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# An Adaptive Large Neighborhood Search Heuristic for the Pickup and Delivery Problem with Time Windows and Scheduled Lines

Veaceslav Ghilas*, Emrah Demir, Tom Van Woensel

*School of Industrial Engineering,*
*Operations, Planning, Accounting and Control (OPAC),*
*Eindhoven University of Technology,*
*Eindhoven, 5600 MB, The Netherlands*

**Abstract**

The Pickup and Delivery Problem with Time Windows and Scheduled Lines (PDPTW-SL) concerns scheduling a set of vehicles to serve freight requests such that a part of the journey can be carried out on a scheduled public transportation line using bus, train, tram, metro, etc. Due to the complexity of the problem, which is NP-hard, we propose an Adaptive Large Neighborhood Search (ALNS) heuristic algorithm to solve the PDPTW-SL. Complex aspects such as fixed lines' schedules, synchronization and time-windows constraints are efficiently considered in the proposed algorithm. Results of extensive computational experiments show that the ALNS is highly effective in finding good-quality solutions on the generated PDPTW-SL instances with up to 100 freight requests that reasonably represent real life situations.

*Keywords:* Freight transportation, Pickup and delivery problem, Heuristic algorithm, Scheduled lines

## 1. Introduction

A successful integration of passenger and freight transportation creates a seamless movement of people and freight. This integration achieves socially desirable transport options economically viable in urban areas as it reduces the impact of congestion and air pollution (Lindholm and Behrends [21]). Actual integration is already being observed in long-haul freight transportation (e.g., passenger aircraft and ferries). Norwegian Hurtigruten carries freight and people efficiently and seamlessly in the region of Northern Europe (Levin et al. [18], Hurtigruten [16]). However, short-haul passenger and freight (i.e., small packages) transportation is rarely integrated, although these services largely use the same infrastructure.

This paper investigates opportunities and the feasibility of using available public transportation vehicles, which operate according to predetermined routes and schedules, for transporting freight.

*Email address:* V.Ghilas@tue.nl, E.Demir@tue.nl, T.v.Woensel@tue.nl (Veaceslav Ghilas*, Emrah Demir, Tom Van Woensel)

* Corresponding author, Tel. +31 40 247 4984

A successful synchronization of pickup and delivery (PD) vehicles with scheduled lines (SLs) is directly related to coordination and consolidation of transport. *Coordination* assures the precision and timing of each leg's movement. On the other hand, *consolidation* implies that the amount of freight transferred to/from SLs fits with capacities of PD and SL vehicles. Considering both coordination and consolidation of such integrated system, we introduce the *Pickup and Delivery Problem with Time Windows and Scheduled Lines* (PDPTW-SL).

There exists a rich literature on PDP-related problems. The interested readers are referred to Berbeglia et al. [3] for a literature survey on the solution methodologies for PDPs. A special case of PDPs where passengers need to be transported from their origin to their destination by considering service level constraints are called dial-a-ride problems (DARP). An overview on the mathematical models and the solution methodologies for single as well as multiple-vehicle DARPs can be found in Cordeau and Laporte [6].

In another extension of the PDP, it is possible to consider transfer opportunity between PD vehicles at predefined transfer nodes (PDP-T). Shang and Cuff [30] proposed an insertion heuristic algorithm to solve instances with up to 167 requests for the PDP-T. Cortes et al. [7] proposed an exact decomposition method, namely Branch-and-Cut (B&C), and solved PDP-T instances with up to six requests. Moreover, Masson et al. [22, 23] proposed an ALNS to solve PDP-T and DARP-T, respectively. In both cases, the authors solved instances with up to 100 requests. The PDP with cross-docking opportunities has been studied by Petersen and Røpke [25], who proposed a large neighborhood search heuristic to solve instances with up to 982 requests.

To the best our knowledge, Nash [24] is the first author who conceptually introduced the idea of transporting freight using public transportation. One of the first attempts to combine scheduled line services with DARP was done by Liaw et al. [20]. The authors formulated the problem where transfers to public scheduled transportation are allowed for passengers and wheelchaired persons. The authors proposed two types of heuristics (i.e., online and offline) and solved instances with up to 120 requests. Later, Aldaihani and Dessouky [1] considered an integrated DARP with public transport and proposed a two-stage heuristic algorithm to solve instances with up to 155 requests. Hall et al. [15] introduced a mixed-integer program to solve an integrated dial-a-ride problem (IDARP). The authors considered transfers to fixed lines without modeling schedules of the public transportation. The authors solved small-sized instances with up to 4 requests. Trentini and Malhene [33] presented a review of solutions for combining freight and passenger transportation used in practice. In a related study, Trentini et al. [34] investigated a two-echelon VRP with transshipment in the context of passenger and freight integrated system. The authors proposed an ALNS to solve instances with 50 customers.

As a real-life application of the integrated transport system, a project, called *City Cargo Amsterdam* [5], was held as a pilot experiment in the Netherlands in 2007. Two cargo trams were used to transport freight in the city centre of Amsterdam. The goods were transferred from cargo trucks onto trams to be delivered to the inner part of the city. In 2009 the project was quit due to lack of funds.

In this paper, we consider two transport scenarios: *(i)* an integrated transportation system and, *(ii)* the pickup and delivery problem where transfers to scheduled lines are not allowed. These two scenarios are intended to provide plausible and sufficient reasons to implement such system by comparing them in terms of the total operating costs of the PD vehicles. The PDPTW-SL is NP-hard since it is an extension of the classical PDPTW. It is shown that only a limited number of requests can be solved to optimality within a reasonable time limit. For this reason, we have developed a metaheuristic to obtain good-quality solutions. More specifically, we propose an ALNS heuristic algorithm which is based on the destroy and re-create principle.

The contribution of the paper is three-fold: *(i)* to adapt the classical ALNS heuristic algorithm to solve PDPTW-SL, and *(ii)* to efficiently handle synchronization constraints within the proposed ALNS framework and finally, *(iii)* to analyze the cost savings due to the use of scheduled lines in freight transportation. The remainder of this paper is organized as follows. In Section 2, we present a mathematical formulation of the PDPTW-SL. Section 3 describes the proposed ALNS heuristic algorithm for the PDPTW-SL. Section 4 presents the results of extensive computational experiments. Conclusions are stated in Section 5.

## 2. The pickup and delivery problem with time windows and scheduled lines

The PDPTW-SL is an extension of the standard PDPTW that additionally considers the flexibility of using available scheduled lines, such as bus, train, metro, etc. Due to the fact that public transportation systems have a certain coverage (i.e., rural or urban), some delivery trips of the PD vehicles may overlap with SL services. Thus, using public transportation as a part of freight transportation may lead to cost and environmental benefits for the whole transportation system. For instance, due to less driving time of the PD vehicles, logistics service providers may experience substantial operating cost savings. As a consequence, less traveling time of the vehicles also leads to fewer carbon dioxide-equivalent ($CO_2$e) emissions at the global level for the whole society Demir et al. [9, 11]. Furthermore, using scheduled lines for carrying freight gives extra cost benefits for public transport service providers as the utilization of SL services increases. An example application which is based on the current metro system of Amsterdam can be illustrated as in Figure 1.

The system depicted in Figure 1 contains four scheduled lines, and five transfer nodes (end-of-lines stations). Note that $T_1^{51}$, $T_1^{53}$, $T_1^{54}$ as well as $T_2^{50}$ and $T_2^{54}$ can be merged into two transfer nodes as these denote the same locations. Each metro line has one single route with one destination in each direction. To use this metro system as a part of the transportation plan, package(s) can be delivered to one of its end-of-line stations and transported to other side of the line considering available capacity and schedules of the metro line.

### 2.1. A formal description of the PDPTW-SL

In this section we give a formal description of the PDPTW-SL. All information (e.g., requests, demands, travel times, time windows) is considered known beforehand, and a possible transport plan for the whole planning horizon (e.g., one day) should be generated before the execution of the transport activities. A solution to the problem is a routing plan and schedules for both requests and PD vehicles. We now define the PDPTW-SL on a digraph $\mathcal{G} = (\mathcal{N}, \mathcal{A})$, where $\mathcal{N}$ represents the set

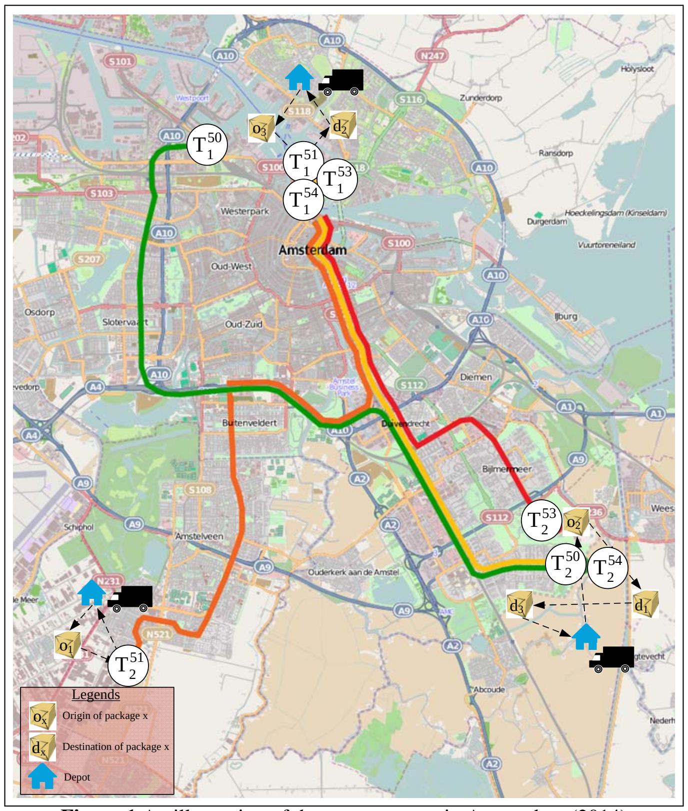


**Figure 1** An illustration of the metro system in Amsterdam (2014)

of nodes (i.e., depots, pickup, delivery and replicated transfer nodes[3]) and $\mathcal{A}$ represents the set of arcs. We note that $i$, $j$, $r$, $v$, $w$, and $t$ are used as indices in this paper.

- *Request:* Each request $r \in \mathcal{P}$ is associated with an origin node $r$ and a destination node $r+n$, where $n$ is the number of requests to be satisfied. Each request is associated with two desired time windows: one for the origin ($[l_r,\ u_r]$), and one for the destination point ($[l_{r+n},\ u_{r+n}]$). Furthermore, demand $d_r$ is known for each request.
- *PD Vehicle:* A set of PD vehicles is given by $\mathcal{V}$. In addition, each vehicle $v \in \mathcal{V}$ is associated with the carrying capacity $Q_v$, the depot (origin and destination) $o_v$, and time window $[l_{o_v},\ u_{o_v}]$.
- *Travel and service time:* Travel and service times are known beforehand and remain unchanged during the planning horizon. Each arc $(i,\ j) \in \mathcal{A}$ is associated with travel time $\Upsilon_{ij}$. The service time at node $i \in \mathcal{N}$ is represented as $s_i$.
- *Scheduled line:* A set of all physical transfer nodes is given as $\mathcal{S}$ and the set of all physical scheduled lines is given as $\mathcal{E}$, which is defined by the directed arc between the start and the end of the line $(i,\ j)$, such that $i,\ j \in \mathcal{S}$. For example, between two transfer nodes $i$ and $j$, there are two scheduled lines considered that are one arc for each direction, $(i,\ j)$ and $(j,\ i)$. Each scheduled line has a set of indices $\mathcal{K}^{ij}$ for the departure times from $i$ (the start of fixed line), such that the departure time is given as $p^w_{ij}$, $\forall\ (i,\ j) \in \mathcal{E}$, $w \in \mathcal{K}^{ij}$ (e.g., $p^0_{T_1,T_2} = 30$). We note that each scheduled line may have different frequencies than other lines, thus the size

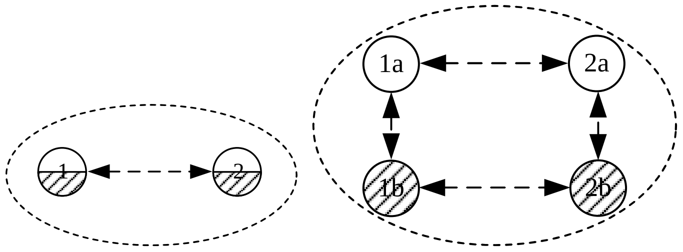
[3]see more detailed explanation at page 5

of the $\mathcal{K}^{ij}$ may differ. Furthermore, it is assumed that SL vehicles are designed to carry a limited number of packages, thus implying a finite carrying capacity $k_{ij}$, $\forall$ $(i, j) \in \mathcal{E}$.

We state the following additional assumptions related to SL services.

