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The Two-Echelon Vehicle Routing Problem with Pickups, Deliveries, and Deadlines

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Abstract

This paper introduces the Two-Echelon Vehicle Routing Problem with Pickups, Deliveries, and Deadlines (2E-VRP-PDD), a new and emerging routing variant addressing the operations of logistics companies connecting consumers and suppliers in megacities. Logistics companies typically organize their logistics in such megacities via multiple geographically dispersed two-echelon distribution systems. The 2E-VRP-PDD is the practical problem that needs to be solved within each of such a single two-echelon distribution setting, thereby merging first and last-mile logistics operations. Specifically, it integrates forward flow, reverse flow, and vehicle time-synchronization aspects such as parcel time windows, satellite synchronization, and customer-dependent deadlines on the arrival of parcels at the hub. We solve the 2E-VRP-PDD with a tailored matheuristic that combines a newly developed Adaptive Large Neighborhood Search (ALNS) with a set-partitioning model. We show that our ALNS provides high-quality solutions on established benchmark instances from the literature. On a new benchmark set for the 2E-VRP-PDD, we show that loosening or tightening time restrictions, such as parcel delivery deadlines at the city hub, can lead to an 8.5% cost increase; showcasing the overhead associated with same-day delivery compared to next-day delivery operations. Finally, we showcase the performance of our matheuristic based on real-life instances which we obtained from our industry collaborator in Jakarta, Indonesia. On these instances, which we share publicly and consists of 1500 - 2150 customers, we show that using our ALNS can significantly improve current operations, leading to a 17% reduction in costs.

Keywords: Routing, City Logistics, Two-echelon Vehicle Routing, Pickup-and-Delivery, Adaptive Large Neighborhood Search

1. Introduction

In recent years, logistics platforms have emerged in megacities to connect customers directly with suppliers of (local) products. Examples of such platforms from Indonesia include GoSend Intercity, SiCepat, and J&T, which coordinate the shipping from (mostly) online merchants' locations to their customers. Within megacities, such platforms facilitate end-to-end logistics; transport is fully arranged between suppliers and customers. To efficiently consolidate logistics streams, such platforms adopt inner-city distribution and collection systems within a series of geographically dispersed two-echelon network

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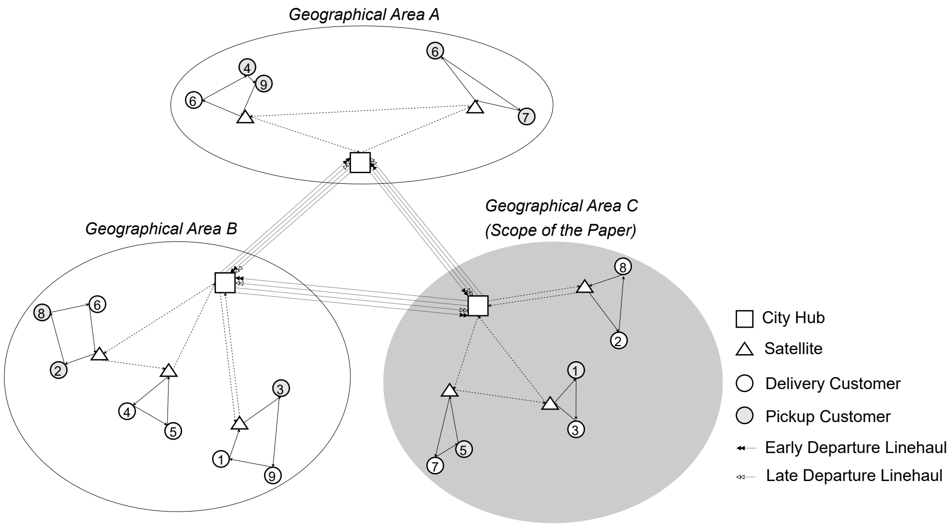

Figure 1: Organization of end-to-end logistics in megacities, inspired upon practices at our industry partner

structures(Crainic et al., 2009; Savelsbergh and Van Woensel, 2016). An example of such a logistics system design can be seen in Figure 1. It consists of multiple urban distribution centers (or hubs), each with several associated intermediary transfer locations (or satellites) through which parcels are collected from suppliers and distributed to customers. Between the hubs, pre-determined line-haul transport takes place to connect the suppliers and customers between different geographical areas.

This paper introduces the Two-Echelon Vehicle Routing Problem with Pickups, Deliveries, and Deadlines (2E-VRP-PDD). It describes the structural logistics operations that arise within a single two-echelon network structure, i.e., the grey area in Figure 1. Motivated by our industry partner operating in megacities in Indonesia, we solely consider customer orders between *different* geographical areas. This results in a forward flow of parcels, from the hub towards customers, and a reverse flow of parcels, from the customers towards the hub. In other words, two types of operations happen simultaneously. First, the first-mile collection of parcels from suppliers to fulfill customer orders in different two-echelon structures. Second, the last-mile distribution of parcels to customers originating from suppliers in different two-echelon structures. To ensure logistics operations are done cost-efficiently, the 2E-VRP-PDD considers the joint optimization of first-mile collection and last-mile distribution.

The joint optimization of first-mile collection and last-mile distribution is complex. Firstly, the flow of parcels must adhere to operation and load synchronization constraints (Drexl, 2012), ensuring the timely availability of parcels at satellites for further transport to either the customer or the city hub. This requires coordinating the departure and arrival times of the vehicles used in both echelons. Secondly, relatively large first-echelon vehicles operate between the hubs and the satellites, while relatively small second-echelon vehicles (e.g., cargo bikes or scooters) operate between the satellites and customers. As is common in practice, second-echelon vehicles can only take the load from a single first-echelon vehicle to not unnecessarily complicate coordination at satellites. Thirdly, the parcels associated with the first-mile collection from suppliers have varying deadlines before they must be delivered at the city hub. This is because the parcels are further transported via line hauls to other geographical areas (outside the 2E-VRP-PDD scope) within the megacity.

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While there is a rich literature stream on routing within two-echelon network structures (see, e.g., Sluijk et al. (2023)), and routing with simultaneous pickup and delivery (see, e.g., Koç et al. (2020)), the combination of the above-mentioned complicating factors is not researched before in the extant literature. Several studies have incorporated timing aspects for the 2E-VRP context, such as time windows (Dellaert et al., 2019) and satellite synchronization (Grangier et al. (2016); Li et al. (2021); Li et al. (2022)), as well as first-mile collection (Belgin et al. (2018); Liu and Jiang (2022); Li et al. (2022); Dumez et al. (2023)). However, considering simultaneous pickups and deliveries of parcels while the first-mile collection is subject to parcel-dependent deadlines has not been studied yet. At the same time, this is crucial for designing logistics networks for megacities because it is a current challenge from our industry partner, as sketched in Figure 1.

The 2E-VRP-PDD aims to find a cost-minimizing set of first-echelon (FE) and second-echelon (SE) routes to simultaneously pick up and deliver parcels from and to all the customer locations via intermediate satellites. We provide a route-based set-partitioning formulation and a tailored Adaptive Large Neighborhood Search (ALNS). The resulting matheuristic comprises two stages. First, we use the ALNS to find high-quality solutions. During the search process, we store all the encountered first and second-echelon routes, that, with some minor modifications, are input for the route-based set-partitioning formulation. We evaluate our matheuristics, and within that, the quality of the ALNS, on well-established benchmark sets on the two-echelon capacitated vehicle routing problem benchmark from Breunig et al. (2016) and Marques et al. (2020). The results show that the ALNS within our matheuristics provides high-quality solutions and is competitive with other approaches from the literature. By modifying instances from Dumez et al. (2023), we create a new and publicly available 2E-VRP-PDD benchmark set to study in a structured way the performance of our matheuristic on the 2E-VRP-PDD. Moreover, structurally evaluate the benefit of combining first and last-mile logistics within such a megacity logistics network using these instances. It is shown that a relatively large share of same-day deliveries compared to next-day deliveries, as expressed via the customer-specific deadlines at the city hub, can lead to cost increases of 8.5%.

We furthermore present a real-life case study with data from our industry collaborator. It comprises large-scale real-life 2E-VRP-PDD instances that range from 1650 to 2100 customers. The datasets are publicly available [1]. We use our matheuristic to solve these real-life instances, which results in several interesting managerial findings. First, total transportation costs can be reduced by 17 % by combining pickup and deliveries within the FE and SE vehicle routes. Part of its success is that combining pickup and deliveries allows for a better loading plan so that, on average, the average fill rate of a vehicle is higher than with other heuristic strategies, such as separating the pickup and delivery of parcels.

Summarizing, this paper contributes to the literature as follows:

- We introduce a new and emerging two-echelon vehicle routing variant, the 2E-VRP-PDD, based on a real-life application at our industry partner. Specifically, within the context of pickups and deliveries within two-echelon network structures, we introduce customer-dependent deadlines for

[1]Data and instances can be found on our public GitHub repository https://github.com/aryazamal/2e-vrp-pdd

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parcels arriving at the city hub. This relates to the practical challenge at our partner, as picked-up parcels are scheduled for further transport outside the two-echelon system on line-haul transport, as is common within logistics systems in megacities.

- We develop an efficient matheuristic that produces high-quality solutions on established benchmark sets, and for the 2E-VRP-PDD.
- We provide a case study based on the operations of our industry partner in Indonesia. Besides showing the importance of combining pickup and deliveries in first and second-echelon vehicle routes, we also provide the datasets publicly. By doing so, we hope to foster future research on designing (meta)heuristics for practically relevant two-echelon vehicle routing problems.

The remainder of the paper is organized as follows. Section 2 presents the relevant literature. Section 3 discusses the 2E-VRP-PDD setting inspired by our industry partner in Indonesia and introduces a route-based formulation. Section 4 describes the matheuristic approach. Section 5 presents the computational results based on benchmark instances and new 2E-VRP-PDD instances. Section 6 discusses a case study and managerial insights from the logistics operations referring to our industry partner. Finally, Section 7 concludes the paper and outlines potential avenues for future research.

2. Related Literature

Our 2E-VRP-PDD shares several characteristics with existing work on the Two Echelon Vehicle Routing Problem (2E-VRP). We, therefore, review that literature, focusing on incorporating pickups and deliveries within the operations. We focus on how preceding studies have modeled time and load synchronization between the first and second-echelon vehicles at the satellites. An essential element of the 2E-VRP-PDD is the inclusion of customer-specific deadlines on when pickups should arrive back at the hub. We, therefore, discuss other studies in which such deadlines are present afterward.

2.1. The two-echelon vehicle routing problem with pickup and delivery

The two-echelon vehicle routing problem with pickup and delivery extends the fundamental Two-Echelon Vehicle Routing Problem (2E-VRP) by integrating pickup and delivery operations. Note that this variant does not include customer-specific deadlines at which pickups must be delivered at the hub. Within the 2E-VRP framework, two distinct pickup and delivery settings are considered. The first setting considers customers simultaneously requiring delivery and pickup, representing a *dual flow system*: the forward flow from the hub, via the satellites, to the customer for delivery, and the reverse flow from the customer location, via the satellites, back to the hub for pickup (Belgin et al., 2018). This has been adopted in subsequent studies (Liu and Jiang (2022); Zhou et al. (2022); Li et al. (2022); Dumez et al. (2023)). Secondly, Li et al. (2021) and Ghilas et al. (2016) conceptualize the pickup and delivery problem as a *singular request*, implying that the pickup demand originates from a specific customer location and is delivered to its customer destination via an intermediate facility. In our 2E-VRP-PDD, we consider the former dual flow system.

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Synchronization is essential in understanding the elementary 2E-VRP and its variants. Synchronization primarily relates to coordinating operations between the first-echelon (FE) and second-echelon (SE) routes at the satellite, encompassing tasks, operations, and load distribution (Drexl, 2012). Previous research (see, e.g., Belgin et al. (2018), Li et al. (2022), and Liu and Jiang (2022)) has considered load synchronization, implying that the load dispatched by the first-echelon vehicle at the satellite should correspond with the load transported by all second-echelon vehicles originating from that particular satellite. Additionally, the aggregated load retrieved from all second-echelon vehicles must equate to the load that the first-echelon vehicle departs from the same satellite. However, in the papers mentioned above, no time windows and customer-specific deadlines when pickups should arrive back at the depot were considered. In the 2E-VRP-PDD, we do consider this, which complicates load synchronization.

Time synchronization is a critical component of the 2E-VRP with Pickups and Deliveries if the problem incorporates time windows, as examined by Li et al. (2021), Zhou et al. (2022), and Dumez et al. (2023). Given the time window constraints imposed by customers, establishing a precise time synchronization model at the satellite is fundamental in ensuring the feasibility and quality of the solution. Despite not providing explicit instructions for synchronization, Zhou et al. (2022) incorporate three stages of routing into their model for the time synchronization: initial delivery of parcels to satellites by first-echelon vehicles, subsequent delivery to and pickup from customers by the second-echelon vehicles, and finally the pickup at satellites for transportation back to the hub by first-echelon vehicles again.

