau\in T, k'\in K^D, (\mathrm{sd},j,t,t')\in A^D, \tag{8}$$

$$\sum_{(j,d,t,t')\in\delta^+(d,t')} x^{\tau d}_{j,d,t,t',k'} = 1 \quad \forall\tau\in T, k'\in K^D, (j,d,t,t')\in A^D, \tag{9}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau d}_{i,j,t,t',k'} - \sum_{(j,j',t',t'')\in\delta^-(j,t')} x^{\tau d}_{j,j',t,t',k'} = 0 \quad \forall\tau\in T, k'\in K^D, j\in N^D, j\neq \mathrm{sd}, d, \tag{10}$$

$$\sum_{k'\in K^D}\sum_{(i,u,t,t')\in\delta^+(u,t')} f^{\tau u}_{i,u,t,t',k'} - \sum_{k'\in K^D}\sum_{(u,j,t',t'')\in\delta^-(u,t')} f^{\tau u}_{u,j,t',t'',k'} = \sum_{i'\in N^L} q^u_{\tau i'} \quad \forall\tau\in T, u\in N^U, \tag{11}$$

$$0\leq \sum_{u\in N^U} f^{\tau u}_{i,j,t,t',k'} \leq Q^{PD}\cdot x^{\tau d}_{i,j,t,t',k'} \quad \forall\tau\in T, k'\in K^D, (i,j,t,t')\in A^D, \tag{12}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau d}_{i,j,t,t',k'} \leq y^{\tau d}_{k'} \quad \forall\tau\in T, j\in N^U, k'\in K^D. \tag{13}$$

Constraints (8)–(10) are flow balance constraints at the delivery stage. Constraints (8) and (9) represent that each logistics vehicle starts from the origin $\mathrm{sd}, \mathrm{sd}\in N^S$ and ends at the destination $d, d\in N^D$, respectively. Constraint (10) ensures that input flow is the same as output flow on other intermediate nodes. Constraint (11) ensures that all delivery requests must be satisfied. Constraint (12) guarantees the capacity of each logistics vehicle for demand delivery. Constraint (13) indicates that logistics vehicle k' can serve the unloading nodes no more than once.

(3) Constraints at the Scheduled Stage

$$\sum_{(\mathrm{so},j,t,t')\in\delta^-(\mathrm{so},t)} x^{\tau s}_{\mathrm{so},j,t,t',k''} = 1 \quad \forall\tau\in T, k''\in K^S, (\mathrm{so},j,t,t')\in A^S, \tag{14}$$

$$\sum_{(j,\mathrm{sd},t,t')\in\delta^+(sd,t')} x^{\tau s}_{j,\mathrm{sd},t,t',k''} = 1 \quad \forall\tau\in T, k''\in K^S, (j,\mathrm{sd},t,t')\in A^S, \tag{15}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau s}_{i,j,t,t',k''} - \sum_{(j,j',t',t'')\in\delta^-(j,t')} x^{\tau s}_{j,j',t',t'',k''} = 0 \quad \forall\tau\in T, k''\in K^S, j\in N^S, j\neq so,\mathrm{sd}, \tag{16}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} f^{\tau u}_{i,j,t,t',k''} - \sum_{(j,j',t',t'')\in\delta^-(j,t')} f^{\tau u}_{j,j',t',t'',k''} = 0 \quad \forall\tau\in T, k''\in K^S, j\in N^S, u\in N^U, \tag{17}$$

$$0\le \sum_{u\in N^U} f^{\tau u}_{i,j,t,t',k''} \le Q^S\cdot x^{\tau s}_{i,j,t,t',k''} \quad \forall\tau\in T, k''\in K^S, (i,j,t,t')\in A^S, \tag{18}$$

$$\sum_{(i,j,t,t')\in\delta^+(j,t')} x^{\tau s}_{i,j,t,t',k''} \le y^{\tau s}_{k''} \quad \forall\tau\in T, k''\in K^S. \tag{19}$$

Constraints (14)–(16) are flow balance constraints at the scheduled stage. Constraints (14) and (15) ensure that each FE vehicle starts from the origin so, so $\in N^S$, and ends at the destination sd, sd $\in N^S$, respectively. Constraint (16) denotes that input flow is the same as output flow on other intermediate nodes. Constraint (17) guarantees the request is consistent on the scheduled nodes. Constraint (18) respects the capacity of each FE vehicle. Constraint (19) guarantees a node is visited no more than once by a FE vehicle.

(4) Synchronization Constraints

$$\sum_{k\in K^P}\sum_{(i,\mathrm{so},t,t')\in\delta^+(\mathrm{so},t')} f^{\tau u}_{i,\mathrm{so},t,t',k} - \sum_{k''\in K^S}\sum_{(\mathrm{so},j,t''',t'')\in\delta^-(\mathrm{so},t''')} f^{\tau u}_{\mathrm{so},j,t''',t'',k''} = 0 \quad \forall\tau\in T, i\in N^P, j\in N^S, u\in N^U, \tag{20}$$

$$\sum_{k''\in K^S}\sum_{(i,\mathrm{sd},t,t')\in\delta^+(\mathrm{sd},t')} f^{\tau u}_{i,\mathrm{sd},t,t'k''} - \sum_{k'\in K^S}\sum_{(\mathrm{sd},j,t''',t'')\in\delta^-(\mathrm{sd},t''')} f^{\tau u}_{\mathrm{sd},j,t''',t'',k'} = 0 \quad \forall\tau\in T, i\in N^S, j\in N^D, u\in N^U. \tag{21}$$

Constraint (20) respects the consistency of demand flows between pickup and scheduled stages in which, $t' + wt = t'''$ guarantees that the departure time of FE vehicles is equal to the sum of the arrival time of logistics vehicles and transfer time at the origin satellite. Constraint (21) respects all demands should be transferred from FE vehicles to logistics vehicles in which, $t' + wt = t'''$ guarantees that the departure time of logistics vehicles is the sum of the arrival time of FE vehicles and transfer time at the destination satellite.

4. An Adaptive Large Neighborhood Search

The ALNS which was proposed to solve PDPTW by Ropke and Pisinger [44] is based on an extension of the large neighborhood search (LNS) [45]. In the ALNS framework, multiple removal and insertion operators are selected differently compared to LNS. The algorithm starts from an initial solution and then applies multiple removal and insertion operators to generate a new acceptable solution based on a predetermined criterion. The probability of selecting these operators at each iteration depends on the performance of each neighborhood operator in previous iterations. The ALNS has been adopted in recent years by some scholars [46–48], and numerous researchers have demonstrated the tremendous effectiveness and flexibility of the ALNS for solving the VRP variants, such as VRPTW [33], the time-dependent profitable pickup and delivery problem with time windows [49], and PDPTW-SL [37]. The operators and adaptive mechanism of the ALNS are illustrated in detail in this paper as well as in our previous paper [50].