- The package carrying capacity is not influenced by the passenger demand on SL services.
- Each transfer node is considered as a coordination and a consolidation point for requests (e.g., DHL-Packstation [12]). In other words, a storage space for to-be-shipped packages is available at the transfer nodes. The packages can be stored until the vehicle's departure time (i.e., scheduled line or PD). Furthermore, it is considered that multiple PD vehicles can be serviced simultaneously at a transfer node. In other words, we assume that the loading/unloading infrastructure is always available for multiple vehicles at a time.
- In case of multiple freight carriers using SL services, it is assumed that each carrier has a limited storage space at the transfer node and on the SL vehicle (e.g., contract-based agreement). Hence, it is assured that the considered capacity is not affected by the demand of other actors involved.
- It is assumed that cost $\eta_{ij}$ per each unit of parcels shipped on the SL $(i, j)$ includes transportation, handling (transshipment) and storage costs. Handling of the packages during transshipment is assumed to be under the responsibility of the SL service provider (e.g., the driver of the SL vehicle).
- Since the focus of the present problem is related to the operational-level aspects, we disregard all investments needed, such as the re-design of the SL vehicle and the physical storage space required at the transfer nodes. Obviously this assumption may affect the outcome of the system (i.e., might lead to less benefits).
- It is assumed that all data is known beforehand. In practice, this might not be the case because of the uncertainty in travel times and demands. Disregarding these aspects in the planning process might eventually lead to infeasible plans and expensive repair (recourse) actions to tackle such violations.

In order to model waiting times of the PD vehicles and multiple visits at the transfer nodes, each physical scheduled line (i.e., $(i, j) \in \mathcal{E}$, e.g., arcs (1, 2) and (2, 1) in Figure 2a) is replicated $n$ times as in Hall et al. [15]. In addition, each replication is assigned to one request, and only that specific request can travel on the assigned scheduled line (see Figure 2b). This is done to reduce the number of decision variables. Therefore, the set of all replicated scheduled lines is given as $\mathcal{F}$ (e.g., $(1a, 2a)$, $(1b, 2b)$, $(2a, 1a)$ and $(2b, 1b)$ in Figure 2b).



**(a)** Physical fixed line **(b)** Virtual fixed line
**Figure 2** An illustration of a replicated fixed line

Furthermore, the replication process means that each physical transfer node in $\mathcal{S}$ (e.g., nodes 1 and 2 in Figure 2a) is replicated $n$ times (e.g., $\mathcal{T} \equiv \{1a, 1b, 2a, 2b\}$ in the considered example). For the sake of modeling let $\psi^t$, $\forall\, t \in \mathcal{T}$ be the physical transfer node represented by the replicated transfer node $t$ (e.g., $\psi^{1a} = \psi^{1b} = 1$). Consequently, set $\mathcal{T}^t$ can be defined as $\{i \in \mathcal{T} | \psi^i = \psi^t, i \neq t\}$, $\forall\, t \in \mathcal{T}$ (e.g., in Figure 2b, $\mathcal{T}^{2a} = \{2b\}$, as $2a$ and $2b$ represent physical transfer node 2).

The proposed model is not limited to only one fixed line (e.g., (1, 2) and (2, 1)). Different topologies may be considered, such as square, triangle, star or any other complex networks. Furthermore, the requests are allowed to be shipped from one scheduled line to the other. The additional parameters used in our model are given in Table 1.

**Table 1**
Parameters

| Notation | Definition |
|---|---|
| $\delta$ | Number of depots |
| $d_r$ | Demand of request $r$ |
| $\Upsilon_{ij}$ | Traveling time from node $i$ to node $j$ |
| $s_i$ | Service time at node $i$ |
| $k_{ij}$ | Freight carrying capacity on the fixed line $(i, j)$ |
| $Q_v$ | Carrying capacity of the vehicle $v$ |
| $[l_i, u_i]$ | Time window of node $i$ |
| $p^w_{ij}$ | Departure time from transfer node $i$ on the scheduled line $(i, j)$, indexed by $w$ |
| $\psi^t$ | Physical transfer node that is represented by replicated transfer node $t$ |
| $\tau$ | Number of replicated transfer nodes (i.e., $\lvert \mathcal{T} \rvert$) |
| $f^r_i$ | $\begin{cases} 1 & \text{if node } i \text{ is } r, \\ 0 & \text{if node } i \in \mathcal{N}_2 \setminus \{r; r+n\} \text{(see Table 2)}, \\ -1 & \text{if node } i \text{ is } r+n. \end{cases}$ |
| $\theta_v$ | The routing cost per one time unit of vehicle $v$ |
| $\eta_{ij}$ | The cost of shipping one unit of package on the SL $(i, j)$ |

Using the parameters above, the notation of sets is given in Table 2.

**Table 2**
Sets

| Notation | Definition |
|---|---|
| $\mathcal{V}$ | Set of PD vehicles |
| $\mathcal{O}$ | Set of depots, $\mathcal{O} \equiv [1, ..., \delta]$ (i.e. $o_v \in \mathcal{O}, \forall\, v \in \mathcal{V}$) |
| $\mathcal{P}$ | Set of requests or pickup nodes, $\mathcal{P} \equiv [\delta + 1, \cdots, \delta + n]$ |
| $\mathcal{D}$ | Set of delivery nodes, $\mathcal{D} \equiv [\delta + n + 1, \cdots, \delta + 2n]$ |
| $\mathcal{T}$ | Set of replicated transfer nodes, $\mathcal{T} \equiv [\delta + 2n + 1, \cdots, \delta + 2n + n\tau]$(see nodes 1a, 1b, 2a and 2b in Figure 2b) |
| $\mathcal{T}^t$ | Set of replicated transfer nodes associated the same physical transfer node as $t$ (e.g. in Figure 2b, $\mathcal{T}^{2a} = \{2b\}$, $\mathcal{T}^{1a} = \{1b\}$, etc.) |
| $\mathcal{N}$ | Set of nodes in the graph $\mathcal{G}$; $\mathcal{P} \cup \mathcal{D} \cup \mathcal{O} \cup \mathcal{T} \equiv \mathcal{N}$ |
| $\mathcal{N}_1$ | Set of nodes that are related to requests ($\mathcal{P} \cup \mathcal{D}$) |
| $\mathcal{N}_2$ | Set of nodes that represent requests and replicated transfer nodes ($\mathcal{P} \cup \mathcal{D} \cup \mathcal{T}$) |
| $\mathcal{E}$ | Set of physical SLs which is defined as $(i, j)$, with associated $\mathcal{K}^{ij}$ and $k_{ij}$ |
| $\mathcal{K}^{ij}$ | Set of indices for the departure times from the physical transfer node $i$ on SL $(i, j) \in \mathcal{E}$ |
| $\mathcal{F}$ | Set of replicated SLs which is defined as $(i, j)$ with associated $\mathcal{K}^{\psi^i \psi^j}$ |
| $\mathcal{F}^r$ | Set of replicated SLs associated with request $r$ (e.g. in Figure 2, $\mathcal{F}^a = \{(1a, 2a), (2a, 1a)\}$) |
| $\mathcal{F}^t$ | Set of replicated SLs connected to the replicated transfer node $t$ (e.g. in Figure 2, $\mathcal{F}^{1a} = \{(1a, 2a), (2a, 1a)\}$) |
| $\mathcal{F}^{ij}$ | Set of replicated SLs associated with a physical SL $(i, j) \in \mathcal{E}$ (e.g. in Figure 2, $\mathcal{F}^{1,2} = \{(1a, 2a), (1b, 2b)\}$, $\mathcal{F}^{2,1} = \{(2a, 1a), (2b, 1b)\}$ |
| $\mathcal{A}$ | Set of arcs in $\mathcal{G}$ defined by $\mathcal{N} \times \mathcal{N}$, (note that $\mathcal{A} \setminus \mathcal{A}^1 \equiv \mathcal{F} \cup \{(i, j) \| i \in \mathcal{O}, j \in \mathcal{N}_2\} \cup \{(i, j) \| i \in \mathcal{N}_2, j \in \mathcal{O}\}$ |
| $\mathcal{A}^1$ | $= \mathcal{N}_2 \times \mathcal{N}_2 \setminus \mathcal{F}$ |

The decision variables used to handle routing and scheduling of the PD vehicles, along with the flow and the timing of the requests are given in Table 3.

**Table 3**
Decision variables

| Notation | Definition |
|---|---|
| $x_{ij}^v$ | A binary variable equal to 1 if arc $(i, j)$ is used by PD vehicle $v$, 0 otherwise, $\forall\ (i, j) \in \mathcal{A}$, $v \in \mathcal{V}$ |
| $\alpha_v$ | A continuous variable which shows the time at which vehicle $v$ returns to its depot, $\forall\ v \in \mathcal{V}$ |
| $\beta_i$ | A continuous variable which shows the departure time of a vehicle from node $i$, $\forall\ i \in \mathcal{N}$ |
| $y_{ij}^r$ | A binary variable equal to 1 if arc $(i, j)$ is used by request $r$, 0 otherwise, $\forall\ i, j \in \mathcal{N}_2$, $r \in \mathcal{P}$ |
| $\gamma_i^r$ | A continuous variable which shows the departure time of request $r$ from node $i$, $\forall\ i \in \mathcal{N}_2$, $r \in \mathcal{P}$ |
| $q_{ij}^{rw}$ | A binary variable equal to 1 if replicated fixed line $(i, j)$ is used by request $r$ that departs from $i$ at time $p_{ij}^w$, 0 otherwise, $\forall\ r \in \mathcal{P}$, $(i, j) \in \mathcal{F}^r$, $w \in \mathcal{K}^{\psi^i \psi^j}$ |

## 2.2. *Mathematical formulation of the PDPTW-SL*

The PDPTW-SL can be formalized as the following mixed-integer program.

$$\min \quad \sum_{(i,j)\in\mathcal{A}} \sum_{v\in\mathcal{V}} \theta_v \Upsilon_{ij} x_{ij}^v + \sum_{r\in\mathcal{P}} \sum_{(i,j)\in\mathcal{F}^r} \sum_{w\in\mathcal{K}^{\psi^i\psi^j}} \eta_{ij} d_r q_{ij}^{rw} \tag{1}$$

Term (1) minimizes the total travel cost of the PD vehicles and the cost of using SLs for transferred requests.

*subject to*

*Routing and flow constraints*

$$\sum_{i\in\mathcal{N}} \sum_{v\in\mathcal{V}} x_{ij}^v = 1 \qquad \forall j \in \mathcal{N}_1 \tag{2}$$

$$\sum_{i\in\mathcal{N}_2} x_{o_v,i}^v \le 1 \qquad \forall v \in \mathcal{V} \tag{3}$$

$$\sum_{i\in\mathcal{N}} \sum_{v\in\mathcal{V}} x_{it}^v \le 1 \qquad \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{j\in\mathcal{N}} x_{ij}^v - \sum_{j\in\mathcal{N}} x_{ji}^v = 0 \qquad \forall i \in \mathcal{N}, v \in \mathcal{V} \tag{5}$$

$$\sum_{j\in\mathcal{N}_2} y_{ij}^r - \sum_{j\in\mathcal{N}_2} y_{ji}^r = f_i^r \qquad \forall r \in \mathcal{P}, i \in \mathcal{N}_2 \tag{6}$$

$$\sum_{i\in\mathcal{N}} \sum_{v\in\mathcal{V}} x_{it}^v \le \sum_{r\in\mathcal{P}} \sum_{(i,j)\in\mathcal{F}^t} y_{ij}^r \qquad \forall t \in \mathcal{T} \tag{7}$$

Constraints (2) assure that all pickup and delivery nodes are visited exactly once. Constraints (3) ensure that each vehicle leaves its depot at most once and Constraints (4) assure that each replicated transfer node is visited at most once. Flow conservation for PD vehicles is considered in Constraints (5). Constraints (6) assure flow conservation for the paths of each request. Constraints (7) ensure that if a request uses a scheduled line, a PD vehicle should pick it up/drop it off at a transfer node related to that specific SL.