Dumez et al. (2023) represents the time synchronization by keeping track of the parcel load at the satellite at each point in time. So, the second and first-echelon vehicles can start the operation when the stored capacity is positive for each forward or reverse flow demand to ensure the availability of given parcels. However, compared to Dumez et al. (2023), our 2E-VRP-PDD considers customer-specific deadlines motivated by the practical application of our model at our industry partner. In practice, the 2E-VRP with Pickups and Deliveries is only a small part of the total logistics flow, and pick-up parcels need to be transported further into the logistics network on scheduled line haul, which we represent by the given customer-specific deadlines for when pickups should arrive at the hub.

First-echelon route strategies are essential, and various heuristic strategies have been employed in the literature to establish the FE routes. These strategies can be classified into three categories according to Berbeglia et al. (2007) as shown in Figure 2. The first strategy involves the FE route allowing delivery or pickup, but not both operations simultaneously (see, i.e., Zhou et al. (2022); Liu and Jiang (2022); Li et al. (2022)). In this tripartite operation, the first-echelon vehicle initially delivers all parcels, returns to the hub, allows the second-echelon vehicle to perform pickup and delivery operations, and finally collects all pickup parcels to return to the hub. As described by Belgin et al. (2018), the second strategy involves the first-echelon vehicle visiting a satellite node once to perform a combined delivery and pickup operation without accounting for time synchronization. This implies that the first-echelon vehicle waits at the satellite and departs only after the SE vehicle completes its operation. The last strategy, as outlined by Dumez et al. (2023), permits the first-echelon vehicle to visit the satellite node multiple times if necessary, possibly performing both operations together or separately. In the 2E-VRP-PDD, we adhere to the strategy by Dumez et al. (2023).

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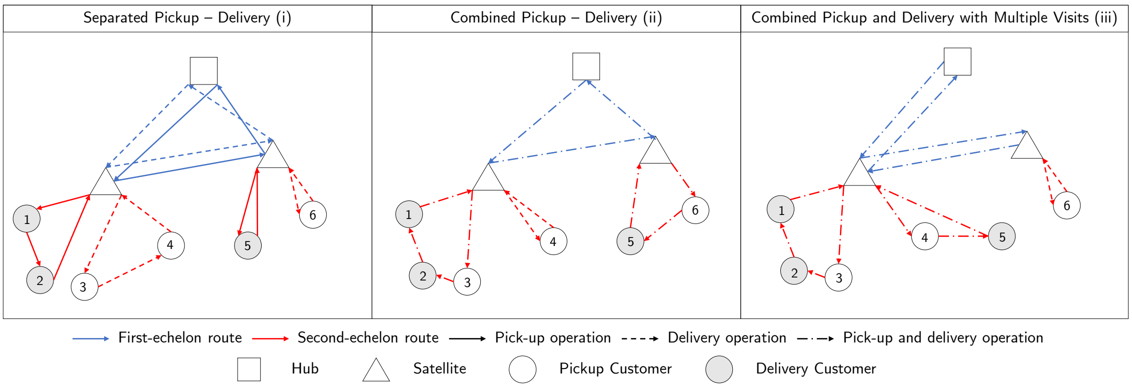

Figure 2: First Echelon Routing Strategy

Solution method. A range of exact and heuristic methods have been developed to address the 2E-VRP with Pickups and Deliveries. Li et al. (2022) constructed a path-based model and a branch-and-cut-and-price algorithm. The approach is not applicable in the 2E-VRP-PDD context because time synchronization is not explicitly discussed.

Various heuristics methods have been developed to solve the 2E-VRP with Pickups and Deliveries Belgin et al. (2018) combined Variable Neighborhood Descend (VND) and Local Search (LS). The VND is implemented in the SE routes, and a solution for the FE route is derived using the Nearest Neighbor heuristic. By construction, the satellite delivery and pickup demands are thus based on the SE routes solution. Liu and Jiang (2022) proposed a penalty-based Variable Neighborhood Search (VNS) method for a Two-Echelon Vehicle Routing Problem with Pickup and Delivery, which functions in feasible and infeasible spaces and applies a range of neighborhood structures to enhance the solution quality. Furthermore, Zhou et al. (2022) built a heuristics incorporating Tabu Search and VNS elements. However, all the mentioned heuristics do not allow carrying pickup and delivery parcels simultaneously in the FE route.

Dumez et al. (2023) proposes an Iterative Two-Stage Heuristics (ITSH) for the 2E-VRP with Capacitated Satellite and Reverse Flow, utilizing a Large Neighborhood Search (LNS) metaheuristics and Mixed Integer Programming (MIP) solver. This technique divides the problem into two subproblems, optimizing each echelon separately with dedicated LNS algorithms. Upon LNS failure, the MIP solver fine-tunes the solution. Unlike our study, their approach does not account for the deadlines related to the first-mile collection to the hub, which increases the complexity of synchronization when connecting the FE and SE routes in the solution.

2.2. Deadlines in Urban Logistics

In the two-echelon city distribution literature, temporal aspects typically relate to customer location (time windows) and satellites or transfer points, which are closely tied to synchronization processes. This paper introduces the notion of a 'customer-specific deadline' as the latest time by which parcels for pickup must reach the hub. The concept of deadlines at logistic facilities is typically explored within models that consider the use of public or scheduled transportation.

Ghilas et al. (2016) examined the pickup and delivery problem with time windows and scheduled lines.

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In their model, parcels travel from station to station using scheduled transportation. At the same time, couriers handle the first and last mile of the journey, but they do not consider two-echelon structures. In contrast, Azcuy et al. (2021) and Masson et al. (2017) investigated scenarios where parcels are delivered to customers using scheduled lines (such as buses or trams) for the FE route, with last-mile delivery fulfilling the final leg of the journey. Specifically, in Azcuy et al. (2021), the 'deadline' at the satellites is defined as the time between the latest time window at the customer location and the travel time from the satellite to the customer location.

A real-life instance of deadlines at hubs for pickup parcels can be found in the operational challenges faced by our industry partner based in Indonesia. Since pickup parcels correspond to different service types (same-day, next-day, or regular) and have different destinations, hubs have distinct cutoff times for further transport into the company's logistics network using service-specific multimodal transport.

3. The two-echelon vehicle routing with pickups, deliveries, and deadlines

The two-echelon vehicle routing problem with pickups, deliveries, and deadlines (2E-VRP-PDD) is defined on a complete directed graph $G = (V, A)$. The vertices are further defined as $V = \{0\} \cup S \cup Z$, where 0 is the city hub, S is the set of satellites, and Z is the set of pickup and delivery customers. We further partition the customers $Z = Z_1 \cup Z_2$, where Z_1 is the set of delivery customers while Z_2 is the set of pickup customers. For modeling purposes, we copy all elements of S into two sets S_1 and S_2, where S_1 is a set of distribution satellites, and S_2 is a set of collection satellites so that each actual satellite is represented by both a distribution satellite and a collection satellite. The arcs are defined as $A = A_1 \cup A_2$, where A_1 represents all arcs on the first echelon (between hub and satellites) and A_2 represents all arcs on the second echelon. That is, $A_1 := \{(i,j) \in O \cup S \mid i \neq j\}$, and $A_2 := \{(i,j) \in S_1 \cup S_2 \cup Z \mid i \neq j,\ (i,j) \notin (S_1 \times S_2)\}$. For each arc $(i,j) \in A$, the cost of traveling it equals c_{ij}.

With each delivery customer $z_1 \in Z_1$, we associate a parcel of weight $q_{z_1} < 0$ that originates at the city hub and has to be delivered to the delivery customer. Similarly, with each pickup customer $z_2 \in Z_2$, we associate a parcel of weight $q_{z_2} > 0$ that has to be collected at the pickup customer and delivered to the city hub. Note that parcels of both the delivery and pickup customers can only traverse between the city hub and customer locations via satellite locations. The distribution satellites of S_1 handle only the parcels associated with the delivery customers, i.e., it *distributes* parcels from the first echelon towards the second echelon. The collection satellites of S_2 handle only the parcels associated with the pickup customers.

Each satellite $s \in S$ and customer node $z \in Z$ have a service time δ_s and δ_z for the satellite and the customer, respectively. Each customer $z \in Z$ has time windows (E_z, L_z), and each pickup customer $z_2 \in Z_2$ has a deadline D_{z_2} at which its associated parcel has to be delivered back to the city hub.

Let K_1 and K_2 be the sets of first- and second-echelon vehicles, respectively, each with given capacities $\bar{Q}_{k_1}$ and $\bar{Q}_{k_2}$. Each first-echelon vehicle, $k_1 \in K_1$, is stationed at the hub and undertakes a single tour collecting and distributing parcels between the hub and satellites. Each second-echelon vehicle, $k_2 \in K_2$, is assigned a particular distribution satellite $s_1 \in S_1$ at which it starts its route and a collection satellite $s_2 \in S_2$ at which it ends its route, belonging to the same physical satellite location.

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We consider sets of feasible FE routes $r \in R$ and the SE routes $p \in P^s$, for all $s \in S$. We let $P := \cup_{s \in S} P^s$. For each SE route $p \in P$, let $\gamma_z^p \in \{0,1\}$ be a binary parameter that equals one if customer $z \in Z$ is visited, and 0 otherwise. Let parameter a_{s,z_2}^p represent the time at which the parcels associated with pickup customer $z_2 \in Z_2$ arrive at the satellite $s \in S$, and let parameter $d_{s,z_1}^p \in \mathbb{R}$ reflects the time at which the delivery parcel $z_1 \in Z_1$ departs from satellite $s \in S$. For a FE route $r \in R$, we let $\beta_{s,z}^r \in \{0,1\}$ be a binary parameter that equals one if customer $z \in Z$ is assigned to a satellite $s \in S$ and it is transported using that route r. Let parameter $\omega_{s,z}^r \in \mathbb{R}$ represent the time at which delivery (pickup) parcel $z \in Z$ arrives at (departs from) the satellite $s \in S$ for route r. Each of these routes respects the vehicle's maximum load, the time windows for the customers, and the deadlines of the pickup customers at the city hub.

We present a route-based formulation as follows. Let $x^r \in \{0,1\}$ be equal to 1 if the FE route $r \in R$ is selected, and 0 otherwise. The associated cost of using the FE route $r \in R$ is given by c^r. Let $y^p \in \{0,1\}$ be equal to 1 if SE route $p \in P$ is selected, and 0 otherwise. The cost of using SE route $p \in P$ is denoted by c^p. We set the costs equal to the total distance of a route. The 2E-VRP-PDD is then formulated as:

$$\min \quad \sum_{r \in R} c^r x^r + \sum_{p \in P} c^p y^p \tag{1}$$

$$\text{s.t.} \quad \sum_{p \in P} \gamma_z^p y^p = 1 \qquad \forall z \in Z, \tag{2}$$

$$\sum_{p \in P^s} \gamma_z^p y^p - \sum_{r \in R} \beta_{s,z}^r x^r \leq 0 \qquad \forall z \in Z, \forall s \in S, \tag{3}$$

$$\sum_{p \in P^s} \gamma_{z_1}^p d_{s,z_1}^p y^p - \sum_{r \in R} \beta_{s,z_1}^r (\omega_{s,z_1}^r + \delta_s) x^r \geq 0 \qquad \forall z_1 \in Z_1, \forall s \in S, \tag{4}$$

$$\sum_{r \in R} \beta_{s,z_2}^r \omega_{s,z_2}^r x^r - \sum_{p \in P^s} \gamma_{z_2}^p (a_{s,z_2}^p + \delta_s) y^p \geq 0 \qquad \forall z_2 \in Z_2, \forall s \in S, \tag{5}$$

$$x^r \in \{0,1\} \qquad \forall r \in R, \tag{6}$$

$$y^p \in \{0,1\} \qquad \forall p \in P. \tag{7}$$

The Objective (1) minimizes the cost of all selected FE and SE routes. Constraints (2) ensures that each customer is visited in a selected SE route. Constraint (3) verifies that for every customer z, the SE Route p carrying the parcel associated with z must align with a corresponding FE route, denoted as r, at a given satellite, s. This only ensures that first and second-echelon vehicles meet at the same satellite, but does not model yet that time synchronization is respected. That is handled by Constraints (4) and (5). Specifically, Constraint (4) ensures the departure of a delivery customer in an SE Route, originating from satellite s, occurs after the arrival and service time of the corresponding FE vehicle at the satellite. Conversely, Constraint (5) stipulates that a pickup customer must reach and complete the service time at the satellite s before the FE vehicle departs to continue the FE route's journey.