4.1. Route Checking across Periods. Given the periodicity of demands, the logistics and FE vehicles should synchronize their arrivals and departures at each period. However, in some cases, some supplier nodes are located far away from the origin satellites, resulting in delivery times that exceed the period duration. One method for circumventing is to preprocess the data to avoid this situation. However, this will be a time-consuming task. Another approach adopted in this paper is to allow demands to be delivered across periods. The demands across periods are delivered to the satellite origin at the next period (see Figure 4). The blue route of logistics vehicles runs within a period, and commodities can be distributed by FE vehicles. The red route of logistics vehicles represents the cross-period distribution, where demands are calculated based on the demands of the third period, and the transportation cost at the pickup area is considered as the cost of the second period.

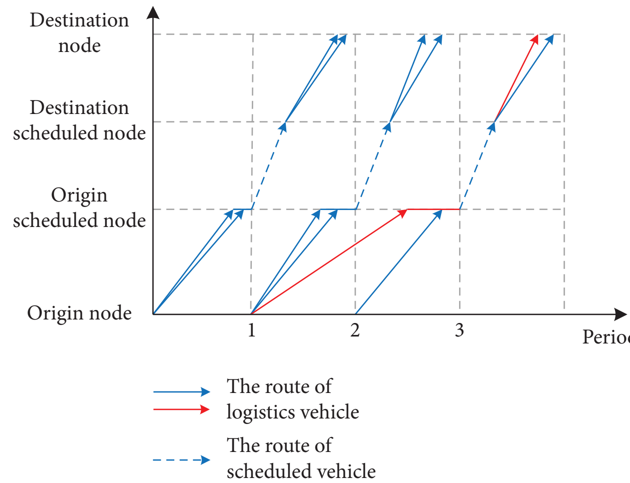

FIGURE 4: Example of the route across periods.

4.2. Initial Solution Construction. Since the 2E-PDP-PT is divided into three stages, the initial feasible solution is generated using a heuristic solution including three steps. First, all demands are stored in a demand list L. To construct initial pickup routes, a logistics vehicle picks up demands from the demand list L while satisfying the time window and capacity constraints. If these constraints are violated, another new logistics vehicle is dispatched to pick up demands until no demand is on the demand list L. Second, demands are first considered to be delivered by public transport. If the free capacity of public transport does not match the demands, trucks are used for delivery. Each satellite is the convergence node of the demands and has sufficient storage capacity. Finally, the demands are delivered to corresponding communities using logistics vehicles at the delivery stage. Based on these three steps, an initial feasible solution is generated, although the solution may be large, it satisfies all constraints.

4.3. Flow of the ALNS. The general framework of the ALNS is provided in Algorithm 1. The heuristic begins with an initial solution s_0 and iterates until the maximum number of iterations is reached. In each iteration, a new solution s' is generated based on a current solution s by applying a pair of removal and insertion operators. The removal and insertion operators are chosen using an adaptive mechanism described in Section 4.4. A new solution s' can be accepted if it satisfies the simulated annealing criterion. Specifically, if $f(s') \le f(s)$, then new solution s' is acceptable; if $f(s') > f(s)$, s' is accepted with a probability function $e^{-(f(s')-f(s))/T}$. T stands for the temperature, and its initial temperature $T_0 = \delta f(s_0), \delta \in (0,1)$. In each iteration, T is decreased according to the following formula, $T = T_0 \times c^{\alpha}$, where $c \in (0,1)$. This process repeats until the termination condition is met.

4.4. The Adaptive Mechanism. In Algorithm 1, the solution process includes the number of optimization phases γ, and the iterations of each optimization phase φ. A Roulette wheel mechanism is adopted to select removal and insertion operators. Initially, the weights of each removal operator $w_d, d \in D$ and insertion operator $w_i, i \in I$ have the same value. In each iteration, the probability of selecting a remove-insert pair is based on the following formulas, $w_d/\sum_{j=1}^{|D|} w_j$ and $w_i/\sum_{j=1}^{|I|} w_j$. In each optimization phase, the weights are estimated as $w_d^{n+1} = w_d^n(1-\eta) + \eta\pi_{\mathrm{dn}}/\theta_{\mathrm{dn}}$ and $w_i^{n+1} = w_i^n(1-\eta) + \eta\pi_{\mathrm{in}}/\theta_{\mathrm{in}}$, respectively. The parameter $\eta \in [0,1]$ is defined as the reaction factor. θ_{dn} and θ_{in} are the number of times the removal operator d and insertion operator i at nth iteration. π_{dn} and π_{in} are the scores of removal operator d and insertion operator i at nth iteration. All scores are set to zero at the beginning of the optimization phase. Moreover, π_{dn} and π_{in} are updated by the constants σ_1, σ_2, and σ_3 depending on operators' performances when a new solution is accepted, where σ_1 denotes that a best new solution is obtained; σ_2 denotes that a new solution is better than the current solution; σ_3 denotes that a new solution is accepted by the simulated annealing criterion.

4.5. Removal and Insertion Operators. We have proposed four removal operators and two insertion operators in our algorithm, where time removal operator is designed based on the characteristics of the 2E-PDP-PT. All removal and insertion operators are adapted from or inspired by Røpke and Pisinger [44].

4.5.1. Removal Operators. At the removal stage, the predetermined removal number is removed from the current solution and placed into the removal list L_r. The general framework of removal operators is shown in Algorithm 2.

(i) Random removal: This operator simply and randomly selects the predetermined removal number of supplier nodes from the current solution. The idea of random removal can ensure the diversity of search space.

(ii) Worst removal: This worst removal operator refers to removing a supplier node that has the greatest effect on the objective value until reaching the predetermined removal number. The removed supplier node can be reinserted into other better locations to obtain a quality solution.