*Scheduling constraints*

$$y^r_{ij} = 1 \implies \gamma^r_j \geq \gamma^r_i + \Upsilon_{ij} + s_j \qquad \forall r \in \mathcal{P}, i, j \in \mathcal{N}_2 \tag{8}$$

$$\sum_{v\in\mathcal{V}} x^v_{ij} = 1 \implies \beta_j \geq \beta_i + \Upsilon_{ij} + s_j \qquad \forall i \in \mathcal{N}, j \in \mathcal{N}_2 \tag{9}$$

$$x^v_{i,o_v} = 1 \implies \alpha_v \geq \beta_i + \Upsilon_{i,o_v} + s_{o_v} \qquad \forall i \in \mathcal{N}_2, v \in \mathcal{V} \tag{10}$$

$$\beta_{r+n} \geq \beta_r + \Upsilon_{r,r+n} + s_{r+n} \qquad \forall r \in \mathcal{P} \tag{11}$$

$$l_i \leq \beta_i - s_i \leq u_i \qquad \forall i \in \mathcal{N}_1 \tag{12}$$

$$l_{g_v} \leq \alpha_v \leq u_{o_v} \qquad \forall v \in \mathcal{V} \tag{13}$$

$$\sum_{w\in\mathcal{K}^{\psi^i\psi^j}} q^{rw}_{ij} = y^r_{ij} \qquad \forall r \in \mathcal{P}, (i, j) \in \mathcal{F}^r \tag{14}$$

$$q^{rw}_{ij} = 1 \quad \textit{and} \quad y^r_{ij} = 1 \implies \gamma^r_i = p^w_{ij} \qquad \forall r \in \mathcal{P}, (i, j) \in \mathcal{F}^r, w \in \mathcal{K}^{\psi^i\psi^j} \tag{15}$$

$$\sum_{r\in\mathcal{P}} \sum_{(a,b)\in\mathcal{F}^{ij}} d_r q^{rw}_{ab} \leq k_{ij} \qquad \forall (i, j) \in \mathcal{E}, w \in \mathcal{K}^{ij} \tag{16}$$

$$\sum_{r\in\mathcal{P}} d_r y^r_{ij} \leq \sum_{v\in\mathcal{V}} Q_v x^v_{ij} \qquad \forall (i, j) \in \mathcal{A}^1 \tag{17}$$

Timing for each request is considered in Constraints (8). Similarly for PD vehicles, scheduling is updated in Constraints (9) and (10). Constraints (11) assure precedence relationship of each request. Constraints (12) and (13) force the time windows to be respected. Constraints (14) – (15) assure that if a request uses a scheduled line, it departs at a scheduled departure time. Constraints (16) ensure that package carrying capacity on the scheduled line is not exceeded. Constraints (17) consider the capacity of each PD vehicle.

*Synchronization constraints*

$$\sum_{j\in\mathcal{N}_1} y^r_{ij} = 1 \implies \gamma^r_i = \beta_i \qquad \forall r \in \mathcal{P}, i \in \mathcal{T} \tag{18}$$

$$\sum_{j\in\mathcal{N}_2} y^r_{ij} = 1 \implies \gamma^r_i = \beta_i \qquad \forall r \in \mathcal{P}, i \in \mathcal{N}_1 \tag{19}$$

$$\sum_{i\in\mathcal{N}_2} y^r_{i,r+n} = 1 \implies \gamma^r_{r+n} = \beta_{r+n} \qquad \forall r \in \mathcal{P} \tag{20}$$

$$y^r_{tj} = 1 \implies \gamma^r_t = \beta_t \qquad \forall r \in \mathcal{P}, t \in \mathcal{T}, j \in \mathcal{T}^t \tag{21}$$

The set of constraints (18) – (21) ensure the synchronization between requests' and vehicles' schedules. Constraints (18) force departure times of requests and vehicles from a replicated transfer node to be equal if there is a request flow from that node towards a pickup/delivery node. Constraints (19) force departure times of requests and vehicles from a pickup/delivery node to be equal if there is a request flow from that node. Constraints (20) force arrival time at the destination node of a request be equal to departure time of a vehicle from that node. Constraints (21) assure time synchronization between vehicles and requests at each transfer node, with regards to flow between replications of the same original transfer node.

*Decision variable domains*

$$x_{ij}^{v} \in \{0,1\} \qquad \forall (i,j) \in \mathcal{A}, v \in \mathcal{V} \tag{22}$$

$$y_{ij}^{r} \in \{0,1\} \qquad \forall i,j \in \mathcal{N}_2, r \in \mathcal{P} \tag{23}$$

$$\alpha_v \in R^+ \qquad \forall v \in \mathcal{V} \tag{24}$$

$$\gamma_i^r \in R^+ \qquad \forall i \in \mathcal{N}_2, r \in \mathcal{P} \tag{25}$$

$$\beta_i \in R^+ \qquad \forall i \in \mathcal{N} \tag{26}$$

$$q_{ij}^{rw} \in \{0,1\} \qquad \forall r \in \mathcal{P}, (i,j) \in \mathcal{F}^r, w \in \mathcal{K}^{\psi^i \psi^j} \tag{27}$$

Note that Constraints (8) – (10), (15) and (18) – (21) are formulated as implications, and standard linearization techniques can be used to express them using one or two linear inequalities.

## 3. An adaptive large neighborhood search heuristic algorithm for the PDPTW-SL

The proposed metaheuristic is an extension of the Large Neighborhood Search (LNS) heuristic, which is first proposed by Shaw [31]. LNS is based on the idea of gradually improving an initial solution by using both destroy and repair neighborhood operators. In other words, LNS consists of a series of removal and insertion moves. If a new solution is better than the current best solution, the algorithm replaces the current solution and uses this new current solution as an input in the next iteration.

ALNS heuristic framework was first introduced in Pisinger and Røpke [26], Røpke and Pisinger [29], Pisinger and Røpke [27] to solve several vehicle routing problems. Instead of using one large neighborhood as in LNS, the ALNS applies several removal and insertion operators to a given solution. The neighborhood of a given set of feasible routes is investigated by removing some requests and reinserting them back to the solution. The removal and insertion operators are dynamically selected according to their past and current performance. To this end, each operator is assigned a *probability* of being selected. The new solution is accepted if it satisfies some criteria defined by the metaheuristic framework (e.g., simulated annealing, tabu search). In the following sections, the main features of the proposed ALNS algorithm are provided in detail.

### *3.1. Initialization stage*

A greedy insertion heuristic is used to obtain a feasible initial solution to the PDPTW-SL. All requests are initially stored in a list $\mathcal{L}$ and inserted one by one in a random order in their best available positions (for more detail on greedy insertion (GI) – see Section 3.4). The feasibility with regard to the capacity of PD and SL vehicles and time windows is always maintained.

## 3.2. Adaptive score adjustment procedure

The selection of the removal and insertion operators is controlled by a roulette-wheel mechanism. Initially, all removal and insertion operators are equally weighted (i.e., for 10 considered removal and 10 insertion operators, *probabilities* of each are set to 0.1). As in the implementation of Røpke and Pisinger [29], during the course of the algorithm, more specifically every $N_w$ iterations, each operator is given a score $\pi_i$ (i.e., to assess its performance). The *probability* is updated as $P_d^{t+1} = P_d^t(1 - r_p) + r_p \pi_i / \omega_i$, where $r_p$ is the roulette wheel parameter, $\pi_i$ is the score of operator $i$ and $\omega_i$ is the number of times it was used during the last $N_w$ iterations. The score $\pi_i$ of each operator measures how well the operator has performed at every iteration. If a new best solution is found, the score of the removal and insertion operators is increased by $\sigma_1$. If the solution is better than the current solution, the score is increased by $\sigma_2$. If the solution is worse than the current solution but accepted, the score is increased by $\sigma_3$.

## 3.3. Removal stage

Ten removal operators are used in our ALNS heuristic algorithm. All operators are adapted from or inspired by Shaw [31], Røpke and Pisinger [29] and Demir et al. [8]. The removal stage mainly consists of removing $\phi$ requests from the current solution and adding them to so-called *removal list* $\mathcal{L}$. A pseudo-code of the removal procedure is presented in Algorithm 1. The algorithm is initialized with a feasible solution $X$ as input and returns a partially destroyed solution. The parameter $\phi$ defines the number of iterations of the search. In Algorithm 1, a chosen operator is used to remove a set of requests (i.e., pickup, delivery and transfer nodes if used) from the solution. Removed pickup and delivery nodes are then inserted into list $\mathcal{L}$.

**Algorithm 1:** The overall structure of the removal operators

```
input  : A feasible solution $X$ and maximal number of iterations $\phi$
output: A partially destroyed solution $X_p$
1 Initialize removal list ($\mathcal{L} \leftarrow \emptyset$)
2 for $\phi$ iterations do
3     Apply removal operator to remove a request r (includes two nodes; pickup and delivery)
4     $\mathcal{L} \leftarrow \mathcal{L} \cup r$
```

The removal operators used in our implementation are introduced below.

- **Random Removal (RR)**: This operator randomly removes $\phi$ requests from the solution, and runs for $\phi \in [\underline{\phi}, \overline{\phi}]$ iterations, where $\underline{\phi}$ and $\overline{\phi}$ are the lower and the upper limits on the number of requests to be removed and $\phi$ is a random integer number within the specified range. The idea of randomly selecting nodes helps diversifying the search space. The worst-case time complexity of the RR operator is found to be $O(|\mathcal{P}|)$.
- **Route Removal (ROR)**: This operator removes a full route from the solution. It randomly selects a route from the set of routes in the solution. The remove operator then repeatedly selects a node $j$ from this route until all nodes are removed. The corresponding node of $j$, i.e., its pickup or delivery node, is removed irrespective of which route it is positioned in. The ROR operator can be implemented in $O(\mathcal{P})$ worst-case time.

- **Late-Arrival Removal (LAR)**: For each request $r$, this operator calculates the deviation of service start time from time $l_r$ and $l_{r+n}$, and then removes the request with the largest deviation (i.e., $r^* = argmax_{r\in\mathcal{P}}\{|[\beta_r - s_r - l_r] + [\beta_{r+n} - s_{r+n} - l_{r+n}]|\}$, where $\beta_x$ is the departure time from node $x$). The idea is to prevent long waits or delayed service start times. The algorithm starts with an empty removal list, and similarly to RR runs for $\phi \in [\underline{\phi}, \overline{\phi}]$ iterations. The worst-case time complexity of the LAR operator is $O(|\mathcal{P}|^2)$.
- **Worst-Distance Removal (WDR)**: This operator iteratively removes high-cost customers, where the cost is defined as the sum of distances from the preceding and following nodes on the tour of both the pickup and the delivery nodes of a request, i.e., it removes node $r^* = argmax_{r\in\mathcal{P}}\{|\Upsilon_{i-1,r} + \Upsilon_{r,i+1} + \Upsilon_{j-1,r+n} + \Upsilon_{r+n,j+1}|\}$, where $i-1$ and $j-1$, are predecessors and $i+1$ and $j+1$ successors of the pickup and delivery nodes, respectively. The worst-case time complexity of the WDR operator is $O(|\mathcal{P}|^2)$.
- **Shaw Removal (SR)**: The objective of the SR operator is to remove a set of customers that are related in a predefined way and therefore are easy to interchange. The algorithm starts by randomly selecting a request $r_1$ and adds it to the removal list. Let $l_{r_1,r_2} = -1$ if two nodes, one related to $r_1$ (i.e., $r_1$ or $r_1 + n$) and another to $r_2$ (i.e., $r_2$ or $r_2 + n$) are in the same route, and 1 otherwise. The operator selects the request $r^* = argmin_{r_2\in\mathcal{P}}\{\Pi_1[\Upsilon_{r_1,r_2} + \Upsilon_{r_1+n,r_2+n}] + \Pi_2[|\beta_{r_1} - \beta_{r_2}| + |\beta_{r_1+n} - \beta_{r_2+n}|] + \Pi_3 l_{r_1,r_2} + \Pi_4|d_{r_1} - d_{r_2}|\}$, where $\Pi_1$–$\Pi_4$ are weights that are normalized to find the best candidate from the considered solution. The operator is applied $\phi \in [\underline{\phi}, \overline{\phi}]$ times by selecting a request not yet in the removal list which is most similar to the one last added to the list. The worst-case time complexity of the SR operator is $O(|\mathcal{P}|^2)$.
- **Proximity-Based Removal (PR)**: The operator removes a set of requests that are related in terms of distance. This operator is a special case of the Shaw removal operator with $\Pi_1 = 1$, and $\Pi_2 = \Pi_3 = \Pi_4 = 0$. The worst-case time complexity of the PR operator is $O(|\mathcal{P}|^2)$.
- **Demand-Based Removal (DR)**: This operator is a special case of the Shaw removal with $\Pi_4 = 1$, and $\Pi_1 = \Pi_2 = \Pi_3 = 0$. The worst-case time complexity of the DR operator is $O(|\mathcal{P}|^2)$.
- **Time-Based Removal (TR)**: The operator is a special case of the Shaw removal with $\Pi_2 = 1$, and $\Pi_1 = \Pi_3 = \Pi_4 = 0$. The worst-case time complexity of the TR operator is $O(|\mathcal{P}|^2)$.
- **Historical knowledge Removal (HR)**: This operator keeps a record of the position cost of every request $r$, defined as the sum of the distances between its preceding and following nodes of its origin and destination nodes, and calculated as $c_r = \Upsilon_{i-1,r} + \Upsilon_{r,i+1} + \Upsilon_{j-1,r+n} + \Upsilon_{r+n,j+1}$ at every iteration of the algorithm. Note that $i-1$ and $j-1$ are the preceding nodes of the origin and, respectively, destination nodes of $r$ and $i+1$ and $j+1$ are their successors in the corresponding PD-vehicle routes. At any point in the algorithm, the best position cost $c^*_r$ of request $r$ is updated to be the minimum of all $c_x$ values calculated until that point. The HR operator then picks the request $r^*$ with maximum deviation from its best position cost, i.e., $r^* = argmax_{r\in\mathcal{P}}\{c_r - c^*_r\}$. Request $r^*$ is then added to the removal list. The operator iterates $\phi \in [\underline{\phi}, \overline{\phi}]$. The worst-case time complexity of the HR operator is $O(|\mathcal{P}|^2)$.
- **Worst Removal (WR)**: This operator removes $\phi \in [\underline{\phi}, \overline{\phi}]$ requests with the highest cost. The cost in this case is computed as follows: given a solution, the cost of a request $r$ is the difference in the objective function between the current solution (with $r$) and the same solution without serving $r$. Note that the difference between WR and WDR is that WR uses the total cost (including transfer cost) of the requests as objective, whereas WDR focuses only on the

distance. In addition, WR also takes into account the length of the newly introduced arcs $(i-1, i+1)$ and $(j-1, j+1)$ when removing nodes $i$ and $j$ from a route.