For given FE and SE route sets, the above 2E-VRP-PDD formulation will ensure that at least (potentially more than 1) FE route delivers or picks up a particular customer. This is not a problem, as we can remove the additional unnecessary customers from the FE routes and obtain a solution with

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the same objective value. In addition, the formulation allows a second echelon route to visit customers that are part of multiple first-echelon routes. In the next section, we introduce our solution approach, detailing how we populate the FE and SE route sets in a heuristic manner.

4. Solution methodology for the 2E-VRP-PDD

This section introduces our matheuristic for solving the 2E-VRP-PDD. An overview is given in Algorithm 1. Our matheuristic considers three stages: initial solution construction (lines 1-6), application of a newly developed Adaptive Large Neighborhood Search (ALNS) heuristic (lines 8-10), and MIP optimization (lines 11-12).

Algorithm 1: Matheuristics for 2E-VRP-PDD

1 $\bar{S}_{initial} \leftarrow \emptyset, \bar{S} \leftarrow \emptyset$
2 $s_{initial}, s_{\text{ALNS}}, s_{\text{MIP}}, s_{best} \leftarrow null$
3 $n \leftarrow 0$
4 **while** $n < \omega_{initial}$ **do**
5     $sn \leftarrow$ build initial solution
6     $\bar{S}_{initial} \leftarrow \bar{S}_{initial} \cup \text{LNS}(sn, \omega_{\text{LNS}})$
7     $n \leftarrow n + 1$
8 $t_0 \leftarrow$ calculate initial temperature $(\bar{S}_{initial})$
9 $s_{initial} \leftarrow \arg\min_s\{\bar{S}_{initial}\}$
10 $s_{\text{ALNS}} \leftarrow \text{ALNS}(s_{initial}, t_0, \bar{S})$
11 $s_{\text{MIP}} \leftarrow \text{MIP}\ (\bar{S})$
12 $s_{best} \leftarrow \arg\min_s\{s_{\text{ALNS}}, s_{\text{MIP}}\}$
13 **return** s_{best}

4.1. Initial Solution

The initialization phase (lines 1-9 in Algorithm 1) aims to generate a batch of initial solutions ($\bar{S}_{initial}$). For this problem, we produce five initial solutions. For each initial solution, we apply a restricted version of our Adaptive Large Neighborhood Search (ALNS), called Large Neighborhood Search (LNS). We pick the solution of the lowest cost for the subsequent phase. The LNS is similar to the ALNS (discussed later) but we exclude the adaptive layers so that all operators are selected with equal probability, and we do not accept solutions that worsen the cost in our search process. The total number of iterations of the LNS is given by the parameter ω_{LNS}.

The process of building an initial solution (line 5 in Algorithm 1) begins by constructing the second-echelon (SE) routes. A constructive heuristic is employed, inserting unassigned customers in a randomized order into an existing SE route. If the SE route capacity is full or the time window constraint is violated, the customer remains not inserted, and the algorithm chooses another random customer. If no customers can be inserted, a new SE route is considered for all remaining unassigned customers.

After creating the SE routes, the first echelon (FE) routes are built, adhering to the SE routes previously established. In this process, a single SE route might comprise either pickup parcels, delivery parcels, or both. In the LNS and subsequent ALNS heuristics phase, we enforce that each pickup or delivery bundle is serviced exclusively by a single FE route.

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4.2. ALNS for the 2E-VRP-PDD

The ALNS is outlined in Algorithm 2. The high-level procedure is as follows. It commences with an initial solution, initializes operator probabilities, iteration variables, and a solution pool (lines 1-4). It should be noted that the initial solution ($s_{initial}$), initial temperature (t_0), and the solution pool ($\bar{S}$) are the input of the ALNS, see line 10 in Algorithm 1.

The algorithm proceeds iteratively, repeatedly improving a "current solution" (s'), which is based on the previously "accepted solution" (s). A restart period counter, denoted as $i_{restart}$, is incorporated for cases when the algorithm fails to discover an improved solution. When $i_{restart}$ equals the parameter $\omega_{\mathrm{restart}}$, the procedure re-initializes from the "best solution" (s_{best}) discovered thus far (lines 7-9).

The algorithm selects a destroy size based on a conditional check of $i_{large} < \omega_{large}$ (lines 10-15). If true, it chooses a small destroy size. Otherwise, a large destroy size is chosen, and the algorithm builds a current solution, s', based on the best solution thus far, s_{best} (line 13). Subsequent operations involve applying the destroy and repair operators adaptively on the current solution (s'), and the current solution is stored in the solution pool for the subsequent MIP execution.

The evaluation process involves comparing the objective $f(s')$ of the current solution s' (after destroy and repair) with the objective of the previously accepted solution s and best solutions s_{best}. The algorithm accepts the current solution as the accepted solution if it offers an improvement compared to s. If the current solution outperforms the best solution, it becomes the new best solution. The algorithm increments a restart counter if the current solution does not provide a new best solution (lines 19-24).

The algorithm also incorporates checks for situations where the current solution's objective $f(s')$ does not surpass the previously accepted solution's cost $f(s)$. If $i_{large} = \omega_{large}$, then the current solution becomes the accepted solution automatically (lines 26-27), meaning that we always accept the solution from the large destroy mechanism. In other cases, we implement simulated annealing criteria, and the algorithm might accept the current solution as the accepted solution, thereby ensuring diversity in the search process (lines 28-30). The operator probabilities are updated every 100 iterations, fostering an adaptive behavior (lines 32-34). Every related parameter for the adaptiveness of operator probabilities is tuned in Appendix A. Finally, the algorithm is stopped when the iteration reaches the $\omega_{iteration}$. The best solution and the solution pools for the MIP process are identified at the end of the search process.

4.3. Destroy Methods

Our proposed destroy methods selectively remove customers from the solution. They are characterized by two distinct levels of disruption - small and large scale. By 'removing' customers, we imply that the SE route no longer visits the customers' locations, and the FE route does not serve the removed customers anymore. Unless indicated otherwise, a small-scale destroy method eliminates a certain member of customers within a predefined range of $[4, N^{UB}_{small}]$. Here, $N^{UB}_{small} = \min(100, \zeta^{UB}_{small} \cdot |Z|)$, where $|Z|$ represents the total number of customers. Conversely, the large-scale destroy method removes a greater quantity of customers within the range $[N^{LB}_{large}, N^{UB}_{large}]$ where $N^{LB}_{large} = \zeta^{LB}_{large} \cdot |Z|$ and $N^{U}_{large} = \zeta^{UB}_{large} \cdot |Z|$. The values of the parameters ζ^{UB}_{small}, ζ^{LB}_{large}, and ζ^{UB}_{large} are tuned in Appendix A.

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Algorithm 2: ALNS Algorithm for 2E-VRP-PDD

input : $s_{initial}$, t_0, $\bar{S}$
$s_{best}, s \leftarrow s_{initial}$
$t \leftarrow t_0, \pi \leftarrow$ initialize operator probabilities
$i, i_{\text{restart}}, i_{\text{large}} \leftarrow 0$
while $i < \omega_{iteration}$ **do**
    $s' \leftarrow s$
    if $i_{restart} = \omega_{restart}$ **then**
        $s' \leftarrow s_{best}$
        $i_{restart} = 0$
    if $i_{large} < \omega_{large}$ **then**
        select small number of customers randomly, $N_{small} \in [4, N^{UB}_{small}]$
    else
        $s' \leftarrow s_{best}$
        select large number of customers randomly, $N_{large} \in [N^{LB}_{large}, N^{UB}_{large}]$
        $i_{large} = 0$
    $s' \leftarrow \mathit{Destroy}(\Theta^-, N, \pi, s')$
    $s' \leftarrow \mathit{Repair}(\Theta^+, N, \pi, s')$
    store solution s' to solution pool $\bar{S}$
    if $f(s') < f(s)$ **then**
        $s \leftarrow s'$
        if $f(s) < f(s_{best})$ **then**
            $s_{best} \leftarrow s$
        else
            $i_{restart} \leftarrow i_{restart} + 1$
    else
        if $i_{large} = \omega_{large}$ **then**
            $s \leftarrow s'$
        else
            if *Acceptance Criteria* (s', s, t) **then**
                $s \leftarrow s'$
        $i_{restart} \leftarrow i_{restart} + 1$
    if $i_{batch} = 100$ **then**
        $\pi \leftarrow$ update operator probabilites (π)
        $i_{batch} = 0$
    $i \leftarrow i + 1, i_{large} \leftarrow i_{large} + i, i_{batch} = i_{batch} + 1$
return s_{best}

The small-scale destroy is employed in most iterations, facilitating improvement and exploiting the solution space. In contrast, large-scale destroy is utilized less frequently to explore and diversify the solution space. The dual-scale destroy strategy has demonstrated efficacy in 2E-VRP settings (see example in Hemmelmayr et al. (2012); Enthoven et al. (2020); Yu et al. (2021, 2023)). In our study, the same destroy operators are employed for both small and large-scale destruction, differing in removal sizes. These operators are classified based on the indicator used to guide the selection of customers for removal. It includes random, distance-related, time-related, and routing-related criteria, which altogether give seven distinct destroy operators, of which six were adopted from previous studies. We introduce one new operator.

The *random-removal* operator arbitrarily picks customers and removes them from the solutions. The next two operators focus on *distance*. The *worst-distance removal* operator calculates an approximate 'removal gain' for each customer i if it is excluded from the solution. Let $c_{i,j}$ denote the cost of a customer from location i to location j in the SE route. The approximate removal gain is obtained from $c_{i,i-1} + c_{i,i+1} - c_{i-1,i+1}$, where $i-1, i, i+1$ indicate subsequent location visits. We then adopt a roulette wheel selection, where the customer to be removed is chosen proportionally to their associated removal

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gain. The *related-distance removal* operator selects a random customer and computes the distance of all other customers from this random customer. The roulette wheel probabilities are inversely related to the distance to the customer, i.e., relatively close customers get selected with higher probabilities.

We introduce a new operator associated with the *time* components of the 2E-VRP-PDD. The *worst-slack removal* works as follows. When a second-echelon vehicle visits a customer i in the SE route, we maintain information of 'Earliest Arrival Time' (e_i) and a 'Latest Arrival Time' (l_i). The earliest arrival time e_i denotes the earliest feasible time a delivery or pickup can be conducted at a customer's location i. In contrast, the latest arrival time signifies the latest feasible time for similar operations. The slack time for a customer i is defined as $l_i - e_i$. Our strategy is to remove customers with a larger slack time with a higher probability in a roulette wheel fashion, as they provide greater flexibility for potential insertion points during the repair phase.

Lastly, we apply three distinct operators based on the similarity of the *routing*. The *satellite removal operator* begins by randomly choosing a satellite that serves customers. In small-scale destroy scenarios, this operator randomly picks a set of customers between $[N^{LB}_{small}, N^{UB}_{small}]$, who are served by routes originating from the selected satellite and removes them from the solution. In situations of large-scale destroy, however, this operator removes all routes, including the customers served by these routes originating from the satellite, effectively causing the satellite to remain non-operational until the subsequent large removal period commences. The *route removal* operator randomly removes routes from the solution within a defined range. The range is between $[1, \lceil \zeta^{UB}_{small} \cdot |P| \rceil]$ for the small destroy and $[1, \lceil [\zeta^{LB}_{large}, \zeta^{UB}_{large}] \cdot |P| \rceil]$ for the large destroy, where $|P|$ is the number of active SE routes and parameter ζ^{LB}_{large}, ζ^{UB}_{large} and ζ^{UB}_{small} will be tuned. The *least-utilized route removal* operator selects ζ^{UB}_{small} of routes with the fewest customer visits from the total active SE routes. Then, the operator randomly chooses the number of routes with uniform probability from that set within the range similar to *route removal* operator to be removed from the solution.

4.4. Repair Methods

To repair a partially complete solution, we employ a rapid improvement technique when inserting a customer to a feasible location, in line with the work Christiaens and Vanden Berghe (2020). It means, we only insert a customer in the best location. The repair methods focus on inserting a selected customer into a feasible and cost-minimizing location in a SE route. If needed, we allow new satellite visits of an FE route after inserting a customer in the second-echelon route. Detailed feasibility checks and associated solution structure are presented in Subsections 4.5 and 4.6.

We calculate the insertion cost estimates in the SE route, and in the FE route if satellite insertion follows the customer insertion. Adhering to the concept proposed by Mühlbauer and Fontaine (2021), we approximate the insertion cost in the FE route as $c_{s,s-1} + c_{s,s+1} - c_{s-1,s+1}$, where $s-1, s, s+1$ indicate subsequent first-echelon node visits (i.e. satellite or hub). In situations with no feasible insertion location in the SE route, we add a second-echelon vehicle route for the inserted customer. If the solution is still not feasible, an additional first-echelon vehicle is dedicated to serving the customer in a new single FE route.