Input: Iterations of each optimization phase φ, number of optimization phases γ, removal operators D, insertion operators I, cooling rate c
Output: A feasible solution s^*
Generate an initial solution s_0 by a heuristic method (Section 4.2)
Initialize probability for each removal operator $d \in D$ and each insertion operator $i \in I$ (Section 4.5)
Initialize best solution $s^* = s_0$, current solution $s = s_0$, $\gamma = 0$, $\alpha = 0$
Repeat
  Initialize $\gamma := \gamma + 1$, $n = 0$
  While $n < \varphi$, **do**
    Use the Roulette wheel mechanism $w_d/\sum_{j=1}^{|D|} w_j$, $w_i/\sum_{j=1}^{|I|} w_j$ to select a remove-insert pair
    Let s' be a new solution after applying a pair of removal and insertion operators
    If $f(s') < f(s^*)$ then
      $s^* = s = s'$, update the score with σ_1
    Else if $f(s') < f(s)$ then
      $s = s'$, update the score with σ_2
    Else if s' is accepted by the simulated annealing criterion then
      $s = s'$, update the score with σ_3
    End if
    $n := n + 1$, adjust weights w_d, w_i, $d \in D, i \in I$
    If the number of iterations reaches φ,
      Reset the weights $w_d = 1, w_i = 1$, $d \in D, i \in I$
$\alpha := \alpha + 1$
Until the maximum number of iterations is reached
Return best solution s^*

Algorithm 1: The general framework of the ALNS algorithm.

Input: The initial solution s_0, the predetermined removal number l_r
Output: A partial solution s_p
Initialize the remove list $L_r = \varnothing$, $r = 0$
While $r < l_r$, **do**
  Apply removal operator to remove one supplier node p
  $L_r = L_r \cup p$
  $r := r + 1$
Return the removal list L_r and a partial solution s_p

Algorithm 2: The general framework of removal operators.

(iii) Shaw removal: This operator removes some supplier nodes that are similar in certain aspects. In this paper, a similar concept includes the transport distance between two supplier nodes, the pickup time of each supplier node, and the demand number of supplier nodes. The similarity between supplier nodes i and j is described as $SC(i, j) = \mu_1 d_{ij} + \mu_2 |t_i - t_j| + \mu_3 |q_i - q_j|$, where μ_1, μ_2, and μ_3 are normalized weights. The smaller value $\mathrm{SC}(i, j)$ indicates a greater similarity between two supplier nodes.

(iv) Time removal: Due to using public transport to deliver commodities, it is necessary to ensure that commodities adhere to the departure times of public transport. The objective of this time removal operator is to select and remove the supplier node with the longest waiting time at the satellite nodes. The removal can help reduce the maximum wait time.

4.5.2. Insertion Operators. After the removal operators, the removed supplier nodes need to be reinserted into the partial solution s_p. The insertion operations ensure the feasibility of a new solution s' and improve the quality of the solution. The general framework of insertion operators is provided in Algorithm 3.

(i) Greedy insertion: This greedy insertion operator inserts a supplier node to the best feasible position of the partial solution s_p. When a supplier node is inserted, the total delivery costs of inserting a supplier node into any feasible position are calculated, and the position with the minimized insertion cost is selected to insert. Then, supplier nodes in the remove list L_r are inserted one by one until no supplier node is in the remove list L_r.

(ii) Regret-n insertion: This operator uses the look-ahead information to select a supplier node and its insertion position. In this paper, regret-3

Input: The partial solution s_p, the demand list L_r
Output: A new solution s'
for supplier node $p \in L_r$, **do**
  Apply insertion operator to insert supplier node p
  If it is not feasible for supplier node p to be inserted into any route, construct a new route.
Return a new solution s'

ALGORITHM 3: The general framework of insertion operators.

insertion is adopted in large instances, and its value is the difference between the cost of the best insertion position and the cost of the 3rd best insertion position. The regret value must be recalculated after each insertion until no supplier node is in the remove list L_r.

5. Computational Experiments

In this section, we assess the performance of the proposed model and the ALNS by running a series of computational experiments. The solution is coded in Python, and all experiments are deployed on a 2.60 GHz Intel(R) Core (TM) i7 processor with 32 GB RAM.

TABLE 3: Parameter values in the proposed ALNS.

Parameter	Value/percentage gaps					
Initial temperature parameter δ	0.2					
Cooling rate c	0.96					
The adaptive weight parameter η	0.2					
The ratio of random removal	0.1–0.3					
The number of worst removals	5–15					
First Shaw parameter μ_1	0.5					
Second Shaw parameter μ_2	0.4					
Third Shaw parameter μ_3	0.1					
The ratio of Shaw removal	0.3					
The route number of time removal	3					
Coefficient of regret-n	3					
Best new solution σ_1		18		12		6
Improving solution σ_2	>0.1	6	>0.01	4	<0.01	2
Deteriorating solution σ_3		1		1		1

5.1. Case Study. In this section, we generate a set of small-scale instances with different network topologies, demand distributions, and the number of periods. Each small-scale instance contains periodic supplier nodes distributed over a 50×50 Euclidean space. Each instance is named numP-numD-numS-numF, where numP is the number of supplier nodes, numD represents the number of delivery nodes, numS denotes the number of scheduled links, and numF is the number of periods. In all instances, logistics vehicles with a capacity of 6 transport the demands at the pickup and delivery stages, while FE vehicles at the scheduled stage are considered. The free capacity of public transport is assumed to be sufficient. We assume the fixed cost for logistics vehicles to be 2 units and the transportation cost for each vehicle is 1 unit. The transfer time for satellites depends on the number of goods delivered by public transport. The instances can be found at https://github.com/Datainstances/Instances.git.

We solve small-scale instances using Gurobi 9.5.1. To get the exact solution, the gap value is set to zero, and the maximum running time is 1 hour. The effectiveness of the ALNS is compared with that of Gurobi. Since the small-scale instances are simple, the exact solution can still be obtained using the ALNS. Before executing the ALNS, several parameters are determined in advance. The parameters are set as follows: the number of worst removals is within [1, 3], the route number of time removal is 1, the coefficient of regret-n is 2, and other values are the same in Table 3. The Gurobi and the ALNS are compared in Table 4.

In Table 4, there are a total of forty small-scale instances. The generated instances are divided into categories according to the number of demand and delivery nodes. The ALNS can obtain the solution of all small-scale instances, while the performance of Gurobi becomes worse with the increase of demand and delivery nodes. By using Gurobi, the solution cannot be found in the 8-4-1-7 and 8-4-1-8 instances and it encounters a memory-error issue. In addition, the ALNS can obtain optimal solutions (Gap = 0) in all small-scale instances, similar to those obtained by Gurobi. This indicates that the ALNS is robust in solving small 2E-PDP-PT instances. Therefore, the ALNS is adopted to solve large instances in Section 5.2.

We further study the effects of the length of time windows, public transport capacity, and the frequency of public transport based on the newly created transportation network, as shown in Figure 5. The instances consist of four supplier nodes, two delivery nodes, and a scheduled line. In all following instances, the total time is set to 40 minutes, and every five minutes is a period. The acceptable delay time for passengers is set to 2 minutes. The fixed cost fc_k^{s2} of trucks is set to 3 units. The other parameter settings are consistent with the above small-scale instances. To gain managerial insights, we conduct a sensitivity analysis for each instance by varying one parameter at a time.