### 3.4. Insertion stage

Five insertion operators are used in the proposed ALNS heuristic algorithm. The aim of these operators is to repair a partially destroyed solution by reinserting the requests from the removal list $\mathcal{L}$ back into the existing routes, if possible. The general schematic overview of an insertion procedure is shown in Algorithm 2. It is noteworthy that in Line 5 of the insertion algorithm, we do not consider every possible insertion. In order to avoid redundant computations in *repairTransfers*$(X, r, T^r)$ and *feasibleSchedule*$(X)$) due to time windows, a preliminary time window check is applied as described in Braekers et al. [4]. Due to the fact that PD-vehicle capacity constraints can be fully verified only after applying *repairTransfers*$(X, r, T^r)$ procedure, capacity violations for the routes with no transferable requests can be easily detected. Note that *feasibleSchedule(X)* and *feasibleCapacity(X, c(X), $\eta_{ij}$)* (see Line 11 in Algorithm 2) methods are described in Section 3.5.

**Algorithm 2:** The generic structure of an *insertion* $i^*$ $(X^*_{new}, \mathcal{L}, X_{current})$ procedure

```
input  : A partially destroyed current solution $X^*_{new}$, a list of removed requests $\mathcal{L}$, and current solution $X_{current}$
output: A feasible solution obtained after the insertion procedure
1  for (each request r in $\mathcal{L}$) do
2      $X_{new} \leftarrow NULL$
3      $c(X^*_{new}) \leftarrow +\infty$
4      for (each route Q and route M) do
5          for (each position q within a route Q and each position m within a route M) do
6              Insert r and r + n in positions q and m, respectively, in solution $X^*_{new}$
7              if (Q ≠ M) then
8                  $(X_t, t^*_r, t^*_{r+n}) \leftarrow repairTransfers(X^*_{new}, r, T^r)$
9              else
10                 $X_t \leftarrow X^*_{new}$
11             if (feasibleCapacity($X_t$, $c(X_t)$, $\eta_{ij}$) and feasibleSchedule($X_t$)) then
12                 if (acceptance criteria of $i^*$ is satisfied) then
13                     $X_{new} \leftarrow X_t$
14     if ($X_{new} \neq NULL$) then
15         $X^*_{new} \leftarrow X_{new}$
16     else
17         return $X_{current}$
18 return $X^*_{new}$
```

The feasibility with regard to the capacity, SL schedules and time windows is always maintained. Note that checking the feasibility is not trivial, since pickup and delivery nodes of the same request can be located in different PD routes, and hence, a tour must include at least one scheduled line. Such partial solutions need to be repaired by adding transfer nodes. Therefore, *repairTransfers(X, r, $T^r$)* procedure is run to insert corresponding replicated transfer nodes in a greedy fashion. As proposed for the MIP formulation, each original transfer node is replicated $n$ (number of requests) times, hence each request gets assigned a list of replicated transfer nodes. The overview of the repair mechanism is shown in Algorithm 3.

**Algorithm 3:** The generic structure of the *repairTransfers(X, r, $T^r$)* procedure

```
input : A partial solution $X$, a request $r$ and $T^r$ replicated transfer nodes related to $r$
output: A feasible solution $X_t$ and a origin and a destination transfer nodes ($t^*_r$, $t^*_{r+n}$) of $r$ in the current
        solution $X_t$
1 $Q \leftarrow$ the route related to $r$
2 $M \leftarrow$ the route related to $r + n$
3 $t^*_r \leftarrow$ transfer node $\in T^r$ with the cheapest insertion in route $Q$, sequenced after $r$
4 $T^r = T^r \setminus t^*_r$
5 $t^*_{r+n} \leftarrow$ transfer node $\in T^r$ with the cheapest insertion in route $M$, sequenced earlier than $r + n$
6 $X_t \leftarrow$ updated $X$ given minimal cost insertions of $t^*_r$ and $t^*_{r+n}$
7 return ($X_t$, $t^*_r$, $t^*_{r+n}$)
```

A transferable request $r$ is assigned two related replicated transfer nodes: $t^*_r$ (i.e., origin transfer node), and $t^*_{r+n}$ (i.e., destination transfer node).

We now briefly define the five insertion operators used in the ALNS algorithm. We note that the requests are randomly chosen from the removal list $\mathcal{L}$.

- **Greedy Insertion (GI)**: This operator repeatedly inserts a request (both pickup and delivery nodes) in the best possible position of the routes. $\Delta^r_{I_iJ_j}$ is the objective function value when the pickup node of $r$ is inserted in route $I$ (position $i$) and its corresponding delivery node is inserted in route $J$ (position $j$). Thus, $\Delta^r_{I_iJ_j}{}^* = argmin\{\Delta^r_{I_iJ_j}\}$. The worst-case time complexity of this operator is $O(|\mathcal{P}|^2)$.
- **Second-best Insertion (SI)**: This new operator chooses the second best insertion for randomly selected unassigned request. The main idea of using this operator is to diversify the search. The worst-case time complexity of the SI is $O(|\mathcal{P}|^2)$.
- **Greedy Insertion with Noise function (GIN)**: This operator is an extension of the greedy algorithm but uses a degree of freedom in selecting the best place for a node. This degree of freedom is achieved by modifying the cost for request $r$: $New\,Cost = Actual\,Cost + \bar{d}\,\mu\,\epsilon$, where $\bar{d}$ is the maximum distance between nodes, $\mu$ is a noise parameter used for diversification and is set equal to 0.1, and $\epsilon$ is a random number between $[-1, 1]$. *New Cost* is calculated for each request in $\mathcal{L}$. The worst-case time complexity of the GIN operator is $O(|\mathcal{P}|^2)$.
- **Second-best Insertion with Noise function (SIN)**: This operator is an extension of the SI and uses the same noise function as the GIN operator. The worst-case time complexity of the SIN operator is $O(|\mathcal{P}|^2)$.
- **Best out of $\lambda$ Feasible Insertions ($\lambda$FI)**: This new operator is similar to GI but chooses the best insertion out of the first $\lambda$ feasible insertions. The parameter $\lambda$ is a randomly generated integer number between 1 and $\psi$. For each unassigned request we generate a set of possible insertions associated with corresponding distance-based costs (disregarding distance to the corresponding transfer nodes), while considering precedence constraints. These positions are not necessary feasible in terms of time windows. Additionally, in order to filter out some more of the infeasible insertions, the time windows of the subsequent nodes visited within the considered routes are verified. The generated set is sorted in increasing order based on insertion costs. Hence the operator investigates the cheapest insertions overall routes first. The worst-case time complexity of the $\lambda$FI operator is $O(|\mathcal{P}|^2)$.

Moreover, additional five variants of these operators are also used, where the requests are sorted in $\mathcal{L}$ in terms of their time flexibility (i.e., the least flexible first). The flexibility of request $r$ can be computed as $|u_{r+n} - l_r|$.

### *3.5. Feasibility of the routes and schedules*

Scheduling (time windows) constraints bring complexity to the PDPTW-SL since the requests may be picked up by a PD vehicle and delivered by another one. This implies that PD vehicles and SLs must be synchronized. This problem can be handled as shown in Algorithm 4.

**Algorithm 4:** The generic structure of the *feasibleSchedule(X)* procedure

```
input  : A solution X
output: Boolean value: TRUE if feasible, FALSE if infeasible
1  list ← ∅
2  $\beta_{t^*_r} \leftarrow 0, \beta_{t^*_{r+n}} \leftarrow 0, \forall\, r \in \mathcal{P}$
3  for (each route I in X) do
4      for (each node i in I) do
5          $\beta_i \leftarrow \max\{\beta_{p_i} + \Upsilon_{p_i,i} + s_i; l_i + s_i\}$
6          if ($\beta_i > u_i + s_i$) then
7              return FALSE
8          if ($i = t^*_{r+n}, \forall r \in \mathcal{P}$) then
9              list ← list ∪ i
10             i ← end route
11 while (list ≠ ∅) do
12     for ($t^*_{r+n}$ in list) do
13         if ($\beta_{t^*_r} > 0$) then
14             $path_r \leftarrow generatePath(t^*_r, t^*_{r+n})$
15             $\beta_{t^*_{r+n}} \leftarrow determineTime(\beta_{t^*_r}, path_r)$
16             for (each successor node i of $t^*_{r+n}$) do
17                 $\beta_i \leftarrow \max\{\beta_{p_i} + \Upsilon_{p_i,i} + s_i; l_i + s_i\}$
18                 if ($\beta_i > u_i + s_i$) then
19                     return FALSE
20                 if ($i = t^*_{r_1+n}, \forall r_1 \in \mathcal{P}$) then
21                     list ← list ∪ i
22                     i ← end route
23             list ← list \ $t^*_{r+n}$
24     if ($\beta_{t^*_r} = 0, \forall\, \beta_{t^*_{r+n}} \in list$) then
25         return FALSE
26 return TRUE
```

All $\beta$ values for the transfer nodes are reset to 0 in Line 2. The first block of the algorithm (Lines 3 – 10) sets the time for all nodes at the earliest possible value (depending on the start of the time window and the departure time from the preceding node $p_i$). The algorithm switches to the next route whenever a destination transfer node is reached. This node is added to a *list* that contains all destination transfer nodes which do not have an updated synchronized time. The second part of the algorithm (Lines 11 – 25) runs until the *list* of destination transfer nodes is emptied or a cycle (see Figure 4) is found.

- For each $t^*_{r+n} \in list$ with the corresponding origin transfer node (i.e., $t^*_r$) that has already received a timing, generate a shortest path (Dijkstra [13]) from $t^*_r$ to $t^*_{r+n}$ (Line 14). Given the shortest path and the departure time from $t^*_r$, the algorithm computes the time at $t^*_{r+n}$ by considering earliest scheduled departure time later than $\beta_{t^*_r}$ (i.e., $\lceil \beta_{t^*_r} \rceil$) for every intermediate line used (Line 15). Considered $t^*_{r+n}$ with a synchronized timing is removed from the *list*. Finally, all succeeding nodes of $t^*_{r+n}$ get assigned a value until a destination transfer node is reached and added to the *list*.
- Whenever all $\beta_{t^*_r}$ is zero $\forall\ t^*_{r+n} \in list$, the algorithm finds a cycle (see Figure 4) and stops. Hence, no feasible schedule is possible for a given solution $X$.

For a better understanding, we refer to the example shown in Figure 3. Three requests, namely $a$, $b$, and $c$, are to be delivered to destination nodes $a+n$, $b+n$ and $c+n$, respectively. All the requests are transferable, thus each request is shipped on a scheduled line. All these transfer nodes are replications of the original transfer nodes and each replication is assigned to only one request. In the present example, $T_a$ represents the origin transfer node of $a$, and $T_{a+n}$ is its destination transfer node. For the sake of simplicity, each arc has one time unit and each node does not require any service time. The numbers on top of the nodes indicate the departure time from that specific node. In this example, three PD vehicles are needed for the transportation of these three requests.