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We use eight repair operators that differ in how they insert customers in their 'best' insertion location.

The first repair operator is a *random-order insertion*. This operator inserts customers into the solution in a randomized order, placing each customer in a position that minimizes the extra transportation cost. The next two operators focus on *distance*. In descending order, the *farthest-first insertion* operator selects the customer that is farthest from the assigned satellite and subsequently from the assigned satellite to the hub. Then, it inserts the customer at the location with the lowest insertion cost. Conversely, the *closest-first insertion* operator works in a similar premise, albeit in ascending order. It inserts the customer with the shortest total distance to the allocated satellite (and from the satellite to the depot)

The fourth repair operator is the *largest-first insertion*. As the name suggests, this operator inserts customers based on the magnitude of their demand, with higher-demand customers given precedence. The remaining four operators focus on time features. The *earliest time-window-first insertion* operator sorts and inserts customers based on the earliest time windows in ascending order. Meanwhile, the *latest time-window-first insertion* operator selects and inserts customers based on the largest latest time windows in descending order. Additionally, we introduce the *earliest-deadline-first insertion* and *latest-deadline-first insertion* operators, which choose customers based on their respective deadlines. For the *earliest-deadline-first insertion* operator, it inserts customers based on the smallest deadline in an ascending manner. In contrast, the *latest-deadline-first insertion* operator inserts customers based on the largest deadline in a descending manner.

4.5. Insertion Mechanism

We now discuss some details of our implementation essential for obtaining a computationally efficient ALNS implementation. We preserve five information elements for each customer visit within each SE route: the Earliest Arrival Time (EAT), Latest Arrival Time (LAT), arrival time, departure time, and the prevailing load. Recall that EAT denotes the earliest feasible time a delivery or pickup can be conducted at a customer's location i, while LAT indicates the latest feasible time for similar operations. Given a customer j located between customers $i-1$ and i, the EAT for a delivery or pickup at customer j is derived as $e_j = \max(E_j, e_{i-1} + c_{i-1,j} + \delta_{i-1})$, where $c_{i-1,j}$ denotes the travel time between $i-1$ and j. Similarly, the LAT for such operation at j can be expressed as $l_j = \min(L_j, l_i - c_{j,i} - \delta_j)$

The SE route p first visit's EAT (e_0) is defined as $\omega^r_{s_1} + \delta_{s_1}$, where $\omega^r_{s_1}$ is the time when the parcels are available at the distribution satellite s_1, transported by FE route r, and δ_{s_1} denotes the corresponding service time. Let m be the index of node visited in the SE route or FE route, the SE route last visit LAT, l_{m+1}, is determined as $l_{s+1} - c_{s+1,s} - \delta_s$, where l_{s+1} represents LAT of the next satellite and $c_{s+1,s}$ is the travel time between the next satellite and the current satellite location in the FE route. To minimize waiting times at customer locations, the second-echelon vehicle is set to depart from the distribution satellite at its LAT. Meanwhile, the second-echelon vehicle leaves after the respective customer EAT and the service time for the subsequent pickup and delivery operations.

At the FE route level, every satellite visit preserves four pieces of data: the arrival and departure time of the first-echelon vehicle at the satellite, the Latest Arrival Time at the satellite, and the current load.

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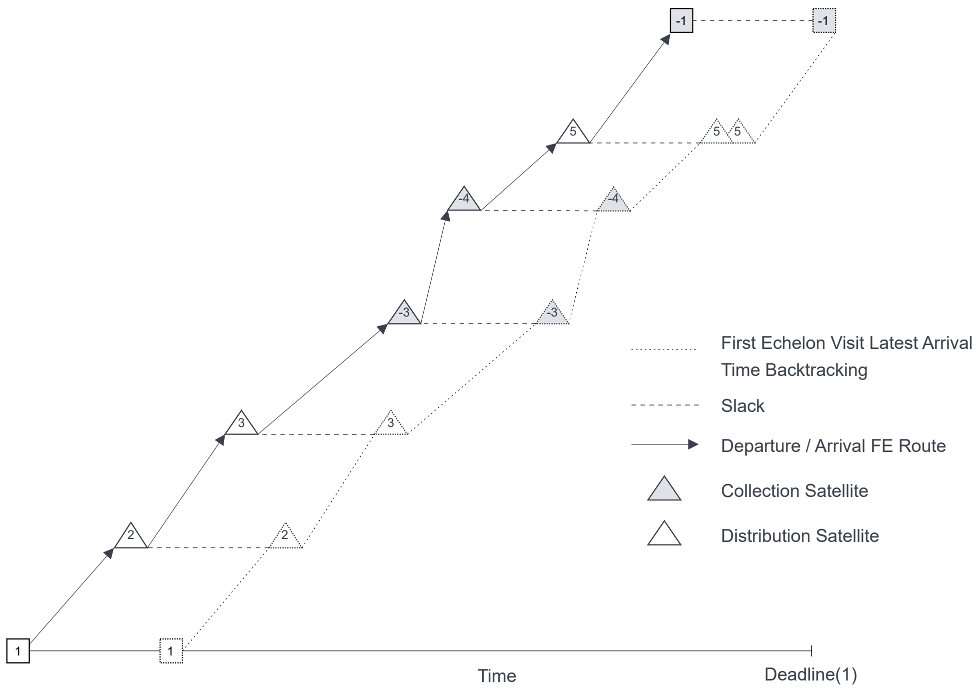

Figure 3: First Echelon Solution Diagram

Figure 3 illustrates a diagrammatic representation of a single FE route within our proposed solution, highlighting the maintained information. The design ensures that the first-echelon vehicle arrives at the satellite as early as possible, while its departure depends on the type of satellite. For a distribution satellite, the vehicle departs immediately after completing the service time. However, in the case of a collection satellite, the departure time is defined by the arrival of the latest pickup parcels assigned to the first-echelon vehicle and the service time at the satellite. For example, refer to Figure 3, where the departure time from the collection satellite -3 is later than the first-echelon vehicle's arrival at distribution satellite 3. This scenario indicates that the first-echelon vehicle waits at satellite 3 until all assigned pickup parcels have arrived.

The Latest Arrival Time (LAT) at a satellite in the FE route represents the latest feasible time for distribution or collection at the satellite s can be conducted. This value is computed reversely (backtracking), based on the earliest deadline of a pickup parcel at the hub assigned to the FE route, as depicted in Figure 3. The LAT for the distribution satellite is influenced by both the deadline at the hub and the first EAT of the SE routes from that satellite. Specifically, the first EAT of the SE routes may impact the FE route satellite LAT due to the time windows assigned to the customers served by the SE route (e.g., the LAT of distribution satellite 5 in Figure 3 is earlier than the subsequent LAT and the travel time).

Customer insertion in FE and SE routes. The solution representation of 2E-VRP-PDD is portrayed in Figure 4. Alterations in a single SE route may trigger changes in the overall solution configuration, particularly affecting vehicle arrival and departure times. For instance, inserting a customer between customers 7 and 11 would shift the second-echelon vehicle arrival time at satellite -3, leading to cascading shifts to the subsequent satellites -4, 5, and -5. Consequently, a single customer insertion impacts the

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FE vehicle arrival at the hub for both FE routes.

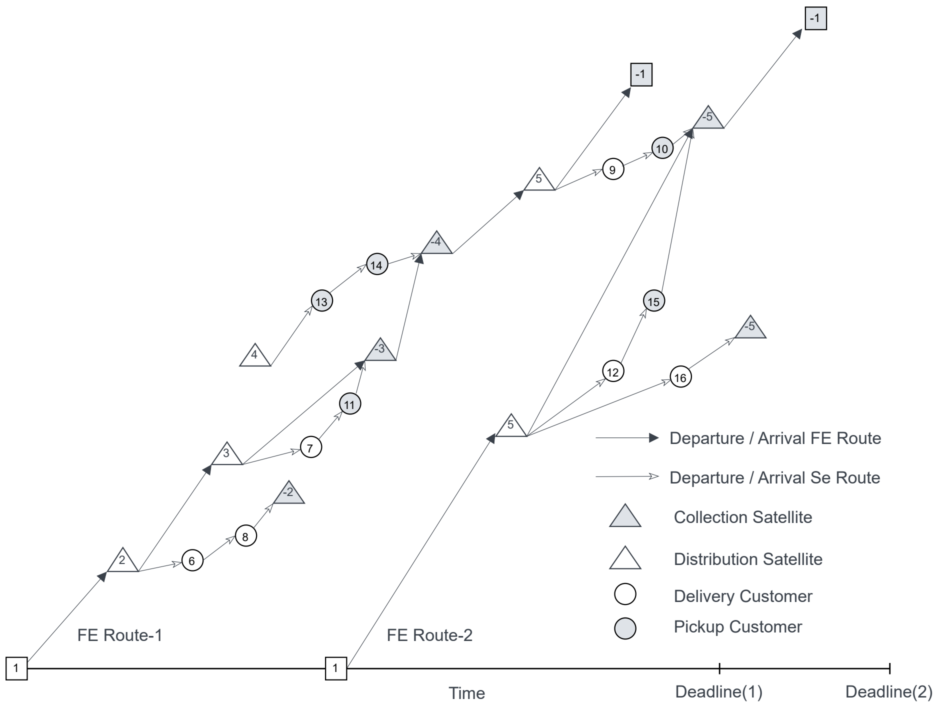

Figure 4: Solution Diagram

Generally, a customer can be inserted into an *existing SE route* or a *new SE route*. Both ways have different prerequisites before the insertion is implemented, but share a similar type of insertion. The insertion type is characterized by a specific adjustment of the solution after the customer inclusion. A summary of the process of inserting a customer to an *existing SE route* can be found in Table 1, while Table 2 presents the process for inserting a customer to a *new route SE route*. For each combination of the route and customer type, we distinguish a particular 'insertion process'.

Type 1: inserting a delivery parcel into a dedicated distribution route. Consider the insertion of delivery customer 22 into SE route 2 - 6 - 9 - -2, as depicted by the blue arrow in Appendix B.9. If the most cost-effective insertion point lies within this distribution SE route, the insertion will not affect subsequent satellite visits. However, it may shift the LAT at the initial SE route visit due to the time window constraint of the inserted customer. Consequently, in this insertion type, we only need to verify the feasibility of the customer within the SE route, without requiring a satellite insertion.

Type 2: inserting a delivery parcel into a dedicated collection route. Consider delivery customer 22 being inserted into SE route 4 - 13 - 14 - -4 as seen in Appendix B.10. In such an instance, the insertion

Table 1: Insert a customer in an existing second-echelon route

Customer to Insert	SE Route Operation	Insertion Process
Delivery	Distribution Collection Distribution and Collection	Type 1 Type 2 Type 3-d
Pickup	Distribution Collection Distribution and Collection	Type 4 Type 3-p Type 3-p

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Table 2: Insert a customer in a new second-echelon route

Customer to Insert	Availability Related Satellite in the FE Route	Type of Related Satellite	Insertion Process
Delivery	Yes	Distribution Satellite	Type 1
	Yes	Collection Satellite	Type 2
	No	-	Type 2
Pickup	Yes	Distribution Satellite	Type 4
	Yes	Collection Satellite	Type 3-p
	No	-	Type 4

of the customer requires a subsequent insertion of the corresponding distribution satellite. Establishing this connection for the distribution satellite ensures that the delivery parcel is transported by the first echelon vehicle from the hub before moving it by the second echelon vehicle.

There are three alternatives for incorporating distribution satellite 4 into the solution diagram: (1) Insert the distribution satellite into the current FE Route (FE Route-1), (2) Insert the distribution satellite into a different FE Route (i.e., FE Route-2), or (3) creating a new FE route if neither option (1) nor (2) proves feasible. In the search process, for alternative (1), we restrict the search location to areas before the related collection satellite (red arrow in the FE route-1, Appendix B.10). In this case, the insertion shifts the second-echelon vehicle's arrival time at the collection satellite. This shift subsequently propagates to the arrival times at the following satellites and influences the originating SE routes from the affected satellites.

Type 3-d: inserting a delivery parcel into a distribution-and-collection route. Consider the insertion of delivery customer 22 into SE route 3 - 7 - 11 - -3 as illustrated in Appendix B.11. In this particular instance, satellite insertion is unnecessary since the distribution and the collection satellite are already connected in the FE route. Suppose this configuration provides the most cost-effective insertion in this neighborhood. In that case, the customer's insertion into the SE route causes a shift in the second-echelon vehicle's arrival time at the assigned satellite. This shift consequently influences the first-echelon vehicle's subsequent arrival time at the next FE route visit, the initial time of the SE route starting from the next satellite, and the arrival time at the hub, as indicated by the dotted line.