5.1.1. The Effect of the Length of Time Windows. The effect of the length of time windows on the performance of the Gurobi and the ALNS is discussed in this section. Twelve instances are used for the sensitivity analysis of time window. We consider two time windows at supplier nodes: [1, 4] and [1, 11]. The computational results are shown in Table 5. We find that the total delivery costs and the number of logistics vehicles decrease correspondingly with the more relaxed time windows.

Table 4: Comparison between the Gurobi and the ALNS solutions.

Instance	Gurobi obj	T_e (seconds)	ALNS obj	T_a (seconds)	Obj gap (%)
4-2-1-1	18	1.28	18	0.01	0
4-2-1-2	36	2.49	36	0.01	0
4-2-1-3	54	4.32	54	0.01	0
4-2-1-4	73	5.19	73	0.05	0
4-2-1-5	92	8.56	92	0.07	0
4-2-1-6	109	11.43	109	0.14	0
4-2-1-7	126	15.86	126	0.21	0
4-2-1-8	146	20.56	146	0.58	0
6-2-1-1	23	3.21	23	0.01	0
6-2-1-2	46	5.99	46	0.03	0
6-2-1-3	69	9.07	69	0.05	0
6-2-1-4	92	12.42	92	0.07	0
6-2-1-5	115	16.55	115	0.16	0
6-2-1-6	138	19.24	138	0.22	0
6-2-1-7	161	23.54	161	0.29	0
6-2-1-8	184	27.24	184	1.42	0
6-3-1-1	27	15.68	27	0.01	0
6-3-1-2	54	32.86	54	0.01	0
6-3-1-3	81	47.31	81	0.08	0
6-3-1-4	108	67.14	108	0.15	0
6-3-1-5	135	85.74	135	0.21	0
6-3-1-6	162	99.06	162	0.37	0
6-3-1-7	189	121.91	189	0.56	0
6-3-1-8	216	173.73	216	2.11	0
8-3-1-1	56	26.43	56	0.01	0
8-3-1-2	112	53.49	112	0.01	0
8-3-1-3	168	82.28	168	0.04	0
8-3-1-4	224	108.73	224	0.07	0
8-3-1-5	320	153.36	320	0.21	0
8-3-1-6	384	227.81	384	0.32	0
8-3-1-7	438	265.13	438	0.31	0
8-3-1-8	512	336.89	512	1.83	0
8-4-1-1	64	43.65	64	0.01	0
8-4-1-2	128	87.37	128	0.01	0
8-4-1-3	192	121.69	192	0.04	0
8-4-1-4	288	193.66	288	0.08	0
8-4-1-5	360	274.58	360	0.15	0
8-4-1-6	432	367.51	432	0.45	0
8-4-1-7	—	—	504	0.56	—
8-4-1-8	—	—	576	1.92	—

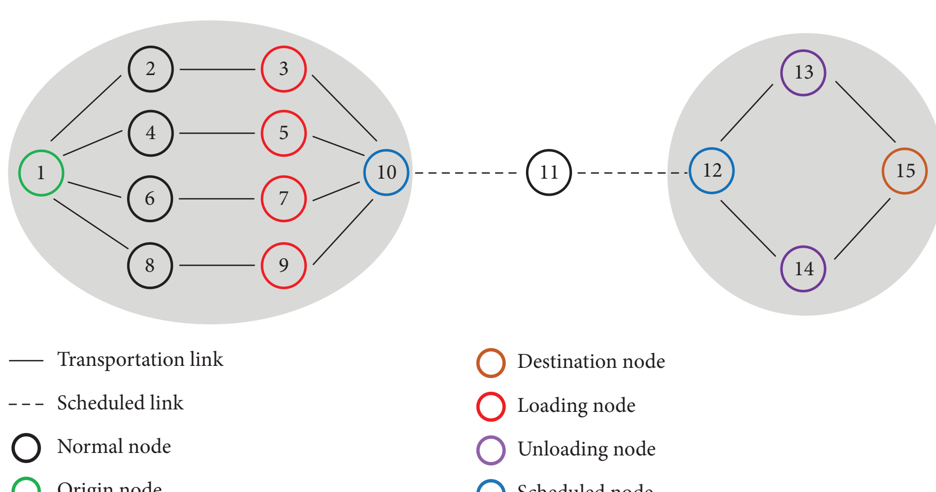

Figure 5: A transportation network for sensitivity analysis.

Table 5: The effect of the length of time windows on the total delivery cost and logistics vehicles.

Instance	Time window				Total delivery costs		Logistics vehicles	
	D1*	D2	D3	D4	Gurobi	ALNS	Gurobi	ALNS
T4-2-1-1	[1, 4]	[1, 4]	[1, 4]	[1, 4]	28	28	6	6
	[1, 4]	[1, 4]	[1, 11]	[1, 11]	25	25	5	5
	[1, 11]	[1, 11]	[1, 11]	[1, 11]	22	22	4	4
T4-2-1-2	[1, 4]	[1, 4]	[1, 4]	[1, 4]	56	56	12	12
	[1, 4]	[1, 4]	[1, 11]	[1, 11]	50	50	10	10
	[1, 11]	[1, 11]	[1, 11]	[1, 11]	44	44	8	8
T4-2-1-3	[1, 4]	[1, 4]	[1, 4]	[1, 4]	84	84	18	18
	[1, 4]	[1, 4]	[1, 11]	[1, 11]	75	75	15	15
	[1, 11]	[1, 11]	[1, 11]	[1, 11]	66	66	12	12
T4-2-1-4	[1, 4]	[1, 4]	[1, 4]	[1, 4]	112	112	24	24
	[1, 4]	[1, 4]	[1, 11]	[1, 11]	100	100	20	20
	[1, 11]	[1, 11]	[1, 11]	[1, 11]	96	96	16	16

*D1: supplier node 1.

In addition, under the scenario of looser time windows of supplier nodes, fewer logistics vehicles deliver the demands. Still, it may cause delays in the departure time of passengers on public transport. Therefore, we must consider passenger acceptance. In this section, each logistics vehicle picks up the demands from two supplier nodes when time window of all supplier nodes is [1, 11]. The earliest time to meet the requirement of public transport is 6 minutes. Since the departure time of public transport at each period is 5 minutes, the integration service succeeds since the delay is less than the acceptable delay time for passengers. Otherwise, more logistics vehicles are needed to meet passenger acceptance. Therefore, within passenger acceptance, the wider the time window length, the more supplier nodes logistics vehicles visit, resulting in lower total delivery costs.