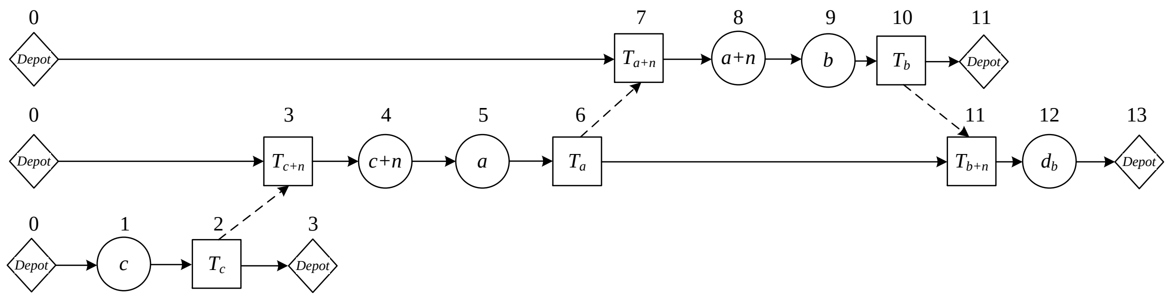


**Figure 3** An interdependency relation of the routes

By referring to Figure 3, the feasibility of the schedule is checked as follows: the process starts in the first route. The algorithm reaches the transfer node $T_{a+n}$ that is a destination transfer node of request $a$. The algorithm moves to the second route and reaches $T_{c+n}$, which is a destination transfer node of request $c$. Finally, it moves to the last route and updates the timing for the whole route as no destination transfer node is encountered. The *list* contains two destination transfer nodes, i.e., $T_{a+n}$ and $T_{c+n}$. A shortest path is generated from $T_c$ to $T_{c+n}$, and the departure time $\beta_{T_{c+n}}$ is updated (i.e., 3). Afterwards, the subsequent nodes of $T_{c+n}$ for a given synchronized time $\beta_{T_{c+n}}$ get assigned time values until $T_{b+n}$ is reached. Similarly, the timing of $T_{a+n}$ is updated and followed by $T_{b+n}$.

Note that a cycle implies that the precedence constraints are violated for at least two transferable requests, since such requests need to be picked up and dropped off twice (see Figure 4). In addition, cycles may be composed of multiple routes and requests.

The procedure *determineTime*($\beta_{t^*_r}$, $path_r$) (see Algorithm 4, Line 15) computes departure time from

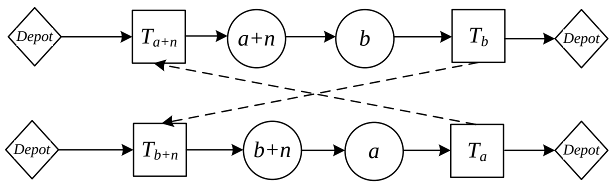


**Figure 4** An example of a two-request cycle

$t^*_{r+n}$ for a given departure time from $t^*_r$.

The capacity constraints of both PD and SL vehicles are verified in Algorithm 5. First, the algorithm checks SL capacity by first generating scheduled line paths along with every scheduled departure time from the considered transfer nodes (Line 3). The capacity variables are updated for each SL and each possible scheduled departure. The cost of the solution is updated in Line 6. Whenever the capacity is violated (Line 7), the algorithm stops and returns *FALSE* value. The PD-vehicle capacity constraints can be checked in a standard way with some preprocessing (Line 9). In particular, the destination transfer node of a transferable request $r$ (i.e., $t^*_{r+n}$) becomes an origin node on a different route, hence it will have a positive demand (i.e., $d_r$) whereas the origin transfer node of $r$ (i.e., $t^*_r$) becomes a destination node and it is assigned a negative demand (i.e., -$d_r$).

**Algorithm 5:** The generic structure of *feasibleCapacity*($X$, c($X$), $\eta_{ij}$) procedure

```
input  : A solution $X$, routing cost of $X$, and cost of using SL $\eta_{ij}$ per unit shipped on $(i, j)$
output: A boolean value $\theta$
1  Initialize $m^w_{ij}$ array for the capacity used on the scheduled line $(i, j)$ at time $p^w_{ij}$ and $\overline{\mathcal{P}}^t \leftarrow$ set of transferable
   requests in solution $X$
2  for ($r$ in $\overline{\mathcal{P}}^t$) do
3      set $(\overline{\mathcal{K}}^r, \gamma) \leftarrow$ scheduled lines $(i, j)$ used by $r$ and corresponding scheduled departure times $\gamma^r_{ij}$
4      for ($(i,j) \in \overline{\mathcal{K}}^r$) do
5          set $m^w_{ij} \leftarrow m^w_{ij} + d_r$
6          set $c(X) \leftarrow c(X) + d_r\,\eta_{ij}$
7          if ($m^w_{ij} > k_{ij}$) then
8              return FALSE
9  if (PDvehicleCapacityViolated($X$)) then
10     return FALSE
11 return TRUE
```

## 3.6. *Acceptance and stopping criteria*

In the ALNS, we have implemented simulated annealing as a master search framework for the PDPTW-SL. The overall framework of the ALNS algorithm with simulated annealing is provided in Algorithm 6.

In the algorithm, $X_{best}$ indicates the best solution found during the search, $X_{current}$ is the current solution obtained at the beginning of an iteration, and $X_{new}$ is a temporary solution found at the end of iteration that can be discarded or become the current solution. The cost of solution $X$ is denoted

**Algorithm 6:** The general framework of the ALNS with simulated annealing

```
input : A set of removal operators $D$, a set of insertion operators $I$, initialization constant $P_{init}$, cooling rate $\kappa$
output: $X_{best}$
1  Generate an initial solution by using the Greedy insertion algorithm
2  Initialize probability $P^t_d$ for each destroy operator $d \in D$ and probability $P^t_i$ for each insertion operator $i \in I$
3  Let $T$ be the temperature and $j$ be the counter initialized as $j \leftarrow 1$
4  Let $X_{current} \leftarrow X_{best} \leftarrow X_{init}$
5  repeat
6      Select a removal operator $d^* \in D$ with probability $P^t_d$
7      Let $X^*_{new}$ be the solution obtained by applying operator $d^*$ to $X_{current}$
8      Select an insertion operator $i^* \in I$ with probability $P^t_i$
9      Let $X_{new}$ be the new solution obtained by applying operator $i^*$ to $X^*_{new}$
10     if $c(X_{new}) < c(X_{current})$ then
11         $X_{current} \leftarrow X_{new}$
12         if $c(X_{current}) < c(X_{best})$ then
13             $X_{best} \leftarrow X_{current}$
14     else
15         Let $\nu \leftarrow e^{-(c(X_{new})-c(X_{current}))/T}$
16         Generate a random number $\epsilon \in [0, 1]$
17         if $\epsilon < \nu$ then
18             $X_{current} \leftarrow X_{new}$
19     $T \leftarrow \kappa T$
20     Update probabilities using the adaptive weight adjustment procedure
21     $j \leftarrow j + 1$
22 until the maximum number of iterations is reached
```

by $c(X)$. A solution $X_{new}$ is always accepted if $c(X_{new}) < c(X_{current})$, and accepted with probability $e^{-(c(X_{new})-c(X_{current}))/T}$ if $c(X_{new}) > c(X_{current})$, where $T$ is the *temperature*. The initial temperature is set at $P_{init}$, where $P_{init}$ is an initialization constant. The current temperature is gradually decreased during the course of the algorithm as $\kappa T$, where $0 < \kappa < 1$ is a fixed parameter. The algorithm returns the best found solution after a fixed number of iterations (i.e., 10,000 iterations).

## 4. Computational results

This section presents the results of extensive computational experiments performed to assess the performance of our ALNS heuristic algorithm. We first describe the generation of the instances and of the parameters. We then present the computational results obtained by the proposed heuristic algorithm.

### 4.1. Data and experimental setting

Three sets of instances, namely *R*, *C*, and *RC*, with three scheduled lines in a triangular topology and a frequency of one departure of every 30 time units are considered. Each instance contains 100 requests (i.e., 100 pick-up and 100 delivery nodes) over 200×200 time units on an Euclidean space. Instances follow a naming convention of *G_n_sl*, where *G* is the geographic distribution of the customers, *n* is the number of requests that needs to be served, and *sl* is the number of SLs.

Instances are classified with respect to the geographical locations of the nodes. For example, *C* involves clustered nodes around transfer nodes, *R* considers uniform-randomly distributed request nodes, and finally *RC* involve randomly clustered nodes. More specifically, *C* and *RC* have the nodes positioned within at most 30, respectively 80 time units to one of its three available transfer nodes. In all cases, two depots with 30 heterogeneous PD vehicles each are considered.

The planning horizon is set to 10 working hours (i.e., 600 time units). The widths of the time windows are randomly generated between 26 and 91 time units. Service times are considered to be up to three time units. Each demand is assigned between one and three units. The capacity of PD vehicle is generated between six and 20 units. The carrying capacity on the considered SLs is assumed to be 15 demand units. Additional instances were also generated such that subsets of requests, PD vehicles, SLs out of *R*, *C*, and *RC* datasets are used. The three main datasets (i.e., *R*, *C*, and *RC*) can be found on the web page of SmartLogisticsLab [32].

## 4.2. Parameter tuning

The proposed algorithm is implemented in NetBeans IDE 7.1.1 using Java. All experiments were conducted on an Intel Core i5 with 2.6 GHz speed and 4 GB RAM. A more detailed tuning was done on the five most sensitive parameters as shown in Table 4. These were identified during some preliminary tests. Three instances of small sizes (i.e., 8, 16 and 25 requests) were solved 10 times each for the given combination of parameters. The rest of the parameters were chosen based on some other experiments and our intuition.

**Table 4**
Results of parameter tuning

| Iterations | Destroy rate % | $\sigma_1$ | $\sigma_2$ | $\sigma_3$ | Average value € | Iterations | Destroy rate % | $\sigma_1$ | $\sigma_2$ | $\sigma_3$ | Average value € |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 10,000 | 0.15 | 1 | 0 | 1 | 954.09 | 15,000 | 0.15 | 1 | 0 | 1 | 953.72 |
| 10,000 | 0.15 | 1 | 0 | 5 | 953.08 | 15,000 | 0.15 | 1 | 0 | 5 | 953.61 |
| 10,000 | 0.15 | 1 | 3 | 1 | 954.18 | 15,000 | 0.15 | 1 | 3 | 1 | 950.98 |
| 10,000 | 0.15 | 1 | 3 | 5 | 951.86 | 15,000 | 0.15 | 1 | 3 | 5 | 954.02 |
| 10,000 | 0.15 | 5 | 0 | 1 | 958.49 | 15,000 | 0.15 | 5 | 0 | 1 | 954.03 |
| 10,000 | 0.15 | 5 | 0 | 5 | 958.52 | 15,000 | 0.15 | 5 | 0 | 5 | 952.59 |
| 10,000 | 0.15 | 5 | 3 | 1 | 954.66 | 15,000 | 0.15 | 5 | 3 | 1 | 952.94 |
| 10,000 | 0.15 | 5 | 3 | 5 | 953.00 | 15,000 | 0.15 | 5 | 3 | 5 | 952.57 |
| 10,000 | 0.25 | 1 | 0 | 1 | 950.04 | 15,000 | 0.25 | 1 | 0 | 1 | 949.80 |
| 10,000 | 0.25 | 1 | 0 | 5 | 953.80 | 15,000 | 0.25 | 1 | 0 | 5 | 953.82 |
| 10,000 | 0.25 | 1 | 3 | 1 | 954.87 | 15,000 | 0.25 | 1 | 3 | 1 | 951.89 |
| **10,000** | **0.25** | **1** | **3** | **5** | **948.25** | 15,000 | **0.25** | **1** | **3** | **5** | 950.64 |
| 10,000 | 0.25 | 5 | 0 | 1 | 953.16 | 15,000 | 0.25 | 5 | 0 | 1 | 951.42 |
| 10,000 | 0.25 | 5 | 0 | 5 | 954.14 | 15,000 | 0.25 | 5 | 0 | 5 | 954.47 |
| 10,000 | 0.25 | 5 | 3 | 1 | 954.10 | 15,000 | 0.25 | 5 | 3 | 1 | 952.34 |
| 10,000 | 0.25 | 5 | 3 | 5 | 951.46 | 15,000 | 0.25 | 5 | 3 | 5 | 953.02 |
| 10,000 | 0.35 | 1 | 0 | 1 | 950.63 | 15,000 | 0.35 | 1 | 0 | 1 | 949.67 |
| 10,000 | 0.35 | 1 | 0 | 5 | 951.08 | 15,000 | 0.35 | 1 | 0 | 5 | 950.36 |
| 10,000 | 0.35 | 1 | 3 | 1 | 950.53 | 15,000 | 0.35 | 1 | 3 | 1 | 954.97 |
| 10,000 | 0.35 | 1 | 3 | 5 | 951.65 | 15,000 | 0.35 | 1 | 3 | 5 | 954.01 |
| 10,000 | 0.35 | 5 | 0 | 1 | 951.77 | 15,000 | 0.35 | 5 | 0 | 1 | 952.77 |
| 10,000 | 0.35 | 5 | 0 | 5 | 949.89 | 15,000 | 0.35 | 5 | 0 | 5 | 950.59 |
| 10,000 | 0.35 | 5 | 3 | 1 | 949.72 | 15,000 | 0.35 | 5 | 3 | 1 | 951.11 |
| 10,000 | 0.35 | 5 | 3 | 5 | 951.88 | 15,000 | 0.35 | 5 | 3 | 5 | 952.34 |

In total, our algorithm contains 16 user-controlled parameters which are listed in Table 5.