Type 3-p: inserting a pickup parcel into a route conducting collection operation. Consider the insertion of pickup customer 23 into SE route 5 - 9 - 10 - -5, as depicted in Appendix B.12. This situation is similar to the Type 3-d insertion case, except that the deadline for FE route-2 is updated. Throughout the search process, each insertion of a pickup parcel necessitates taking into account the shift in the deadline at the end of the FE Route that services the pickup parcel. In the provided example, the deadline at the hub for FE route-2 is reduced (dashed blue arrow) because pickup customer-23 has an earlier deadline than all currently served pickup parcels in FE route-2.

Type 4: Inserting a pickup parcel into a dedicated distribution route. Consider pickup customer 23 being inserted into the SE route 2 - 6 - 8 - -2 as portrayed in Appendix B.13. The pickup customer insertion in this neighborhood necessitates a subsequent collection satellite insertion. The alternatives for the insertion of the collection satellite are: (1) in the same FE route as the distribution satellite (FE route-1), (2) in a different FE route (FE route-2), or (3) in a new FE route. During the search

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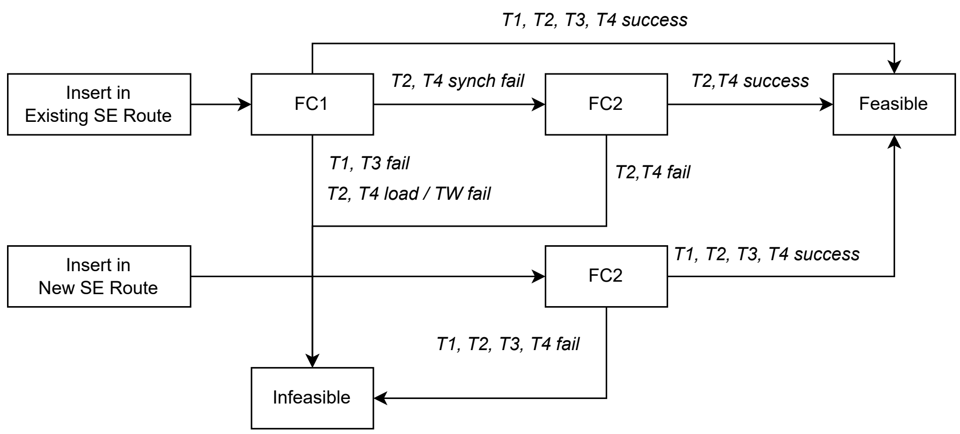

Figure 5: Feasibility Check Framework

process, the location of the collection satellite insertion in alternative (1) is limited only to the area after the corresponding distribution satellite. The pickup customer insertion in this neighborhood results in a shift of the first-echelon vehicle's arrival at the subsequent satellite and a shift in the deadline if the pickup customer has an earlier deadline than the existing pickup parcels transported by the selected FE route.

4.6. Feasibility Check

This section presents an efficient evaluation procedure to check the feasibility of insertion location in the SE and FE routes. We design a high-level feasibility check (FC) framework as depicted in Figure 5. The framework flow differs based on the customer insertion, whether an insertion into an *existing* or a *new* SE route. The difference between feasibility check 1 (FC^1) and 2 (FC^2) is based on the implementation of the evaluation procedure. The FC^1 consists of four evaluations: SE load, time windows, FE load, and synchronization, while FC^2 only evaluates the FE load and the synchronization constraint.

Feasibility check 1 (FC^1) operates under the pre-condition that we insert a customer into an existing SE route. As such, the FC^1 procedure applies across all types of insertions. This feasibility check exclusively evaluates when the related satellites are incorporated into the SE current route. Under this circumstance, if we need to insert a distribution (collection) satellite into the FE route, the satellite will be inserted right after (before) the collection (distribution) satellite. For instance, as shown in Appendix B.13, if we aim to insert pickup customer 23 into an SE route starting from satellite 2, the FC^1 would assess the insertion in SE route 2 - 6 - 8 - -2 and FE route-1 at satellite 2. The collection satellite -2 would be inserted in FE route-1 right after the distribution satellite 2.

The evaluation process for (FC^1) is structured in a sequence beginning with evaluating the SE load, progressing to the FE load, then to the SE route time windows, and concluding with synchronization. This sequencing strategy facilitates early detection of infeasibility, considerably reducing computational time. After the evaluation, the insertion is classified as feasible, and the corresponding insertion cost is computed. Conversely, the insertion is deemed infeasible if the FC^1 evaluation for insertion types 1 and 3 encounters failure, or if insertion types 2 and 4 fail during the SE/FE load or the time windows evaluation. However, if insertion types 2 and 4 fail at the synchronization evaluation, the procedure

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transitions to applying Feasibility Check-2 (FC^2).

Feasibility Check-2 (FC^2) applies in two cases. First, insertion types 2 and 4 fail at the synchronization evaluation under FC^1. Second, all insertion types when inserting a customer into a new SE route.

In the first case, when insertion types 2 and 4 do not pass the synchronization evaluation in FC^1, a feasible insertion may still be possible if the satellite is inserted in a different location. This is because the SE route remains feasible in terms of load and possibly the time windows. For instance, in Appendix B.13, if the insertion of collection satellite -2 after satellite 2 proves unsuccessful, FC^2 evaluates other potential locations. This implies that the first-echelon vehicle in FE route-1 could make a detour, provided it proves advantageous, or the SE route could be served by a first-echelon vehicle from an alternative FE route, such as FE route-2.

In the second case, the insertion of a customer into a new SE route precludes the need to verify the load and time windows at the SE route. Nonetheless, it is still necessary to examine the available capacity in the first-echelon vehicle (FE load) and to assess the synchronization of the new SE route within the FE route solution. Consequently, the procedures within FC^2 begin with evaluating the FE load, followed by synchronization examination.

In the following, we provide the essential information of the above-outlined evaluations. For time-windows evaluation, we adopt the forward-time slack (FTS) methods from Savelsbergh (1985), and the calculation is based on Campbell and Savelsbergh (2004). The feasibility of inserting the customer j between $i-1$ and i evaluated by computing the $e_j = max(E_j, e_{i-1} + c_{i-1,j} + \delta_{i-1})$ and the $l_j = min(L_j, l_i - c_{j,i} - \delta_j)$. Given the result, checking the time window feasibility is by verifying whether $e_j \leq l_j$.

For synchronization evaluation, The evaluation examines the feasibility of the timing at the satellite, ascertaining whether an insertion can be successfully implemented concerning time windows, deadlines, and synchronization. In this evaluation, we look into (1) the timing at the beginning of the SE route with the distribution satellite and (2) the timing at the end of the SE route with the collection satellite. However, there is a different approach to evaluating the synchronization between delivery and pickup customers.

For a delivery customer insertion, we check the distribution satellite visit at the beginning of the SE route. Specifically, we *update* each node LAT information in the SE route from the insertion location j until the beginning of the SE route (i.e., distribution satellite). Then, after we obtain the *updated* SE route LAT information at the distribution satellite, we compare it with the first-echelon vehicle arrival at that distribution satellite. Suppose the insertion is type 2 (i.e., a delivery customer is inserted in a dedicated collection SE route). In that case, we need to update the new timing of the first-echelon vehicle ready at the distribution satellite, that is, after the departure from the preceding satellite and the travel time between the preceding satellite and the current satellite. However, suppose the insertion is type 1 (i.e., a delivery customer is inserted in a dedicated distribution SE route) or 3-d (i.e., a delivery customer is inserted in a collection-and-distribution SE route). In that case, the timing when the first-echelon vehicle is ready at the distribution satellite does not need to be updated. Then, the feasibility

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check evaluates whether the first-echelon vehicle is ready at the distribution satellite before the *updated* SE route LAT at that satellite.

If feasible, we check the collection satellite visit at the end of the SE route. Specifically, except for insertion type 1 (i.e., a delivery customer is inserted in a dedicated distribution SE route), we *update* each node EAT information in the SE route from the insertion location j to the end (i.e., collection satellite). After the *updated* SE route EAT at the collection satellite is obtained, we compare it with the current FE route LAT at that collection satellite. The synchronization is feasible if the *updated* SE route EAT at the collection satellite is smaller than the FE route LAT. Otherwise, it is infeasible.

For a pickup customer insertion, we need to evaluate the pickup parcel deadline. If the deadline is earlier than the current pickup parcels deadline served by the FE route, we *update* the associated FE routes LAT until the collection satellite location. Also, we *update* the SE route LAT from where the pickup parcel is inserted to the beginning SE route (i.e., distribution satellite). Then, the subsequent procedure is the same as delivery parcel insertion. We check the distribution satellite visit at the beginning of the SE route, particularly the arrival of the FE vehicle at that distribution satellite. If the arrival time of the FE vehicle is greater than the *updated* SE route LAT at the distribution satellite, then it is infeasible.

If feasible, we check the collection visit at the end of the SE route. Each node EAT in the SE route is *updated* forward from the insertion location j to the end of the SE Route. After obtaining the SE route EAT at the collection satellite, we compare the maximum EAT from all SE routes ending at the collection satellite to the *updated* FE route LAT at the collection satellite. The synchronization is infeasible if that maximum EAT exceeds the updated FE route LAT. Otherwise, it is feasible.

The synchronization procedure is also applied to all SE routes affected by the shifts of satellite visits at the FE route.

4.7. Acceptance Criterion

The acceptance of a new solution is evaluated after each destroy and repair procedure. Each current solution, denoted as s', is accepted with a probability $e^{-(f(s')-f(s))/t}$, wherein $t > 0$ represents the temperature at the given iteration and $f(\cdot)$ the objective value. As the ALNS algorithm initiates, the temperature begins at $t = t_0$ and gradually declines at each iteration following the formula $t = t \cdot c_{rate}$ where c_{rate} is the cooling rate. In line with the work of Ropke and Pisinger (2006), we set an initial temperature control parameter equal to 5% for determining t_0. This parameter is configured such that a solution that performs 5% worse than the average initial solution in a batch is accepted with an initial acceptance probability parameter denoted as η.

4.8. Mixed Integer Programming (MIP)

Upon the completion of the ALNS, the MIP is called. The initial step entails decoding the solution derived from the ALNS phase to extract all FE and SE routes from the solution pools ($\bar{S}$). Subsequently, we eliminate duplication within the FE and SE routes to reduce the input size. All the parameters required for MIP execution are then stored, consistent with the discussion in Section 3, and are based on the information collated from the FE and SE route pools.

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The FE and SE routes generated by the ALNS algorithm are all feasible routes, meaning that the SE route adheres to the load and time window constraints, and the FE route fulfills the load and deadline constraints for all serviced parcels. As a result, the MIP has a task to ascertain the operation and time synchronization between the selected SE and FE routes, a factor articulated in the route-based formulation constraint.

During the MIP process, the bundling constraint from the ALNS algorithm is relaxed and allows split pickup and delivery operations. This implies that, as long as the parcel satisfies the operation and the time synchronization at the satellite, the second-echelon vehicle can receive the parcel from any first-echelon vehicle. The MIP is solved using a commercial solver, subject to a specified time limit (in this study, we set 5400 s). Upon reaching the minimum relative gap or the time limit, the minimum solution from the ALNS is compared with the solution derived from the MIP. The cost-minimizing solution is then chosen to represent the outcome of the matheuristic.

5. Computational Results

This section presents the computational experiments to analyze the performance of our matheuristic for solving the 2E-VRP-PDD. We first discuss the benchmark instances used from the literature and provide an overview of the performance of our matheuristic on solving 2E-VRP benchmark instances from the literature in Section 5.1. We present how we create our 2E-VRP-PDD instances and then solve the new 2E-VRP-PDD instances and derive valuable insights regarding the impact of varying parcel deadlines on transportation costs in Section 5.2. Section 5.3 discusses the impact of the individual operators on the ALNS, and Section 5.4 discusses the impact on the solution for varying customer pickup deadlines at the hub. Details on tuning the parameters of our matheuristic can be found in Appendix A.

We coded the matheuristic in Java and compiled it using JDK-17.0.1 and CPLEX 22.1.1.0 is used as a MIP solver. The computational experiments were conducted on the Snellius Cluster High-Performance Computer, specifically, an AMD Rome 7H12 that comprises CPUs at 2.6 GHz with 32GB of RAM unless specified otherwise. All experiments are conducted single-threaded.