5.1.2. The Effect of Public Transport Capacity. The public transport capacity depends on the number of passengers. We evaluate the effect of public transport capacity on the total delivery costs. In generated instances, the transportation cost $c_{i,j}^{s1}$ and fixed cost fc_k^{s1} are zero. The transportation cost $c_{i,j}^{s2}$ is 1 unit and the fixed cost fc_k^{s2} is 3 units if the demand is delivered by truck k of capacity 12 units. Under various demands, we test four extra spaces Q^{S1} of public transport: 0, 6, 9, sufficient for demand units. The results are presented in Table 6.

In Table 6, we observe that with more public transport capacity, the total delivery costs are more likely to reduce. The total delivery costs decrease only when the demand is lower than public transport capacity, which means the free capacity can be used to deliver the demands. Furthermore, Figure 6 depicts the total delivery costs of four free capacities' changes when the volume of demand varies. There are six scenarios generated based on the public transport capacity, the capacity of freight vehicles, and the varying demands. Overall, such integration is more likely to reduce the total delivery costs during off-peak hours of public transport.

5.1.3. The Effect of Frequency of Public Transport. We further analyze the effect of the frequency of public transport on the total delivery costs. In generated instances, the free capacity of public transport is considered as 6 units. The transportation cost $c_{i,j}^{s2} = 1$ unit and the fixed cost $fc_k^{s2} = 3$ units of truck k of capacity 12 units are set. We consider four frequencies of public transport, namely, once every one period, once every two periods, once every four periods, and no public transport. The results are shown in Figure 7.

Figure 7 presents a summary of statistics under varying frequencies of public transport and varying volumes of demand. This result shows that a higher frequency of public transport can result in lower total costs, with the number of shipments varying in [0, 6] and [13, 18]. For the other demand domains, the total costs remain constant despite the changes in the frequency of public transport. It implies that the total delivery costs can be reduced only when the suitable demand is distributed by public transport. In some cases, increasing the frequency of public transport does not reduce total delivery costs but increases the operational pressure. Therefore, changes in the frequency of public transport should consider the possibility of integrating freight and public transport services to avoid unnecessary operational pressure for public transport operators.

5.2. Tests Using a Real-World Transportation Network

5.2.1. Data and Parameter Setting. To further evaluate the practicality of the 2E-PDP-PT and ALNS, the larger case of the Beijing Yizhuang transportation network, as shown in Figure 8, is used for testing. The open-source datasets are obtainable from https://github.com/Datainstances/Beijing_YiZhuang_network.git.

The network settings for the Beijing Yizhuang transportation network are shown in Figure 9. We design two scheduled links and the FE vehicle transport from the origin satellite to the destination satellite in one direction. Seven communities are designed at the delivery stage. At the

Table 6: The effect of public transport capacity on the total delivery cost.

Instance	Demand number				Total cost of PVRPTW-SL			
	D1*	D2	D3	D4	$Q^{S1}=0$	6	9	Sufficient
1	[3, 1]	[0, 0]	[0, 0]	[0, 0]	24	11	11	11
2	[0, 0]	[2, 2]	[0, 0]	[0, 0]	24	11	11	11
3	[3, 1]	[2, 2]	[0, 0]	[0, 0]	31	31	18	18
4	[0, 0]	[0, 0]	[2, 2]	[2, 1]	31	31	18	18
5	[3, 1]	[2, 2]	[1, 2]	[0, 0]	36	36	36	23
6	[0, 0]	[1, 2]	[2, 1]	[2, 2]	36	36	36	23
7	[3, 1]	[2, 2]	[1, 2]	[2, 1]	58	45	45	32
8	[1, 1]	[1, 2]	[2, 2]	[1, 4]	58	45	45	32
9	[3, 2]	[2, 2]	[2, 3]	[2, 3]	62	62	49	36
10	[2, 3]	[1, 4]	[2, 3]	[3, 2]	62	62	49	36
11	[3, 3]	[2, 3]	[2, 3]	[3, 3]	62	62	62	36
12	[2, 4]	[3, 3]	[4, 1]	[2, 4]	62	62	62	36

*D1: supplier node 1.

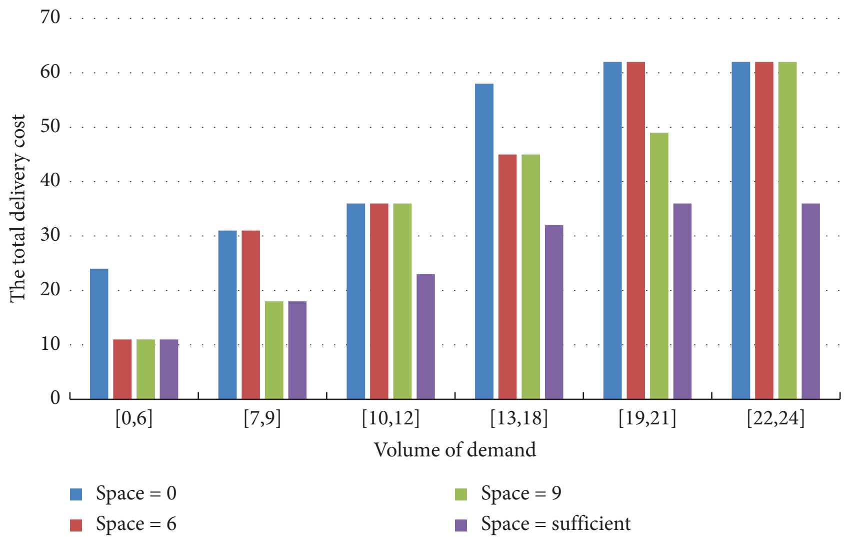

Figure 6: Summary of the statistics on four capacities of public transport.

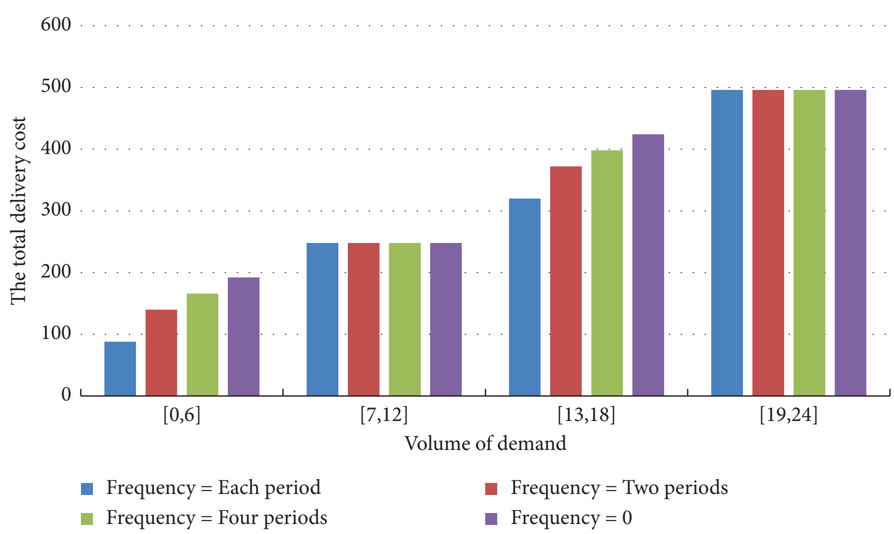

Figure 7: Summary of the statistics on four frequencies of public transport.