**Table 5**
Parameters used in the ALNS heuristic

| Category | Description | Typical values |
|---|---|---|
| A | Total number of iterations ($N_i$) | 10,000 |
| | Number of iterations for roulette wheel ($N_w$) | 200 |
| | Roulette wheel parameter ($r_p$) | 0.1 |
| | New global solution ($\sigma_1$) | 1 |
| | Better solution ($\sigma_2$) | 3 |
| | Worse solution ($\sigma_3$) | 5 |
| B | Startup temperature parameter ($P_{init}$) | 200 |
| | Cooling rate ($\kappa$) | 0.9995 |
| | Lower limit of removable requests ($\underline{\phi}$) | 2.5% of $\lvert\mathcal{P}\rvert$ |
| | Upper limit of removable requests ($\overline{\phi}$) | 25% of $\lvert\mathcal{P}\rvert$ |
| | First Shaw parameter ($\Pi_1$) | 0.5 |
| | Second Shaw parameter ($\Pi_2$) | 0.2 |
| | Third Shaw parameter ($\Pi_3$) | 0.1 |
| | Fourth Shaw parameter ($\Pi_4$) | 0.2 |
| | Noise parameter ($\mu$) | 0.1 |
| | Number of feasible insertions ($\psi$) | 30 |

It is noted that a driving cost of the PD vehicles is assumed to be 0.5 € per minute. It seems reasonable considering all operational costs, such as fuel consumption, driver wage, insurance, and tax. The cost of each demand unit of package request shipped on a fixed line is set to 1 €, which includes handling, storage and transportation costs. The parameters used in the ALNS algorithm are categorized into two categories as described below.

- Group A defines the selection procedure with the roulette wheel mechanism. We note that our setting of the parameters $\sigma_1$, $\sigma_2$ and $\sigma_3$ is contrary to the expected setting $\sigma_1 \geq \sigma_2 \geq \sigma_3$, normally used to reward an operator for good performance. In our implementation and similar to Demir et al. [8, 10], we have chosen (based on parameter tuning) an unconventional setting of these parameters whereby the discovery of a worse solution is rewarded more than the discovery of a better solution. This is to help diversify the search in the algorithm.
- Group B of parameters is used to calibrate the simulated annealing acceptance mechanism and the removal and insertion operators.

To show the number of times each operator called within the ALNS, we give relevant information in Table 6 and Table 7. These tables show, for each operator, the frequency of use during the course of the algorithm. The total time spent to run each operator is also shown in the parentheses. We note that the results are obtained using only one instance of each different size in terms of the number of requests.

The results shown in Table 6 indicate that operators RR, SR, PR and HR are used almost equally often. In many cases, the most widely used operators are LAR, TR and WR.

As seen in Table 7, most used insertion operators are the ones that have ordered $\mathcal{L}$. Since least flexible requests are inserted first, these operators have higher chances to insert all requests within the existing routes. More specifically, oGI, oSI and their variants with noise functions are widely

**Table 6**
Number of iterations and the CPU times required by the removal operators

| Instance | RR | ROR | LAR | WDR | SR | PR | DR | TR | HR | WR |
|---|---|---|---|---|---|---|---|---|---|---|
| R_25_1 | 986(0.0) | 800(0.0) | **1,358(0.1)** | 766(0.0) | 979(0.0) | 938(0.0) | 900(0.0) | **1,121(0.0)** | 904(0.0) | **1,248(0.0)** |
| R_50_1 | 946(0.0) | 947(0.0) | 900(0.0) | 951(0.0) | **1,051(0.0)** | 963(0.0) | 826(0.0) | **1,241(0.0)** | 946(0.0) | **1,229(0.0)** |
| R_75_1 | 995(0.0) | 893(0.0) | **1,104(0.0)** | 943(0.1) | 958(0.1) | 933(0.1) | 769(0.0) | **1,196(0.1)** | 936(0.1) | **1,273(0.0)** |
| R_100_1 | 1,024(0.0) | 640(0.0) | **1,323(0.1)** | **1,294(0.1)** | 907(0.1) | 926(0.1) | 743(0.1) | **1,205(0.1)** | 1,096(0.1) | 842(0.1) |

**Table 7**
Number of iterations and the CPU times required by the insertion operators

| Instance | GI | SI | GIN | SIN | $\lambda$FI | oGI | oSI | oGIN | oSIN | o$\lambda$FI |
|---|---|---|---|---|---|---|---|---|---|---|
| R_25_1 | 860(0.2) | 855(0.2) | 537(0.1) | 510(0.2) | 451(0.0) | **1,843(0.9)** | **1,945(1.2)** | 1,024(0.6) | **1,045(0.6)** | 930(0.3) |
| R_50_1 | 655(0.7) | 631(0.5) | 312(0.1) | 414(0.4) | 453(0.1) | **2,359(11.2)** | **2,332(10.8)** | **971(4.5)** | 941(4.5) | 932(1.1) |
| R_75_1 | 636(1.4) | 532(0.9) | 404(0.6) | 263(0.5) | 286(0.0) | **2,697(44.9)** | **2,643(42.5)** | **1,040(13.5)** | 832(13.0) | 667(1.5) |
| R_100_1 | 531(4.2) | 485(2.1) | 212(1.3) | 252(1.1) | 273(0.2) | **3,315(285.0)** | **3,095(263.8)** | **875(56.7)** | 510(42.5) | 452(4.7) |

selected. It is noted that randomly-ordered insertion operators do not perform well, as many times the algorithm cannot insert all unassigned requests back to the solution due to their order of insertion.

Tables 8 – 9 indicate the number of times an operator has found the best and a better solution compared to the current one, respectively. It is noted that the number in parenthesis indicates the number of times a current solution is improved, but not to become a best known.

**Table 8**
Number of global best solutions found and number of improving solutions achieved by the removal operators

| Instance | RR | ROR | LAR | WDR | SR | PR | DR | TR | HR | WR |
|---|---|---|---|---|---|---|---|---|---|---|
| R_25_1 | 1(61) | 0(47) | 1(29) | 0(4) | 0(77) | 0(43) | **2(48)** | **4(97)** | 1(60) | **2(152)** |
| R_50_1 | **24(179)** | 2(111) | **6(205)** | 3(68) | 4(188) | **5(137)** | 1(72) | 5(257) | 1(56) | 1(154) |
| R_75_1 | **14(195)** | 6(94) | 3(208) | 1(154) | **7(235)** | 6(178) | 4(42) | 6(290) | **9(189)** | 4(168) |
| R_100_1 | **17(226)** | **9(73)** | **9(292)** | 4(107) | 7(228) | 7(196) | 2(32) | 4(306) | 8(163) | 7(256) |

**Table 9**
Number of global best solutions found and number of improving solutions achieved by the insertion operators

| Instance | GI | SI | GIN | SIN | $\lambda$FI | oGI | oSI | oGIN | oSIN | o$\lambda$FI |
|---|---|---|---|---|---|---|---|---|---|---|
| R_25_1 | 1(7) | 1(7) | 0(3) | 0(2) | 0(0) | **3(253)** | **4(210)** | **2(73)** | 0(63) | 0(0) |
| R_50_1 | **18(36)** | 0(10) | 0(3) | 0(1) | 0(0) | **19(755)** | **15(575)** | 0(25) | 0(22) | 0(0) |
| R_75_1 | **8(21)** | 0(5) | 0(0) | 0(2) | 0(0) | **28(1069)** | **23(628)** | 1(15) | 0(13) | 0(0) |
| R_100_1 | **12(27)** | 0(6) | 0(1) | 0(0) | 0(0) | **32(1211)** | **30(630)** | 0(2) | 0(2) | 0(0) |

The results indicate that all removal operators, to some extent, contribute to achieving improved solutions. On the other hand, some insertion operators (i.e., $\lambda$FI and o$\lambda$FI) do not improve a current solution at any time. However, as it will be shown below, these operators are needed to diversify the search and achieve better overall performance of the algorithm. Furthermore, as expected, greedy operators (i.e., best and second-best) help obtaining improved solutions.

In order to identify the usefulness of the new insertion operators proposed in this article, we tested four configurations of the ALNS. These are shown in Table 10, along with the average objective function values over ten runs of the algorithm. We used the same instances as in Table 4.

According to the obtained results, using SI, SIN and $\lambda$FI operators leads to the best performance of the algorithm. These operators are mainly destined to diversify the search. As seen in Table 10,

**Table 10**
A tuning of insertion operators

| Configuration | Average value € |
|---|---|
| Without SI and SIN | 949.61 |
| Without $\lambda$FI and o$\lambda$FI | 952.15 |
| Without SI, SIN, $\lambda$FI and o$\lambda$FI | 956.13 |
| With all operators | **948.25** |

it seems imperative to use such operators along with the unconventional scoring setting.

## 4.3. Results of the ALNS heuristic on the PDPTWs

In this section, we provide in Tables 11 – 13 computational results on the PDPTW benchmark instances (i.e., Li and Lim [19]), which come in three sets: *R*, *C* and *RC* classified with respect to the positioning of the customers (i.e., random, clustered and randomly-clustered). The reason for choosing these instances is that Røpke and Cordeau [28] and Baldacci et al. [2] provided their results by using the minimization of operating costs as our algorithm does. Tables 11 – 13 compare published results to the ones obtained by our ALNS heuristic algorithm. The comparison is made in terms of the average solution values obtained through 10 runs of the algorithm. This table presents, for each instance, the value of the best known or optimal solution compiled from [28, 2, 29] under column "Best known value". Note that the values in bold emphasize that the proposed algorithm found the best known solution. The symbol "*" indicates that the values are not necessary optimal and are obtained by Røpke and Pisinger [29]. Moreover, we note that all figures presented in these tables use a single decimal digit. For the ALNS algorithm, we then present the best solution value obtained in column "ALNS best found". In addition, we indicate "ALNS average value" after 10 runs with the corresponding average GAP (%) (i.e., let $\upsilon(ALNS)$ be the solution value produced by our algorithm, then, the GAP (%) = $100\,(\upsilon(ALNS){-}\upsilon(\text{Best}))\;/\upsilon(ALNS)$, where $\upsilon(\text{Best})$ is the best known solution value for each instance). Finally, we show the corresponding average CPU times required to run the algorithm.

**Table 11**
Results of the ALNS heuristic on benchmark PDPTW-*C* instances

| Li and Lim [19] instances | # of requests | Best known value | CPU seconds | ALNS best found | ALNS average value | GAP % | CPU seconds |
|---|---|---|---|---|---|---|---|
| LC1_2_1 | 106 | 2,704.6 | 3.3 | **2,704.6** | **2,704.6** | 0.00 | 47 |
| LC1_2_2 | 105 | 2,764.6 | 21.5 | **2,764.6** | 2,764.8 | 0.01 | 51 |
| LC1_2_3 | 103 | 2,772.2 | 114.9 | **2,772.2** | 2,779.3 | 0.26 | 121 |
| LC1_2_4 | 105 | $2,661.4^*$ | 209 | **2,661.4** | 2,684 | 0.84 | 123 |
| LC1_2_5 | 107 | 2,702 | 4.8 | **2,702** | **2,702** | 0.00 | 40 |
| LC1_2_6 | 107 | 2,701 | 7.4 | **2,701** | **2,701** | 0.00 | 42 |
| LC1_2_7 | 107 | 2,701 | 7.7 | **2,701** | **2,701** | 0.00 | 38 |
| LC1_2_8 | 105 | 2,689.8 | 16 | **2,689.8** | 2,689.9 | 0.00 | 43 |
| LC1_2_9 | 105 | 2,724.2 | 55.3 | **2,724.2** | 2,758.1 | 1.23 | 63 |
| LC1_2_10 | 104 | 2,741.6 | 137.1 | 2,743.9 | 2,763.8 | 0.80 | 67 |
| Average | | | 58 | | | 0.31 | 66 |

**Table 12**
Results of the ALNS heuristic on benchmark PDPTW-*RC* instances

| Li and Lim [19] instances | # of requests | Best known value | CPU seconds | ALNS best found | ALNS average value | GAP % | CPU seconds |
|---|---|---|---|---|---|---|---|
| LRC1_2_1 | 106 | 3,606.1 | 3.1 | **3,606.1** | 3,608.9 | 0.08 | 45 |
| LRC1_2_2 | 103 | 3,292.4 | 322.3 | **3,292.4** | 3,304.3 | 0.36 | 67 |
| LRC1_2_3 | 105 | $3,079.5^*$ | 183 | 3,108.5 | 3,121.2 | 1.34 | 107 |
| LRC1_2_4 | 106 | $2,525.8^*$ | 284 | 2,552.1 | 2,583.2 | 2.22 | 190 |
| LRC1_2_5 | 107 | 3,715.8 | 42.1 | 3,766.2 | 3,788.3 | 1.91 | 55 |
| LRC1_2_6 | 105 | 3,360.9 | 7 | 3,382.4 | 3,401 | 1.18 | 39 |
| LRC1_2_7 | 106 | 3,317.7 | 408.2 | 3,344.3 | 3,377.1 | 1.76 | 52 |
| LRC1_2_8 | 104 | 3,086.5 | 1562.7 | 3,129.5 | 3,143.7 | 1.82 | 63 |
| LRC1_2_9 | 104 | 3,053.8 | 1757.2 | 3,093.6 | 3,141.5 | 2.79 | 54 |
| LRC1_2_10 | 105 | $2,837.5^*$ | 156 | 2,857.2 | 2,881.3 | 1.52 | 51 |
| Average | | | 473 | | | 1.49 | 72 |