5.1. Performance of our ALNS on 2E-VRP benchmark instances

Because the 2E-VRP-PDD is a new problem, benchmark instances do not exist in the extant literature. We therefore evaluate our matheuristic, and specifically the ALNS within, on well-established 2E-VRP instances that are publically available. We do so on the instances provided by Breunig et al. (2016), along with the new set of instances (called Set 7) proposed by Marques et al. (2020). Notice that benchmark sets 4a and 6b from Breunig et al. (2016) do not apply to our setting. To provide a fair comparison, we incorporated some minor modifications to the ALNS to not spend unnecessary time on computations that are irrelevant for 2E-VRP instances:

- We skip checking the feasibility of the time constraints (such as time windows, synchronization, and deadlines).

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- We allow SE vehicles to carry loads from multiple FE vehicles.
- We exclude all time-related operators, leaving us with six destroy and four repair operators.
- We impose penalties on any additional routes for the SE or the FE if the total exceeds the maximum fleet size stipulated by the instances.

Table 3: Performance of 2E-VRP-PDD compared to 2E-VRP benchmark result from Voigt et al. (2022) and Mühlbauer and Fontaine (2021)

Instance set	#Inst.	#Customers	#Satellites	Δ best (%)	Δ avg (%)	t(s)	t*(s)
2a	6	21	2	0.00	0.00	36	1
	6	32	2	0.00	0.04	56	4
2b	9	50	2,4	0.00	0.22	95	26
2c	9	50	2,4	0.00	0.09	99	21
3a	6	21	2	0.00	0.00	36	1
	6	32	2	0.00	0.00	54	8
3b	12	50	2	0.17	0.38	157	27
4b	54	50	2,3,4	0.02	0.13	111	23
5	6	100	5	0.04	0.95	305	171
	6	100	10	0.64	1.27	350	181
	6	200	10	1.09	1.78	1169	791
6a	9	50	4,5,6	0.00	0.17	93	18
	9	75	4,5,6	0.00	0.27	147	63
	9	100	4,5,6	0.24	0.48	249	114
7*	10	100	5,10	1.27	1.51	327	129
	17	200	10,15	1.92	2.73	1420	1071
	24	300	10,15	1.92	2.90	3166	2708

Table 3 shows the performance of the ALNS on the benchmark instance sets compared to the results from Voigt et al. (2022) (Sets 2a - 6) and Mühlbauer and Fontaine (2021) (Set 7). We solve each instance within each benchmark set five times with our ALNS. The initial four columns depict the instance set name, the number of instances, the number of customers in the instances comprising that set, and the number of satellites. The "Δ best" column denotes the average best solution (of the five ALNS runs) over all instances within the benchmark set relative to the best-known solution. The column "Δ avg" corresponds to the average of five ALNS runs for all instances within each set. Finally, "t(s)" indicates the average runtime for 1 million iterations, whereas "t*(s)" indicates the average time until the best-found solution. The detailed results on each instance are provided in Appendix C.9 to C.16.

The findings show that our algorithm effectively finds the best-known solution in nearly all instance sets derived from Breunig et al. (2016). The gap between the BKS and the average of 5 runs for all instances remains below 2%. Upon examining the new large and complex instance set from Marques et al. (2020), our ALNS demonstrates competitive results both compared to the heuristic from Mühlbauer and Fontaine (2021) and the exact result from Marques et al. (2020). Furthermore, our algorithm showed competitive run-time performance and results compared to previous studies utilizing the same benchmark, according to the overview by Sluijk et al. (2023).

5.2. *Evaluation of 2E-VRP-PDD*

This subsection presents the computational results of our matheuristic on the 2E-VRP-PDD. We start by introducing the specific instances deployed in our computational experiments. Following this, we evaluate our matheuristic, focusing on the MIP and ALNS components. We conclude this section by providing a performance review of the ALNS operators.

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Table 4: Matheuristic Performance on the 2E-VRP-PDD instances

		ALNS 30K				MIP				ALNS 100K			
#C	#S	*Avg. 5*	*Best 5*	*t(s)*	*t*(s)*	*Avg. 5*	*Best 5*	*t(s)*	*% Gap*	*Avg 5*	*Best 5*	*t(s)*	*t*(s)*
50	2	1482.47	1470.39	67	36	1471.98	1467.65	894	0.08	1473.88	1467.99	178	85
	4	1410.04	1397.87	100	60	1401.22	1392.39	1631	0.65	1401.04	1388.4	276	140
	8	1322.50	1301.68	204	113	1314.56	1296.39	2535	0.85	1321.67	1300.62	584	281
100	2	2465.05	2430.01	234	188	2528.75	2399.55	5164	6.97	2439.63	2412.83	628	460
	4	2251.88	2212.96	366	297	2394.16	2220.59	5402	9.65	2231.40	2203.28	933	650
	8	2072.26	2038.49	681	531	2099.96	2018.16	5329	6.44	2057.56	2026.29	1834	1346

We generate new 2E-VRP-PDD instances based on the instances provided by Dumez et al. (2023). To make the instances fit our problem setting, we removed the restrictions on the fleet size in both the first- and second-echelon. Furthermore, we disregard the capacity limit at the satellite which Dumez et al. (2023) considers. Then, we separated customers comprising both pickup and delivery demand into separate customers. One of the key elements of the 2E-VRP-PDD is the presence of customer-specific deadlines on the arrival of the pickup parcels at the city hub. To do so, we differentiate between same-day and next-day services. For the same-day service, we set the time window cut-off time at 300 time units. Accordingly, the pickup parcels with a time window that extends beyond 300 time units are assumed to be a next-day service. We consider for both services either an early or a late deadline. Same-day service's early and late deadlines are set at 420 and 480 units, respectively. For next-day service, these deadlines are set to 720 and 840 units. We assigned parcel deadlines uniformly at random.

In the formulation of the 2E-VRP-PDD instances, travel time is denoted in minutes, and distances, representing routing costs, are calculated using Euclidean metrics. For other details for the instance generation, we follow the description from Dumez et al. (2023). Finally, the evaluation of the MIP components hinges upon the First Echelon (FE) and Second Echelon (SE) route pools produced by the ALNS. We consider two variants of our matheuristic. A version in which we run the ALNS for 30K iterations and afterward run the MIP with a time limit of 5400 seconds for CPLEX, and a version that runs only the ALNS for 100K iterations without using the MIP afterward.

The results of our matheuristic are summarized in Table 4. Detailed results are provided in Appendix D.17. The table is categorized based on the number of customers (50 and 100) and the number of satellites (2, 4, and 8). Each of these combinations of customers and satellites consists of 10 instances, that we each solve 5 times with our matheuristic. The first column group delineates the cost and time metrics for the ALNS algorithm executed over 30K iterations. The cost metrics incorporate the average cost from five runs (Avg. 5) and the best cost from these five runs (Best 5). Time metrics include the duration of the algorithm's execution (t) and the time taken to identify the optimal cost (t^*) in the second unit. Both time and cost metrics are averages derived from all instances within each customer and satellite group. The second column group features metrics associated with MIP implementation, with the added consideration of the % gap, which shows the average relative gap to the lower bound considering the routes encountered by the ALNS 30 K

In general, an increased number of satellites corresponds to a reduction in cost, as can be expected, suggesting that expanding the satellite number can help mitigate routing costs. However, when focusing on the ALNS runtimes, we see a clear increase in more satellites as the search space is expanded in such

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cases.

Comparing the scenario wherein only the ALNS is applied (executed over 30K iterations) with the scenario in case the computation is extended via the MIP, highlights the benefits of allowing second-echelon vehicles to use demand from multiple first-echelon vehicles. Although in our practical setting, this is not feasible, we observe a marginal reduction (approximately 0.64%) in the average cost across five runs for the MIP compared to the ALNS for the 50 customers instances. On the contrary, a larger customer base (100 customers) results in a higher average cost (around 3.34%). In these cases, on average, the MIP is terminated before achieving the minimum relative gap, as indicated by the % gap column, which still exhibits a gap exceeding 5%. Furthermore, considering the best result of the five runs, applying the MIP after the ALNS appears beneficial in almost all instances (reducing the objective on average by 0.65%). This finding suggests that employing a split operation in the FE route can yield a more cost-effective solution, and might be considered in practice.

We also solved the 2E-VRP-PDD instances using 100K iterations of the ALNS (called ALNS 100K in Table 4), aimed at quantifying the potential advantages of increasing the number of iterations. Naturally, runtimes increase, but specifically, the difference between the best and average performance of the ALNS reduces, giving an indication that the ALNS provides stable performance in the case of 100K iterations. The differences in best solutions are, however small, making the 30K version of our ALNS suitable for analyzing the problem structure in detail.

5.3. Impact of operators

Next, we investigate our ALNS operators' performance based on three key metrics: the average number of new optimal solutions identified by each operator, the average cost-saving achieved per use for each operator, and the average solution deviation resulting from the absence of a particular operator. These metrics are summarized in Table 5. The first two columns are derived from the ALNS 30K results, while the solution deviation is calculated through an additional series of experiments, each of which omits one group of operators.

The worst-distance removal operator consistently outperforms its counterparts in identifying new optimal solutions. Conversely, both route and least-utilized route removal operators, despite demonstrating a relatively lower propensity to discover new best solutions, are associated with significant cost savings when implemented. Regarding the insertion method, the farthest-first insertion operator shows superior effectiveness in finding a new best solution. The average cost-saving associated with each repair operator is comparable, with no significant disparities. A sensitivity analysis conducted for each group of operators indicates that the average deviation in the absence of a particular operator group is negligible, with values ranging from -0.001 to 0.005. This suggests the overall system's performance remains relatively robust even when specific operator groups are excluded.

Furthermore, we underscore the distinctive advantage of the *worst-slack removal* operator, as illustrated in Figure 6. Though the worst removal operator exhibited superior performance initially, it was overtaken by worst-slack removal during the later iterations (surpassing worst removal after 12,000 iterations, yet remaining subpar to random removal). This suggests that removing customers with higher

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Table 5: Operator Performance Measures

Indicator	Operator	Avg. number of new best solutions each operator finds	Avg. cost saving per usage for each operator	Avg. solution deviation without the operator
Destroy(Removal)				
Random	Random	11.09	13.58	0.000
Distance-related	Worst-distance	12.54	32.51	0.005
	Related-distance	4.77	18.80	
Time-related	Worst-slack	9.41	15.53	-0.001
Routing-related	Route	0.29	34.37	0.008
	Least-utilized route	1.36	29.54	
	Satellite	4.99	18.87	
Repair(Insertion)				
Random	Random-order	5.03	21.10	0.002
Distance-related	Farther-first	10.67	21.09	0.002
	Closest-first	3.11	20.99	
Demand-related	Largest-first	6.26	20.36	0.001
Time-related	Earliest Time Widows-first	4.57	20.73	-0.001
	Latest Time Widows-first	5.12	20.96	
	Earliest Deadline-first	4.61	21.46	
	Latest Deadline-first	5.08	20.70	

slack time can improve the advanced stages of the destroy and repair process. This is attributable to the reduced prohibited insertion area caused by the time-related feasibility check. Additionally, the customer with a tight customer slack indicates that it is already inserted in a relatively cost-minimized location.

5.4. Impact of the Deadline

In this section, we report on the influence of deadlines on 2E-VRP-PDD. Three distinct instance sets are generated for comparison from the base scenario (which we will call "Deadline"), distinguished solely by the imposed deadline constraints. The generation of these sets aligns with the instance explanation delineated in Section 5.2. The newly generated sets differ as follows:

- *Without Deadline (WD)*: Deadlines are eliminated by setting all pickups to the maximum possible number. This results in the problem becoming a Two-Echelon Vehicle Routing Problem with Pickup, Delivery, and Time Windows.
- *Loose Deadline (LD)*: Each pickup customer has a 75% probability of being assigned a late deadline, applicable to both same-day and next-day services.
- *Tight Deadline (TD)*: In this set, each pickup customer has a 75% probability of receiving an early deadline for either same-day or next-day service.

The deadline's impact is quantified in Table 6, presenting averages over all the instances in our benchmark sets. The detailed results are provided in Appendix D.19 and D.20. Evaluation criteria include the cost (as the minimum over 5 runs), the "# FE vehicles" and "# SE vehicles" show the average number of first- and second-echelon vehicles deployed, the "FE Max Load" and "SE Max Load" denote the average of the maximum parcel load carried by first- and second-echelon vehicles, and "FE parcels" and "SE parcels" represents the average number of parcels transported by each first- and second-echelon vehicle.