Figure 8: The Beijing Yizhuang transportation network.

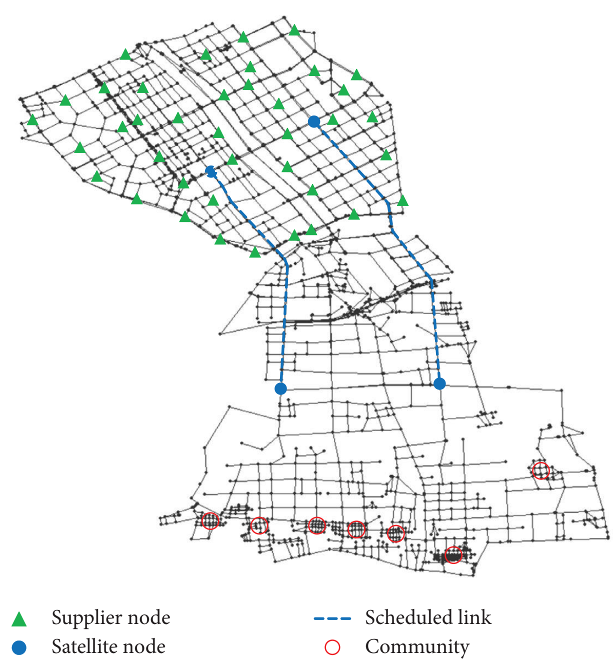

Figure 9: The network settings in the transportation network.

pickup stage, the supplier nodes are generated with random distribution. Each supplier node randomly generates commodities of seven communities, and the number of commodities in each community ranges from 0 to 4, i.e., [1, 3, 4, 0, 1, 0, 4]. The total demands at each period are calculated as the sum of the demands of all supplier nodes at this period and the cross-period demands.

In the tested instances, each instance has a total of 9 periods. Public transport and trucks on scheduled links are set to hourly delivery at each period. The pickup service time is required before the departure time of FE vehicles, which is within an hour at each period. The service time of pickup and delivery is one min, and the transfer time on the satellites depends on the number of goods delivered by public transport. We still assume that the capacity of one standard-size box is 10 and the transfer time of one box is 1 minute. Goods delivered by public transport must ensure that capacity constraints and the predetermined schedule are not violated, otherwise the goods must be delivered by trucks. The costs $c_{i,j}^{s1}$ and fc_k^{s1} are zero. The first period and the last period are set as the peak period, and free capacity Q^{S1} of public transport at the periods is randomly set within [10, 20]. At other periods, the free capacity Q^{S1} is randomly generated within [40, 70]. Due to the limited capacity of public transport, trucks can still deliver commodities. The transportation cost $c_{i,j}^{s2} = 1.5$ unit/km and the fixed cost $fc_k^{s2} = 40$ units of truck k with capacity $Q^{S2} = 100$ units are set. The capacity of logistics vehicles Q^{PD} is set to 50 units; travel cost and fixed cost of each logistics vehicle are 1 unit/km and 20 units, respectively. The average velocity of logistics vehicles is set as 15 kilometers/hour, and the average velocity v_k^{s2} of trucks is 30 kilometers/hour. The penalty cost across periods per demand is set to 1 unit.

The Gurobi cannot obtain an exact solution for large-scale instances. We use the ALNS to solve large-scale instances. The parameter values used for the ALNS are included in Table 3.

5.2.2. Computational Results. The time limit for the ALNS algorithm is 4 hours per instance. Each instance is computed ten times to obtain its mean and best results. The results of 12 instances are shown in Table 7. Here, Column 1 represents the instances. Column 2 and Column 3 indicate the number of supplier nodes and the total volumes of demands, respectively. Columns 4–10 demonstrate the best cost values of several parts of the objective function: Cost_1, i.e., the variable cost at the pickup stage; Cost_2, i.e., the fixed cost at the pickup stage; Cost_3, i.e., the variable cost at the delivery stage; Cost_4, i.e., the fixed cost at the delivery stage; Cost_5, i.e., the variable cost of FE vehicles; Cost_6, i.e., the fixed cost of FE vehicles; and Cost_7, i.e., the penalty cost of demands across periods. Column 11 represents the best total delivery costs and Column 12 indicates the mean total delivery costs of ten times.

Based on the computational results, we can find that the total delivery costs are generally on the rise as the number of supplier nodes increases. It is the positive correlation between total delivery costs and the number of supplier nodes, aligning with theoretical expectations. However, the increasing trend in the total delivery costs is slightly irregular, attributed to randomly varying demand volumes and locations. Meanwhile, we find that the fixed cost of vehicles, including Cost_2, Cost_4, and Cost_6, accounts for an average of 73% of the total delivery costs, while the variable cost of vehicles accounts for 27%. The fixed cost of vehicles accounts for a substantial proportion of the total delivery costs. Therefore, it is preferable for logistics companies to take advantage of the capacity of public transport to reduce the number of vehicles used, resulting in a decrease in the total delivery costs.

Furthermore, we test the scenario of only using trucks to transport commodities to evaluate the benefits of using public transport, and the remaining conditions are the same as in Table 7. Figure 10 shows the total delivery costs of using public transport or not and the percentage cost reduction resulting from the integration of passenger and freight services. We find that the total delivery costs of using public transport can be reduced by an average of 4.5%, and the highest improvement value is 6.9% on Instance R_3. However, the improvement in the use of public transport shows a downward trend in our study. Due to the limited free capacity of two public transport links per period, the cost saving of integration will decrease with the increase of the supplier nodes. Thus, the model can help determine when the availability of public transport services for freight deliveries could be increased for reducing total delivery costs.

The computational results of Instance R_3 are represented in Table 8, with the rightmost column indicating the relative improvement in total delivery costs of 2E-PDP-PT using public transport at each period. We find that the routes are not optimized in the first period and the last period of Instance R_3. It demonstrates that when the capacity of public transport does not match the quantity of demands, especially during commute time, using public transport for logistics distribution is not recommended.