**Table 13**
Results of the ALNS heuristic on benchmark PDPTW-*R* instances

| Li and Lim [19] instances | # of requests | Best known value | CPU seconds | ALNS best found | ALNS average value | GAP % | CPU seconds |
|---|---|---|---|---|---|---|---|
| LR1_2_1 | 105 | 4,819.1 | 1.6 | **4,819.1** | **4,819.1** | 0.00 | 42 |
| LR1_2_2 | 105 | 4,093.1 | 20.6 | **4,093.1** | 4,101.4 | 0.20 | 96 |
| LR1_2_3 | 104 | 3,486.8 | 3690.8 | **3,486.8** | 3,503.6 | 0.48 | 162 |
| LR1_2_4 | 105 | $2,830.7^*$ | 228 | 2,839.1 | 2,873.1 | 1.48 | 201 |
| LR1_2_5 | 106 | 4,221.6 | 2.6 | **4,221.6** | 4,239.2 | 0.42 | 42 |
| LR1_2_6 | 107 | 3,763 | 180.9 | **3,763** | 3,769.9 | 0.18 | 70 |
| LR1_2_7 | 103 | $3,112.9^*$ | 173 | **3,112.9** | 3,124.9 | 0.38 | 107 |
| LR1_2_8 | 103 | $2,645.4^*$ | 226 | 2,652.4 | 2,664.7 | 0.72 | 159 |
| LR1_2_9 | 105 | 3,953.5 | 15.4 | **3,953.5** | 3,961 | 0.19 | 52 |
| LR1_2_10 | 104 | 3,386.3 | 1376.7 | 3,390.4 | 3,411.2 | 0.73 | 62 |
| Average | | | 592 | | | 0.48 | 99 |

As shown in Table 11 – 13, the ALNS heuristic performs very well on the PDPTW instances considered in our tests. For the majority of instances, our heuristic algorithm was able to obtain the best known solutions published in the literature in at least one out of the 10 runs. For the rest of the instances, the percentage deviations are found to be not greater than 2.79%. The average CPU time required for the algorithm on the instances is found to be around 78 seconds.

## *4.4. Results of the generated instances*

This section presents the results obtained by the proposed heuristic on the four generated sets of PDPTW-SL instances. These sets are generated from the three main datasets described in Section 4.1, by considering subsets of request, transfer node and PD vehicle sets. For the first group (with up to 12 requests and one SL), each instance was solved 10 times with the proposed heuristic and once with the PDPTW-SL MIP model by using CPLEX 12.3 (IBM ILOG [17]) with its default settings and the valid inequalities proposed by Ghilas et al. [14]. A common time-limit of ten hours was imposed to CPLEX on the solution time for all instances. The following three groups were solved 10 times using the proposed ALNS in the context of PDPTW-SL and PDPTW. The detailed results of these experiments are presented in Table 14 – 15.

In most of the cases, Table 14 indicates that the ALNS algorithm generated the same solution values as those of CPLEX, but in a substantially smaller amount of time. For the instances solved to optimality, the average CPU time required by CPLEX is approximately 8,251 seconds where the

**Table 14**
Computational results for the instances with up to 12 requests

| Instance | CPLEX | | | | ALNS | | |
|---|---|---|---|---|---|---|---|
| | Upper bound | Lower bound | GAP % | CPU seconds | Value | GAP % | CPU seconds |
| C_6_1 | 369.36 | 369.36 | 0.00 | 5,267 | 369.36 | 0.00 | 1 |
| C_7_1 | 390.30 | 390.30 | 0.00 | 3,762 | 390.30 | 0.00 | 1 |
| C_8_1 | 446.34 | 384.93 | 13.76 | 36,000 | 446.34 | - | 2 |
| C_9_1 | 493.66 | 327.43 | 33.67 | 36,000 | 472.68 | - | 2 |
| C_10_1 | - | 335.89 | - | 36,000 | 510.01 | - | 2 |
| C_11_1 | - | 347.68 | - | 36,000 | 522.84 | - | 2 |
| C_12_1 | - | 366.81 | - | 36,000 | 541.60 | - | 2 |
| RC_6_1 | 572.75 | 572.75 | 0.00 | 185 | 572.75 | 0.00 | 1 |
| RC_7_1 | 575.95 | 575.95 | 0.00 | 368 | 575.95 | 0.00 | 1 |
| RC_8_1 | 585.32 | 585.32 | 0.00 | 961 | 585.32 | 0.00 | 1 |
| RC_9_1 | 593.69 | 593.69 | 0.00 | 32,204 | 593.69 | 0.00 | 2 |
| RC_10_1 | 599.94 | 599.94 | 0.00 | 24,925 | 599.94 | 0.00 | 2 |
| RC_11_1 | 624.47 | 624.47 | 0.00 | 18,128 | 624.47 | 0.00 | 2 |
| RC_12_1 | - | 608.89 | - | 36,000 | 662.03 | - | 2 |
| R_6_1 | 416.16 | 416.16 | 0.00 | 2 | 416.16 | 0.00 | 1 |
| R_7_1 | 473.05 | 473.05 | 0.00 | 5 | 473.05 | 0.00 | 1 |
| R_8_1 | 558.17 | 558.17 | 0.00 | 16 | 558.17 | 0.00 | 1 |
| R_9_1 | 632.41 | 632.41 | 0.00 | 8,782 | 632.41 | 0.00 | 1 |
| R_10_1 | 636.05 | 636.05 | 0.00 | 3,421 | 636.05 | 0.00 | 2 |
| R_11_1 | 748.28 | 748.28 | 0.00 | 17,493 | 748.28 | 0.00 | 2 |
| R_12_1 | - | 771.01 | - | 36,000 | 934.73 | - | 2 |

same statistic for the ALNS to produce the reported solutions is approximately 2 seconds. In some cases where CPLEX could not find any solution or could obtain a sub-optimal one, the proposed ALNS was able to find solutions that have a tighter GAP relative to the best lower bound found within the imposed time limit.

Tables 15 – 17 provide the results obtained for larger instances. The column *Instance* indicates the instance identification. The *Best known cost* column indicates the best objective value found after 10 runs of the algorithm. In addition, columns *Average cost* and *Average GAP* show the average objective values over 10 runs and respectively the average GAP from the best solution found. The *Cost savings* column indicates the cost savings of the best PDPTW-SL solution compared to the best corresponding PDPTW solution. The *Best driving time* column shows the total driving time of the best solution found and the *Driving time savings* indicate the savings with regard to the total driving time. *CPU* indicates the average computational time for solving the instances. *Vehicles used* and *Units on SLs* provide the number of PD vehicles used and the number of shipments (demand units) on the available SLs in the best solution found.

The proposed algorithm is relatively fast. For example, instances of up to 100 requests are solved in less than 40 minutes. As it can be noticed from the Tables 15 – 17, the ALNS algorithm for the PDPTW-SL is substantially slower than the same algorithm in case of the PDPTW. The main reason is the extra complexity that is induced by having the flexibility of using available scheduled lines, thus making multiple PD-vehicle routes depend on each other. In particular synchronization constraints (i.e., time windows and capacity) require extra computation time (e.g., 20 – 30% of the CPU time).

It is noted that the efficiency of the proposed system may be highly dependent on both the spatial pattern of the requests and the configuration of the scheduled lines. Unless the design of the scheduled line services (routes and schedules) is integrated with vehicle routing, it is likely that the

**Table 15**
Results of *C* instances

| Instance | Best known value | Average value | Average GAP % | Cost savings % | Best driving time | Driving time savings % | CPU seconds | # of vehicles used | Units on SLs |
|---|---|---|---|---|---|---|---|---|---|
| C_25_0 | 997.83 | 997.83 | 0.00 | | 1,995.66 | | 1 | 5 | |
| C_25_1 | 943.92 | 944.25 | 0.04 | 5.40 | 1,873.84 | 6.10 | 10 | 7 | 14 |
| C_25_2 | 927.40 | 935.25 | 0.84 | 7.06 | 1,828.79 | 8.36 | 11 | 8 | 26 |
| C_25_3 | 818.46 | 824.20 | 0.70 | 17.98 | 1,586.93 | 20.48 | 17 | 8 | 50 |
| C_50_0 | 1,529.37 | 1,541.56 | 0.79 | | 3,058.73 | | 4 | 8 | |
| C_50_1 | 1,415.60 | 1,425.67 | 0.71 | 7.44 | 2,793.19 | 8.68 | 124 | 10 | 14 |
| C_50_2 | 1,342.23 | 1,356.01 | 1.02 | 12.24 | 2,634.47 | 13.87 | 121 | 10 | 50 |
| C_50_3 | 1,214.16 | 1,229.30 | 1.23 | 20.61 | 2,354.31 | 23.03 | 144 | 10 | 74 |
| C_75_0 | 2,040.54 | 2,069.10 | 1.38 | | 4,081.09 | | 12 | 10 | |
| C_75_1 | 1,807.33 | 1,829.14 | 1.19 | 11.43 | 3,558.66 | 12.80 | 411 | 12 | 56 |
| C_75_2 | 1,686.85 | 1,702.30 | 0.91 | 17.33 | 3,283.70 | 19.54 | 528 | 12 | 90 |
| C_75_3 | 1,621.18 | 1,641.60 | 1.24 | 20.55 | 3,112.36 | 23.74 | 650 | 13 | 130 |
| C_100_0 | 2,349.46 | 2,378.79 | 1.23 | | 4,698.91 | | 34 | 12 | |
| C_100_1 | 2,112.73 | 2,126.42 | 0.64 | 10.08 | 4,167.47 | 11.31 | 2378 | 13 | 58 |
| C_100_2 | 2,040.36 | 2,069.71 | 1.42 | 13.16 | 3,964.72 | 15.62 | 2224 | 14 | 116 |
| C_100_3 | 1,915.40 | 1,939.87 | 1.26 | 18.47 | 3,662.80 | 22.05 | 2357 | 14 | 168 |

**Table 16**
Results of *RC* instances

| Instance | Best known value | Average value | Average GAP % | Cost savings % | Best driving time | Driving time savings % | CPU seconds | # of vehicles used | Units on SLs |
|---|---|---|---|---|---|---|---|---|---|
| RC_25_0 | 1,633.56 | 1,633.56 | 0.00 | | 3,267.11 | | 2 | 8 | |
| RC_25_1 | 1,393.59 | 1,394.94 | 0.10 | 14.69 | 2,779.19 | 14.93 | 5 | 7 | 8 |
| RC_25_2 | 1,338.54 | 1,338.54 | 0.00 | 18.06 | 2,665.08 | 18.43 | 5 | 7 | 12 |
| RC_25_3 | 1,328.42 | 1,328.42 | 0.00 | 18.68 | 2,642.84 | 19.11 | 5 | 7 | 14 |
| RC_50_0 | 2,445.38 | 2,456.61 | 0.46 | | 4,890.76 | | 3 | 11 | |
| RC_50_1 | 2,348.14 | 2,365.36 | 0.73 | 3.98 | 4,684.27 | 4.22 | 28 | 11 | 4 |
| RC_50_2 | 2,348.14 | 2,366.23 | 0.76 | 3.98 | 4,684.27 | 4.22 | 33 | 11 | 12 |
| RC_50_3 | 2,337.20 | 2,356.19 | 0.81 | 4.42 | 4,656.39 | 4.79 | 36 | 10 | 18 |
| RC_75_0 | 2,863.05 | 2,868.34 | 0.18 | | 5,726.11 | | 9 | 12 | |
| RC_75_1 | 2,814.39 | 2,825.63 | 0.40 | 1.70 | 5,616.78 | 1.91 | 143 | 12 | 12 |
| RC_75_2 | 2,814.39 | 2,836.39 | 0.78 | 1.70 | 5,616.78 | 1.91 | 155 | 12 | 12 |
| RC_75_3 | 2,814.39 | 2,839.05 | 0.87 | 1.70 | 5,616.78 | 1.91 | 181 | 12 | 12 |
| RC_100_0 | 3,114.35 | 3,119.10 | 0.15 | | 6,228.70 | | 25 | 12 | |
| RC_100_1 | 3,088.07 | 3,093.66 | 0.18 | 0.84 | 6,164.13 | 1.04 | 794 | 12 | 12 |
| RC_100_2 | 3,088.07 | 3,100.22 | 0.39 | 0.84 | 6,164.13 | 1.04 | 677 | 12 | 12 |
| RC_100_3 | 3,088.07 | 3,134.30 | 1.48 | 0.84 | 6,164.13 | 1.04 | 985 | 12 | 12 |

gains from an integrated system operation would be very small. Hence, designing such a system involves tactical decisions related to the pattern of the scheduled lines (positioning of the transfer nodes relative to the demand nodes clusters), the storage areas at the transfer nodes, and the redesign of the SL vehicles (e.g., freight compartment), that are not taken into consideration in this paper as the focus was on operational costs of the proposed system.