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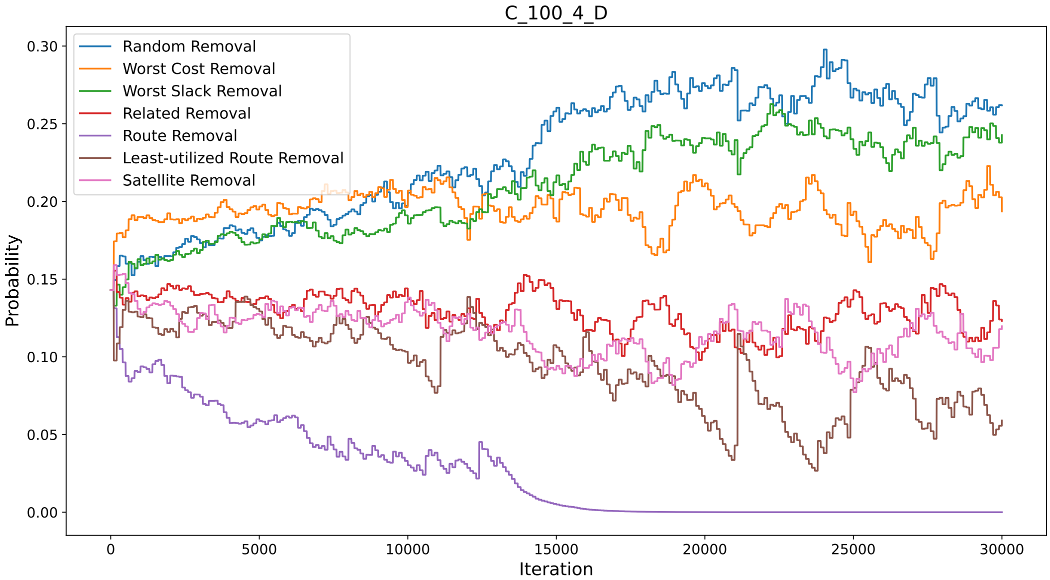

Figure 6: Operator Performance over Iterations Time in Instance C-100-4-D

Table 6: Sensitivity of customer deadlines on the total transport cost

	Without Deadline	Loose Deadline	Deadline	Tight Deadline
Cost	1692.34	1777.06	1808.57	1836.74
# FE Vehicles	2.72	3.14	3.13	3.30
# SE Vehicles	16.95	16.97	16.99	16.88
FE Max Load	0.69	0.61	0.61	0.58
SE Max Load	0.92	0.91	0.91	0.91
FE Parcels	34.19	30.09	30.11	28.59
SE Parcels	5.52	5.52	5.51	5.55

Comparing the Without Deadline (WD) case with the Tight Deadline(TD), we observe a cost increase of 8.5% on average. This increase is largely driven by the need for additional first-echelon vehicles to meet tighter deadlines, while the number of second-echelon vehicles remains relatively stable. In practical scenarios, such a small increase in cost might make the difference between operating a profitable business or not.

The maximum load carried by the first-echelon vehicles decreases by around 5.3% as deadlines tighten, suggesting a spread of load distribution across the larger first-echelon vehicle fleets. Similarly, the average number of parcels transported by the first-echelon vehicles reduces by approximately 5.7%, due to the increased number of vehicles sharing the load. However, second-echelon vehicles' maximum load and parcel number remain stable, indicating minimal impact on SE operations regardless of deadline conditions. This stability suggests a possible redistribution of parcels from FE to SE routes as the deadline becomes stricter.

6. Case Study

This section applies our matheuristic approach to a case study replicating operations of our industry collaborator based in the Jakarta Metropolitan Area, Indonesia. We propose a comparative study of three distinct heuristic routing strategies. One is the 2E-VRP-PDD proposed in this paper. The two other

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strategies are based upon the existing literature and the current operational strategies of our industry collaborator. These strategies are as follows:

- *Strategy 1 (S_1)*: This strategy, proposed in the present paper as the 2E-VRP-PDD, advocates for integrating pickup and delivery operations within both the FE and SE routes.
- *Strategy 2 (S_2)*: This alternative strategy segregates pickup and delivery operations into distinct operational sequences in both the FE and SE routes.
- *Strategy 3 (S_3)*: The third strategy, mirroring the current practices of our industry partner, segregates the pickup and delivery operations at the FE level, yet integrates these operations at the SE level. This approach is also in line with strategies proposed in the literature, including Li et al. (2021), Liu and Jiang (2022), Zhou et al. (2022), and Li et al. (2022).

6.1. Case study Description and Setup

We mimic one typical day of operation in five hubs of our industry collaborator. We adopt the logistics facilities' location and customer spread to make the instance realistic by converting the original data to the Universal Transverse Mercator (UTM) coordinates in a planar graph using 'pyproj' package from Python. We round the point to the nearest integer. In this case, the hub also plays a role as a satellite. So, from the operational perspective, we put a similar location for the hub with one satellite location. We label the new instances as CS-1-D to CS-5-D. The instances have 6 to 9 satellites with 1500 to 2150 customers. The instances are publicly available at our GitHub repository: `https://github.com/aryazamal/2e-vrp-pdd`.

We consider the customer demand as the parcel's weight. The time windows are based on the original time stamp data and then converted to minutes. We consider the initial planning horizon to start at minutes 0 or 7:00 in the morning. The cut-off time for the same-day service is 13:00. We set the same-day delivery deadline as equal to 420 (14:00) and 540 (16:00) for the early and late deadlines at the hub, respectively. We also consider another deadline at 19:00 for the same-day delivery, but the latest time windows are started later than the cut-off time. We set the next-day delivery deadline as equal to 780 (20:00) and 900 (22:00) for the early and late deadlines at the hub, respectively.

The company utilizes a minivan from their partners for the first-echelon vehicle and a motorbike for the second-echelon vehicle. The capacity is set for 750 and 160 for the first- and second-echelon vehicles, respectively. No maximum fleet size is considered. Finally, we set travel time based on the average speed in the Jakarta Metropolitan area, slightly below the average morning rush and the evening rush reported by TomTom (2023), which is 350 (meters per minute).

To solve the problem, we implement our matheuristics approach for 2E-VRP-PDD to this large-scale problem instance limited to 30K iterations in one run for each instance. We set $\zeta_{small}^{UB} = 0.1$, $\zeta_{large}^{LB} = 0.45$ and $\zeta_{large}^{UB} = 0.55$ to better deal with the large number of customers to be inserted in each iteration. Finally, since this case considers the vehicle's average speed, the objective is to minimize the cost, represented by the total travel times.

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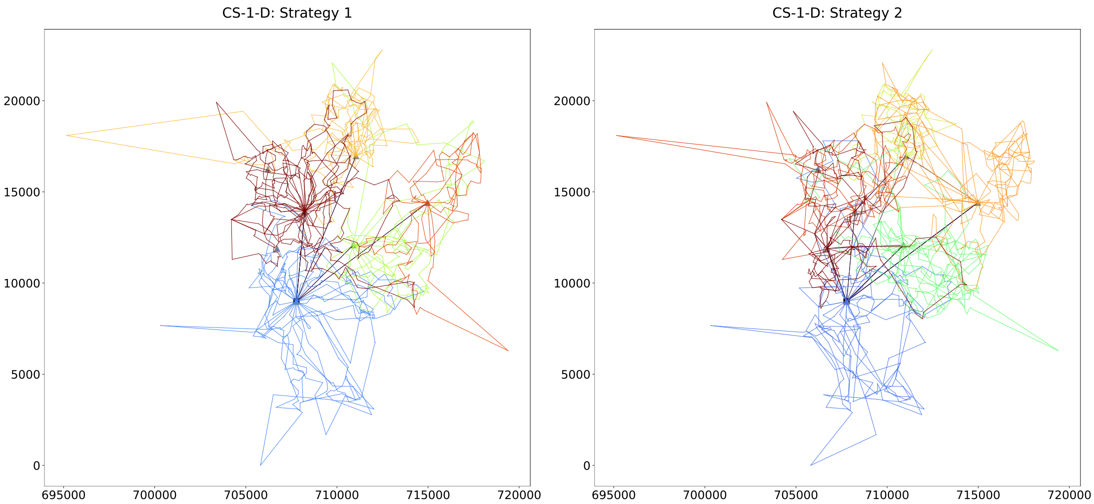
6.2. *Case Study Results and Analyses*

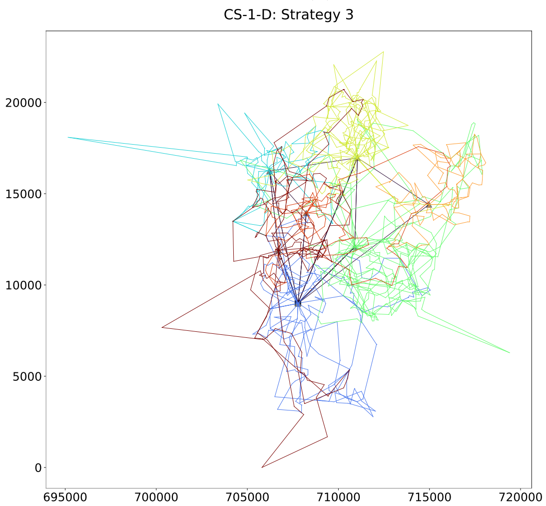
This section presents and discusses the key findings from our case study of a 2E-VRP-PDD. Figure 7 presents the solution representation for the CS-1-D while Figure 8 summarizes the solution characteristic of each strategy for every case. Detailed results can be found in Appendix E.21.

We first summarize each strategy's main findings and afterward, draw three insights important for practitioners.

Strategy 1: The results show that this strategy has the lowest average cost due to integrating pickup and delivery operations within both FE and SE routes. This integration allows for more flexible and efficient use of each vehicle's capacity (particularly first-echelon vehicles) over time, reducing the number of vehicles needed and, thus, the overall cost. The maximum load at any time might not be as high because of the continual loading and unloading. This strategy also requires the highest number of second-echelon vehicles due to the increased complexity caused by the synchronization of routes when combined with pickup and delivery operations. This strategy utilizes the least number of satellites from



(a) Result: 8 FE vehicles, 56 SE vehicles, and 5 satellites (b) Result: 14 FE vehicles, 52 SE vehicles, and 6 satellites



(c) Result: 16 FE vehicles, 51 SE vehicles, and 7 satellites

Figure 7: Result of CS-1-D instances using Strategy 1 (a), Strategy 2 (b), and Strategy 3 (c) with 7 satellites available, 1331 delivery customers, and 815 pickup customers

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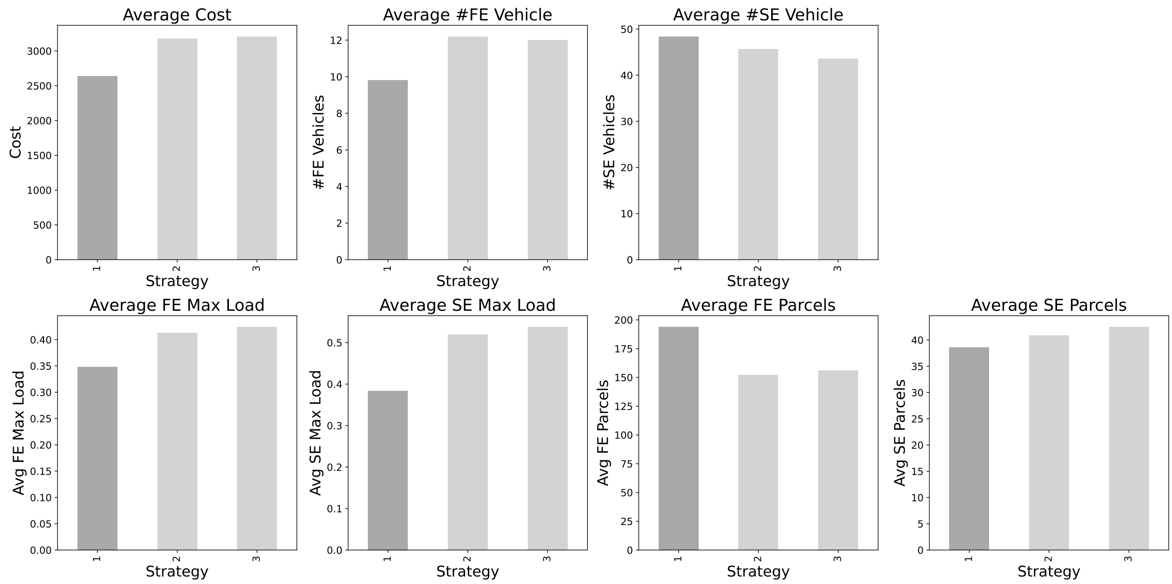

Figure 8: Characteristics of strategy results in five hubs

the currently available satellites in each case, indicating the potential of satellite efficiency after employing the strategy while respecting the time constraints.

Strategy 2: This strategy separates pickup and delivery operations in both FE and SE routes, leading to the highest average cost and usage of first-echelon vehicles. Separating the operations means more vehicles are needed to perform each operation individually. This separation allows for a more focused loading plan for each operation, resulting in a higher maximum load and more parcels carried per vehicle. However, a higher load planning at the FE level is contributed by the delivery (last-mile distribution) operation. In contrast, due to the deadlines, the pickup (first-mile collection) operation has less than half of the vehicle capacity.