5.2.3. The Impact of Demand Distributions. To assess the impact of demand distributions, we design two demand distributions, random and clustered at the pickup stage. Figure 9 presents the random distribution of supplier nodes, while Figure 11 visualizes the clustered distribution of supplier nodes. In clustered distribution, we generate two clusters at different locations and place a few supplier nodes at random locations. With the other parameters unchanged, each instance defines two scenarios based on random and cluster distributions of supplier nodes for comparison. The comparison results are presented in Table 9, and the values in Table 9 are means of 10 instances.

From Table 9, we find that in designed instances, the vehicles required at the pickup stage under the scenario of demand clustered distribution are on average 13 fewer vehicles than those under the scenario of demand random distribution. In addition, the total costs of the demand clustered distribution scenario gradually decrease compared to those of the demand random distribution scenario as the demand volume increases. Hence, when demand volume reaches a sufficient scale, the clustered distribution of demands will yield greater advantages.

5.2.4. Comparing the ALNS with the LNS. Large neighborhood search (LNS) is a metaheuristic proposed by Shaw [45]. In LNS, the main idea is that the current solution has continuously improved by using a remove operator and an insert operator until the maximum number of iterations is reached. The LNS has been applied to various VRPs, such as in the studies by Wolfinger [51] and Dumez et al. [52]. In this section, we adapt the LNS to solve the 2E-PDP-PT and compare the results with the ALNS in Table 10. We construct three groups of remove-insert pairs of LNS algorithms and ALNS algorithms for comparison under the same experimental settings.

From Table 10, we find that for the 2E-PDP-PT, the ALNS outperforms the LNS on all designed instances in terms of total costs. Furthermore, the LNS algorithm using the Shaw regret pair has better results than the LNS algorithm using other pairs. The average gap value between LNS using the Shaw regret pair and ALNS is 3.11%, and the gap value decreases as the size of the instance increases.

Table 7: Computational results based on the Beijing Yizhuang transportation network.

Instance	Supplier nodes	Demand volume	Cost_1	Cost_2	Cost_3	Cost_4	Cost_5	Cost_6	Cost_7	Best total costs	Mean total costs of 10 times
R_1	256	3418	824.25	1640	714.07	2180	368.26	1360	0	7086.58	7341.92
R_2	271	3738	846.82	1760	722.16	2220	397.81	1480	0	7426.79	7779.06
R_3	289	4034	976.43	1940	764.31	2360	422.28	1560	16	8039.02	8347.93
R_4	318	4313	1132.84	2080	785.82	2400	447.07	1680	32	8557.73	8693.35
R_5	350	4838	1200.97	2260	827.61	2560	530.31	1960	13	9351.89	9617.48
R_6	383	5422	1252.17	2520	941.09	2900	598.94	2200	8	10420.2	10564.49
R_7	407	5632	1361.29	2680	989.49	3060	604.03	2240	25	10959.81	11257.05
R_8	448	6128	1579.55	3020	1023.33	3180	662.81	2440	43	11948.69	12366.46
R_9	497	6771	1767.12	3300	1134.74	3480	741.29	2720	14	13157.15	13375.54
R_10	547	7678	1860.64	3600	1233.06	3820	832.33	3080	8	14434.03	14952.33
R_11	626	8723	2158.28	4120	1316.62	4200	933.21	3480	36	16244.11	16504.27
R_12	718	9898	2505.39	4760	1424.27	4560	1051.09	3920	95	18315.75	18597.97

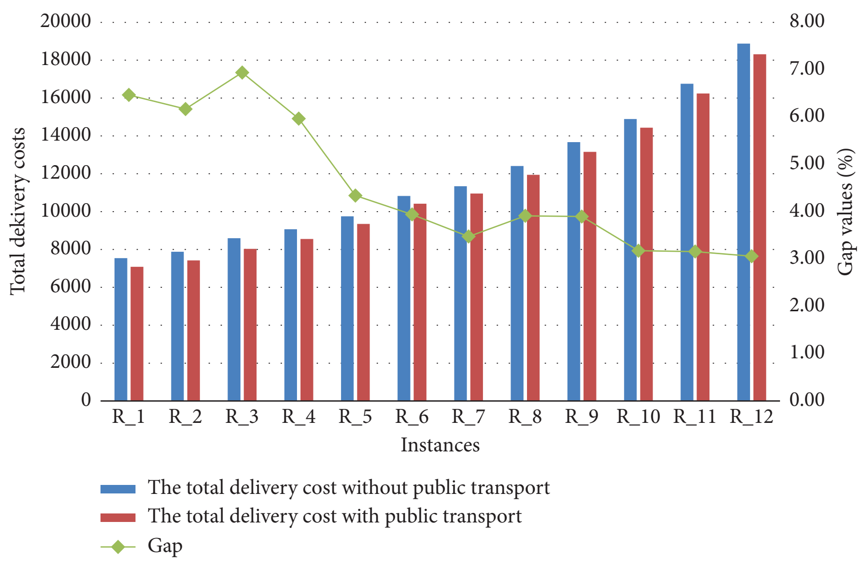

Figure 10: The total delivery costs of using public transport or not with random demands.

Table 8: Detailed computational results at each period on instance R_3.

Period	Demand node	Demand number	Obj_1	Obj_2	Obj_3	Obj_4	Obj_5	Obj_6	Obj_7	Improvement
1	31	426	94.46	200	81.82	260	54.02	200	0	0
2	31	437	125.65	220	78.46	240	44.17	160	0	49.85
3	31	405	101.51	200	78.46	240	44.17	160	16	49.85
4	33	463	114.59	220	92.72	280	41.78	160	0	102.08
5	33	465	107.13	240	87.44	280	44.17	160	0	102.08
6	32	461	104.16	220	86.23	260	41.78	160	0	102.08
7	33	459	117.04	220	84.09	260	44.17	160	0	49.85
8	31	451	101.19	200	87.64	260	41.78	160	0	102.08
9	34	467	110.71	220	87.44	280	66.25	240	0	0

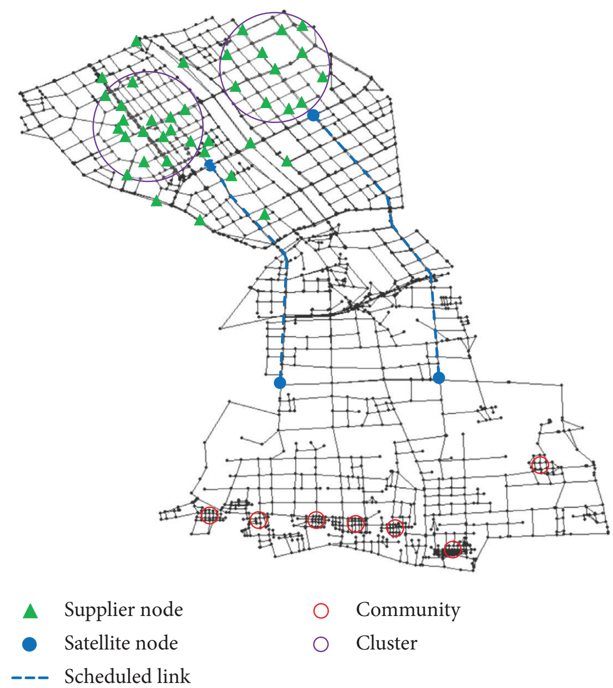

FIGURE 11: The clustered distribution of supplier nodes.