Overall, the results indicate the potential operating costs due to available scheduled lines. In particular, the savings range from 0 to 20% with regard to operating costs and from 0 to 23% in terms of driving time. Note that in this study the amount of $CO_2e$ emissions is directly proportional to

**Table 17**
Results of *R* instances

| Instance | Best known value | Average value | Average GAP % | Cost savings % | Best driving time | Driving time savings % | CPU seconds | # of vehicles used | Units on SLs |
|---|---|---|---|---|---|---|---|---|---|
| R_25_0 | 1,774.75 | 1,774.75 | 0.00 | | 3,549.50 | | 1 | 8 | |
| R_25_1 | 1,747.61 | 1,750.59 | 0.17 | 1.53 | 3,491.22 | 1.64 | 2 | 8 | 4 |
| R_25_2 | 1,560.51 | 1,576.77 | 1.03 | 12.07 | 3,109.01 | 12.41 | 3 | 8 | 12 |
| R_25_3 | 1,560.51 | 1,570.65 | 0.65 | 12.07 | 3,109.01 | 12.41 | 3 | 8 | 12 |
| R_50_0 | 2,614.49 | 2,623.19 | 0.33 | | 5,228.98 | | 3 | 12 | |
| R_50_1 | 2,614.49 | 2,624.28 | 0.37 | 0.00 | 5,228.98 | 0.00 | 15 | 12 | 0 |
| R_50_2 | 2,553.97 | 2,570.34 | 0.64 | 2.31 | 5,075.95 | 2.93 | 20 | 13 | 32 |
| R_50_3 | 2,531.17 | 2,559.32 | 1.10 | 3.19 | 5,036.33 | 3.68 | 22 | 13 | 26 |
| R_75_0 | 3,337.85 | 3,337.85 | 0.00 | | 6,675.70 | | 7 | 14 | |
| R_75_1 | 3,337.85 | 3,355.41 | 0.52 | 0.00 | 6,675.70 | 0.00 | 69 | 14 | 0 |
| R_75_2 | 3,321.14 | 3,361.77 | 1.21 | 0.50 | 6,630.28 | 0.68 | 98 | 15 | 12 |
| R_75_3 | 3,321.14 | 3,349.07 | 0.83 | 0.50 | 6,630.28 | 0.68 | 110 | 15 | 12 |
| R_100_0 | 3,643.07 | 3,646.89 | 0.10 | | 7,286.14 | | 26 | 15 | |
| R_100_1 | 3,643.07 | 3,665.31 | 0.61 | 0.00 | 7,286.14 | 0.00 | 538 | 15 | 0 |
| R_100_2 | 3,628.87 | 3,646.65 | 0.49 | 0.39 | 7,245.74 | 0.55 | 690 | 16 | 12 |
| R_100_3 | 3,628.87 | 3,637.37 | 0.23 | 0.39 | 7,245.74 | 0.55 | 725 | 16 | 12 |

total driving time as we disregard the extra emissions produced by the SLs due to extra carried weight (i.e., packages).

The most of the savings can be achieved by shipping requests on the available SLs. However, the number of PD vehicles used slightly increases in PDPTW-SL compared to the solutions for PDPTW, especially in *C* instances. It is explained by the fact that the number of vehicles used depends on the time windows, capacities, and demands. Moreover, we note that savings decrease along with the increase in the number of requests for *R* and *RC* instances. This can be explained by the increasing density of the requests over the considered area (200×200 time units). Hence, driving time from one demand node to another becomes shorter. For *C* instances the savings remain significant for larger instances as well. Hence, we can conclude that the more demand points are clustered around transfer nodes, the better performance of the system is. An obvious point that is supported by the results is that the more SLs are available, more savings can be achieved compared to the classical PDPTW.

## *4.5. The effect of heterogeneous routing costs on the algorithm performance*

In this section, we present computational experiments on the instances with heterogeneous vehicle routing costs that are based on the vehicle capacity. The minimum-capacity vehicle is assumed to cost 0.5 € per operating time unit. Larger vehicles are assigned a cost that increases linearly along with the carrying capacity. Each instance is run ten times and the results are given in Table 18. The columns are self-explanatory, similar to previously presented tables.

According to the obtained results, the proposed ALNS seems to perform stable when considering heterogeneous costs, leading to solutions with an average GAP of 0.88% compared to the best known solutions. In addition, the results indicate that objective function values tend to increase due to larger routing costs (heterogeneous costs) for the considered vehicles, compared to homogeneous case (i.e., 0.5 € for all vehicles). In this context, making use of available SLs leads to

**Table 18**
An analysis of heterogeneous vehicle routing costs

| Instance | Best known value | Average value | Average GAP % | Cost savings % | CPU seconds | # of vehicles used | Units on SLs |
|---|---|---|---|---|---|---|---|
| 25_C_0 | 1,106.39 | 1,113.83 | 0.67 | | 1 | 5 | - |
| 25_C_1 | 998.32 | 1,010.29 | 1.18 | 9.77 | 6 | 6 | 10 |
| 25_RC_0 | 1,704.62 | 1,714.14 | 0.56 | | 1 | 7 | - |
| 25_RC_1 | 1,449.07 | 1,456.16 | 0.49 | 14.99 | 4 | 7 | 4 |
| 25_R_0 | 1,916.39 | 1,942.96 | 1.37 | | 1 | 8 | - |
| 25_R_1 | 1,861.04 | 1,878.43 | 0.93 | 2.89 | 2 | 8 | 3 |
| 50_C_0 | 1,623.09 | 1,635.45 | 0.76 | | 3 | 8 | - |
| 50_C_1 | 1,459.64 | 1,489.81 | 2.03 | 10.07 | 127 | 9 | 17 |
| 50_RC_0 | 2,603.40 | 2,639.39 | 1.36 | | 4 | 11 | - |
| 50_RC_1 | 2,476.35 | 2,510.05 | 1.34 | 4.88 | 24 | 11 | 6 |
| 50_R_0 | 2,796.81 | 2,815.62 | 0.67 | | 4 | 12 | - |
| 50_R_1 | 2,796.81 | 2,802.74 | 0.21 | 0.00 | 15 | 12 | 0 |
| 75_C_0 | 2,278.57 | 2,309.17 | 1.33 | | 8 | 11 | - |
| 75_C_1 | 1,955.53 | 1,972.39 | 0.85 | 14.18 | 698 | 11 | 25 |
| 75_RC_0 | 3,164.14 | 3,183.45 | 0.61 | | 7 | 12 | - |
| 75_RC_1 | 3,144.66 | 3,155.30 | 0.34 | 0.62 | 122 | 12 | 6 |
| 75_R_0 | 3,583.39 | 3,603.99 | 0.57 | | 5 | 14 | - |
| 75_R_1 | 3,572.31 | 3,586.76 | 0.40 | 0.31 | 138 | 15 | 2 |
| 100_C_0 | 3,985.45 | 4,017.42 | 0.80 | | 22 | 12 | - |
| 100_C_1 | 3,557.39 | 3,576.59 | 0.54 | 10.74 | 2178 | 13 | 36 |
| 100_RC_0 | 3,420.74 | 3,461.23 | 1.17 | | 9 | 13 | - |
| 100_RC_1 | 3,344.28 | 3,362.95 | 0.56 | 2.24 | 644 | 12 | 6 |
| 100_R_0 | 3,758.27 | 3,792.44 | 0.90 | | 13 | 15 | - |
| 100_R_1 | 3,758.27 | 3,825.33 | 1.75 | 0.00 | 668 | 15 | 0 |

average cost savings of 5.89% compared to the corresponding best-known PDPTW solutions.

## 4.6. *An application study*

In this section we investigate the performance of the PDPTW-SL environment on a realistic scheduled lined system. In particular, we solve one instance of 100 randomly generated requests on a 60 x 60 time-units area, three depots and 20 PD vehicles. The scheduled lines graph is shown in Figure 5 and it is inspired from the current metro system in Amsterdam (see Figure 1). The distances are considered Euclidean and time windows are randomly generated.

**Table 19**
Results on a realistic real-life scheduled line system

| Instance | PDPTW-SL | | | | | PDPTW | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Driving time | # of shipments on scheduled lines | Cost € | CPU seconds | # of vehicles | Driving time | Cost € | CPU seconds | # of vehicles |
| Amsterdam 100 requests | 1,767.22 | 36 | 919.61 | 1,258.52 | 10 | 1,945.69 | 972.85 | 34.62 | 7 |

The results shown in Table 19 are obtained after five runs of the algorithm and indicate the best solutions found for both PDPTW-SL and PDPTW. In particular, the PDPTW-SL integrated transportation system led to 5% savings in terms of operating costs and 9% in fewer total driving time.

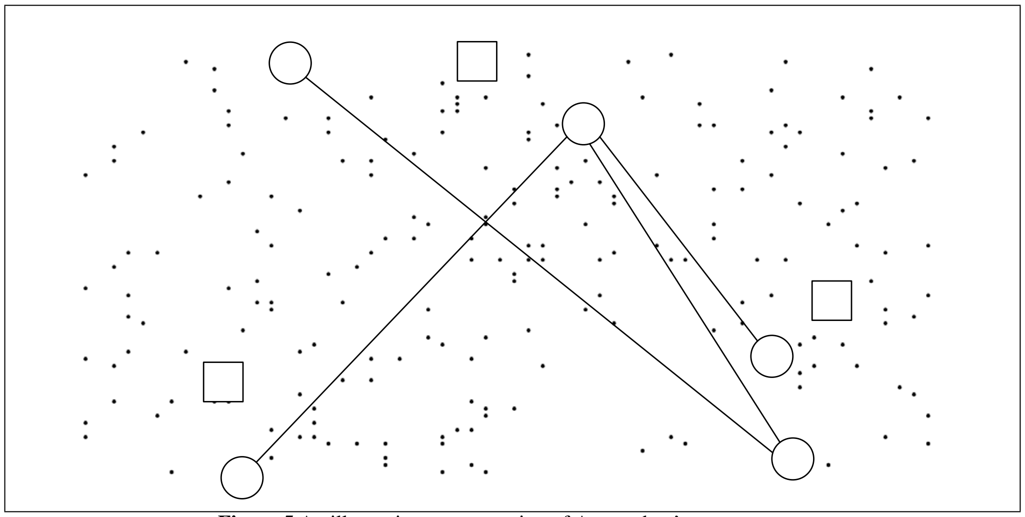


**Figure 5** An illustrative representation of Amsterdam's metro system

Even though PDPTW-SL system can lead to operating costs and $CO_2e$ emissions benefits, the number of vehicles used is increased as compared to PDPTW.

## 5. Conclusions

We have described a metaheuristic algorithm to solve the PDPTW-SL. To fully evaluate the effectiveness of the algorithm, we have generated different sets of instances and compiled a library of PDPTW-SL instances. Compared to the existing solutions on a set of PDPTW instances, the proposed algorithm performed well in terms of both, solution quality (with a maximum GAP of 2.79%) and CPU time (78 seconds on average). Furthermore, we have also shown that small PDPTW-SL instances can be solved optimally by the proposed formulation. The solutions obtained from solving larger instances, up to 100 requests, were compared to their corresponding PDPTW solutions and it is concluded that the flexibility of using scheduled line services leads to significant cost savings and fewer $CO_2$e emissions. However, note that the performance of the PDPTW-SL system may be highly dependent on the relative positioning of the scheduled lines to the request nodes. In addition, investment costs needed for implementing such system may affect its outcome.

The reliability of such a system may decrease due to extra causes of delays and cargo damages (i.e., transfers to/from SLs, delays in SL schedules). Therefore, shippers may not be willing to use PDPTW-SL system. In order to tackle such issues, more advanced planning tools are needed, which consider stochastic aspects of the problem. The current research state of the considered problem is yet young and further industry collaborations are to be done in order to learn more about practical issues that may or may not prevent the implementation and the execution of such a system.

Overall the numerical experiments show that the proposed algorithm is highly effective in finding good-quality solutions for relatively large instances in a reasonable amount of time (up to 40 minutes). Regarding extensions of the investigated problem, additional aspects may be considered such as driver-related constraints, stochastic aspects (demands, travel times) or passenger requests, and the other related constraints (e.g., maximum ride-time). Investigation of exact decomposition algorithms (e.g., Branch & Price) could also be an interesting research direction. In addition, since the results show that the number of PD vehicles used may increase when SLs are introduced, it would be interesting to introduce fixed costs for the PD vehicles as well to make more clear the trade-off between using fewer PD vehicles or using SLs with more PD vehicles.

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