TABLE 9: Impact of two demand distributions.

Instance	Supplier nodes	Demand volume	Random demand distributions		Clustered demand distributions	
			Total cost	Logistics vehicles	Total cost	Logistics vehicles
R_C_1	251	3455	7136.12	83	7215.24	78
R_C_2	256	3674	7488.3	88	7553.71	83
R_C_3	290	4065	8088.18	101	8122.69	90
R_C_4	294	4051	8194.03	99	8052.19	91
R_C_5	339	4675	9249.09	110	9073.39	104
R_C_6	343	4774	9364.02	117	9327.64	105
R_C_7	413	5939	11353.44	145	11325.13	133
R_C_8	422	5956	11467.39	145	11360.37	133
R_C_9	495	6986	13419.61	169	13141.54	156
R_C_10	510	7110	13670.44	186	13336.03	160
R_C_11	616	8813	16563.14	218	16086.22	196
R_C_12	635	8992	16814.11	224	16183.63	199

TABLE 10: Comparison result between ALNS and LNS.

Instance	Supplier nodes	Demand volume	Total costs of LNS			Total costs of ALNS	Gap (%)
			Worst greedy	Shaw regret	Time regret		
A_L_1	251	3543	8499.88	7721.27	7816.09	7268.28	6.23
A_L_2	296	4189	9544.97	8774.36	9249.94	8411.03	4.32
A_L_3	309	4408	10245.54	9202.52	9682.53	8712.91	5.62
A_L_4	357	4971	11199.68	10127.87	10792.47	9730.44	4.08
A_L_5	389	5512	12106.24	11030.52	11766.55	10794.42	2.19
A_L_6	422	6013	13367.79	12046.08	12938.83	11759.61	2.44
A_L_7	460	6354	13850.87	12641.26	13688.09	12220.83	3.44
A_L_8	496	6771	14479.98	13181.78	14472.53	13155.24	0.96
A_L_9	550	7621	16253.18	14753.81	16236.27	14707.47	1.00
A_L_10	615	8525	17930.36	16073.23	18145.61	16046.09	0.79

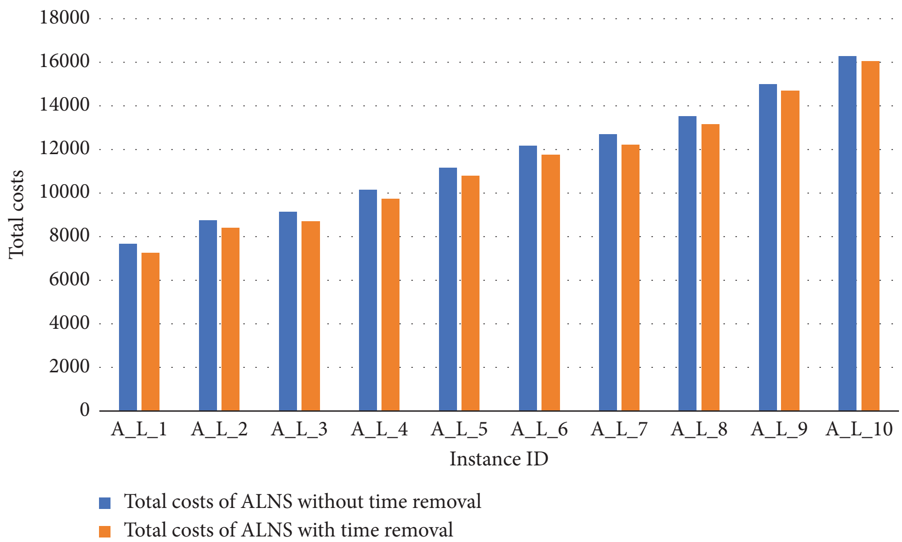

Figure 12: The impact of time removal operator on total costs.

In addition, we tested the impact of the newly designed time removal operator on total costs, as shown in Figure 12. We find that the ALNS with the time removal operator performs better than the ALNS without the time removal operator. In the tested instances, the total costs of the ALNS considering the time removal operator can be reduced by 3.62% on average.

6. Conclusions

This paper introduces the two-echelon pickup and delivery problem using public transport (2E-PDP-PT). Freight is picked up at supplier nodes by logistics vehicles, transported through scheduled links, and delivered to communities within a planning horizon. At the scheduled stage, freight can be delivered using either public transport with free capacity or dedicated trucks. The aim of this problem is to minimize total delivery costs and improve capacity utilization of public transport.

A mathematical model for the 2E-PDP-PT based on a space-time network is constructed, which is solved using Gurobi. This paper designs an ALNS algorithm to deal with the 2E-PDP-PT for larger instances. The gap value between the optimal solution obtained by Gurobi and ALNS is 0% on newly generated small-scale instances, showing that the ALNS is robust in solving small-scale instances. Furthermore, we solve large-scale instances generated on the Beijing Yizhuang transportation network. The results indicate that solutions for large-scale instances can be obtained within 4 hours. The 2E-PDP-PT can achieve an average cost saving of 4.5% by utilizing public transport, with a peak saving of 6.9% observed. Therefore, such integration is beneficial for logistics companies to reduce total delivery costs. Public transport operators are also expected to benefit as this integration increases capacity utilization of public transport.

Future work could consider the following areas. First, the optimal solution may not be obtained as a heuristic is used for larger-scale instances. Future studies will consider developing exact algorithms to solve the 2E-PDP-PT. Second, although total delivery costs are reduced when freight is delivered by public transport, it might cause damage or additional time delays to freight and delays to public transport. These factors and associated risks could be considered. At last, consumers' willingness to use public transport to deliver demands could be modeled according to the related attributes of public transport.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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