Strategy 3: This strategy, which mixes pickup and delivery operations in SE routes and separates them in FE routes, has a relatively similar average cost to Strategy 2 but uses fewer first- and second-echelon vehicles. This suggests that mixing operations in SE routes can increase operation flexibility. Still, organizing the synchronization between echelons is much more challenging, resulting in difficulties in saving costs. The solution suggests relatively longer FE routes than Strategy 1, especially in the delivery operation, and it uses more satellites compared to the other strategies.

Based on the solution characteristics and results, we draw insights to offer a clearer picture of each strategy's potential benefits and trade-offs, especially the value of integrating pickup and delivery operations in both FE and SE routes.

Insight 1 - Efficiency of Integrated Operations: Strategy 1, integrating pickup and delivery operations, reduces the average cost by approximately 17% compared to Strategy 2 and Strategy 3. Moreover, on average, the company has the option to use fewer satellites when integrating the pickup and delivery operations.

Insight 2 - Vehicle Usage Optimization: Strategy 1 uses fewer first-echelon vehicles on average, specifically around 20% less than other strategies. This efficient utilization could result in significant

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cost savings, especially for larger operations. In contrast, integrating pickup and delivery operations at the SE level has no real impact on the efficiency of the operations.

Insight 3- Load Efficiency: Strategy 1 has the lowest average FE max load because of the continual loading and unloading of the parcels, but it carries around 28% more parcels on average in FE routes than Strategy 2 and Strategy 3. Also, the load for pickup and delivery of parcels is evenly distributed in Strategy 1. At the same time, Strategy 2 and Strategy 3 have almost full load for the delivery operation but less than half load for the pickup operation because of the deadline at the hub.

7. Conclusion

Inspired by current operational challenges at our industry partner, we introduce a new two-echelon vehicle routing problem variant that integrates first and last-mile operations within megacities. Specifically, we introduce the Two Echeon Vehicle Routing Problem with Pickups, Deliveries, and Deadlines. The deadlines are the result of pickup up customer parcels that need further transportation within the megacity logistics' network via prescheduled linehaul transport.

We propose matheuristics to solve our new optimization problem. The approach consists of three main parts; generating a batch of initial solutions using Large Neighborhood Search (LNS), solving and generating a pool of routes using Adaptive Large Neighborhood Search (ALNS), and employing a set-partitioning formulation that is filled with routes encountered during the ALNS. The computational experiments show the quality of the developed approach. The ALNS is competitive with state-of-the-art approaches for solving established benchmark instances from the literature on the two-echelon vehicle routing problem. We also introduce new benchmark instances tailored to our problem setting. We show that the considering relatively tight deadlines increases cost by on average 8.52%. The cost increase is caused by the need for more first echelon routes.

Furthermore, we introduce five new publicly available datasets based on the actual operations of our industry partner. This case study compares the proposed strategy in this paper with the current industry-standard. We show that we can save 17% of the total routing cost compared to the current strategy by efficiently deploying and utilizing the first-echelon vehicles by full integration of first and last-mile delivery processes.

Potential avenues for further research lie in adopting machine learning techniques to foster the performance of our matheuristic approach. In addition, it is interesting to extend the scope towards fully integrated megacity logistics operations, by considering the scheduling of linehauls between the different neighborhoods as well.

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References

Azcuy, I., Agatz, N., Giesen, R., 2021. Designing integrated urban delivery systems using public transport. Transportation Research Part E: Logistics and Transportation Review 156, 102525. doi:https://doi.org/10.1016/j.tre.2021.102525.

Belgin, O., Karaoglan, I., Altiparmak, F., 2018. Two-echelon vehicle routing problem with simultaneous pickup and delivery: Mathematical model and heuristic approach. Computers & Industrial Engineering 115, 1–16. doi:https://doi.org/10.1016/j.cie.2017.10.032.

Berbeglia, G., Cordeau, J.F., Gribkovskaia, I., Laporte, G., 2007. Static pickup and delivery problems: a classification scheme and survey. TOP 15, 1–31. doi:https://doi.org/10.1007/s11750-007-0009-0.

Breunig, U., Schmid, V., Hartl, R.F., Vidal, T., 2016. A large neighbourhood based heuristic for two-echelon routing problems. Computers & Operations Research 76, 208–225. doi:https://doi.org/10.1016/j.cor.2016.06.014.

Campbell, A.M., Savelsbergh, M., 2004. Efficient insertion heuristics for vehicle routing and scheduling problems. Transportation Science 38, 369–378. doi:doi10.1287/trsc.1030.0046.

Christiaens, J., Vanden Berghe, G., 2020. Slack induction by string removals for vehicle routing problems. Transportation Science 54, 417–433. doi:https://doi.org/10.1287/trsc.2019.0914.

Crainic, T.G., Ricciardi, N., Storchi, G., 2009. Models for evaluating and planning city logistics systems. Transportation Science 43, 432–454. doi:https://doi.org/10.1287/trsc.1090.0279.

Dellaert, N., Dashty Saridarq, F., Van Woensel, T., Crainic, T.G., 2019. Branch-and-price–based algorithms for the two-echelon vehicle routing problem with time windows. Transportation Science 53, 463–479. doi:https://doi.org/10.1287/trsc.2018.0844.

Drexl, M., 2012. Synchronization in vehicle routing—a survey of vrps with multiple synchronization constraints. Transportation Science 46, 297–316. doi:https://doi.org/10.1287/trsc.1110.0400.

Dumez, D., Tilk, C., Irnich, S., Lehuédé, F., Olkis, K., Péton, O., 2023. A matheuristic for a 2-echelon vehicle routing problem with capacitated satellites and reverse flows. European Journal of Operational Research 305, 64–84. doi:https://doi.org/10.1016/j.ejor.2022.05.022.

Enthoven, D.L., Jargalsaikhan, B., Roodbergen, K.J., Uit het Broek, M.A., Schrotenboer, A.H., 2020. The two-echelon vehicle routing problem with covering options: City logistics with cargo bikes and parcel lockers. Computers & Operations Research 118, 104919. doi:https://doi.org/10.1016/j.cor.2020.104919.

Ghilas, V., Demir, E., Van Woensel, T., 2016. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows and scheduled lines. Computers & Operations Research 72, 12–30. doi:10.1016/j.cor.2016.01.018.

Electronic copy available at: https://ssrn.com/abstract=4565559

Grangier, P., Gendreau, M., Lehuédé, F., Rousseau, L.M., 2016. An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. European Journal of Operational Research 254, 80–91. doi:https://doi.org/10.1016/j.ejor.2016.03.040.

Hemmelmayr, V.C., Cordeau, J.F., Crainic, T.G., 2012. An adaptive large neighborhood search heuristic for two-echelon vehicle routing problems arising in city logistics. Computers & Operations Research 39, 3215–3228. doi:https://doi.org/10.1016/j.cor.2012.04.007.

Koç, Ç., Laporte, G., Tükenmez, İ., 2020. A review of vehicle routing with simultaneous pickup and delivery. Computers & Operations Research 122, 104987. doi:https://doi.org/10.1016/j.cor.2020.104987.

Li, H., Wang, H., Chen, J., Bai, M., 2021. Two-echelon vehicle routing problem with satellite bi-synchronization. European Journal of Operational Research 288, 775–793. doi:10.1016/j.ejor.2020.06.019.

Li, J., Xu, M., Sun, P., 2022. Two-echelon capacitated vehicle routing problem with grouping constraints and simultaneous pickup and delivery. Transportation Research Part B: Methodological 162, 261–291. doi:https://doi.org/10.1016/j.trb.2022.06.003.

Liu, R., Jiang, S., 2022. A variable neighborhood search algorithm with constraint relaxation for the two-echelon vehicle routing problem with simultaneous delivery and pickup demands. Soft Computing 26, 8879–8896. doi:https://doi.org/10.1007/s00500-021-06692-3.

Marques, G., Sadykov, R., Deschamps, J.C., Dupas, R., 2020. An improved branch-cut-and-price algorithm for the two-echelon capacitated vehicle routing problem. Computers & Operations Research 114, 104833. doi:https://doi.org/10.1016/j.cor.2019.104833.

Masson, R., Trentini, A., Lehuédé, F., Malhéné, N., Péton, O., Tlahig, H., 2017. Optimization of a city logistics transportation system with mixed passengers and goods. EURO Journal on Transportation and Logistics 6, 81–109. doi:https://doi.org/10.1007/s13676-015-0085-5.

Mühlbauer, F., Fontaine, P., 2021. A parallelised large neighbourhood search heuristic for the asymmetric two-echelon vehicle routing problem with swap containers for cargo-bicycles. European Journal of Operational Research 289, 742–757. doi:https://doi.org/10.1016/j.ejor.2020.07.034.

Ropke, S., Pisinger, D., 2006. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. Transportation Science 40, 455–472. doi:https://doi.org/10.1287/trsc.1050.0135.

Savelsbergh, M., Van Woensel, T., 2016. 50th anniversary invited article—city logistics: Challenges and opportunities. Transportation Science 50, 579–590. doi:https://doi.org/10.1287/trsc.2016.0675.

Savelsbergh, M.W., 1985. Local search in routing problems with time windows. Annals of Operations Research 4, 285–305. doi:https://doi.org/10.1007/BF02022044.

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Sluijk, N., Florio, A.M., Kinable, J., Dellaert, N., Van Woensel, T., 2023. Two-echelon vehicle routing problems: A literature review. European Journal of Operational Research 304, 865–886. doi:https://doi.org/10.1016/j.ejor.2022.02.022.

TomTom, I.B., 2023. Tomtom traffic index - jakarta. URL: https://www.tomtom.com/traffic-index/jakarta-traffic/. accessed: 2023-06-10.

Voigt, S., Frank, M., Fontaine, P., Kuhn, H., 2022. Hybrid adaptive large neighborhood search for vehicle routing problems with depot location decisions. Computers & Operations Research 146, 105856. doi:https://doi.org/10.1016/j.cor.2022.105856.

Yu, V.F., Jodiawan, P., Hou, M.L., Gunawan, A., 2021. Design of a two-echelon freight distribution system in last-mile logistics considering covering locations and occasional drivers. Transportation Research Part E: Logistics and Transportation Review 154, 102461. doi:https://doi.org/10.1016/j.tre.2021.102461.

Yu, V.F., Jodiawan, P., Schrotenboer, A.H., Hou, M.L., 2023. The two-echelon vehicle routing problem with time windows, intermediate facilities, and occasional drivers. Expert Systems with Applications 234, 120945. doi:https://doi.org/10.1016/j.eswa.2023.120945.

Zhou, H., Qin, H., Zhang, Z., Li, J., 2022. Two-echelon vehicle routing problem with time windows and simultaneous pickup and delivery. Soft Computing 26, 3345–3360. doi:https://doi.org/10.1007/s00500-021-06712-2.

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Appendix A. Parameter Tuning

This appendix shows how to obtain parameter values for our Adaptive Large Neighborhood Search (ALNS). This was achieved through a sequence of computational experiments that used the 2E-VRP-PDD instances. The execution of these campaigns proceeded as follows.

We initiated the process by randomly selecting two samples from each customer and satellite instance set, culminating in 10 instance sets. The preliminary parameter values were derived from initial campaigns, supplemented by prior studies' insights that applied the ALNS methodology from Ropke and Pisinger (2006) to the Two-Echelon Vehicle Routing Problem (2E-VRP). In particular, we sourced from research efforts that incorporated both small and large destroy operations within their algorithms, as exhibited in Hemmelmayr et al. (2012), Enthoven et al. (2020), and Yu et al. (2021). As shown in Table A.7, initial values are indicated in bold.

Modifying parameter values was done sequentially, within the range detailed in Table A.7. For the adaptive parameter, particularly the score (σ), adjustments were made as a bundle based on previous literature, except for bundles (18,10,4) and (9,5,2). Five runs of 100K iterations were conducted for each parameter, with a total of 10 rounds of parameter tuning.

Finally, we selected the setting that exhibited the most efficient average performance-determined by the average deviation from the best-known solutions—and reasonable computational time. The final value is displayed in Table A.8. The final values for parameters $\omega_{restart}$ and ω_{large} were re-scaled when the ALNS was executed with 30K iterations.

It should be noted, that the ALNS algorithm is executed for 1 million iterations in Section 5.1, applying the parameters specified for 100K iterations. Notably, for four instances in Set 7 (instances with 300 customers and 15 satellites: 3a, 3c, 4a, and 4c), we set $\zeta_{small}^{UB} = 0.15$.

Table A.7: Parameter Tuning Value

Parameters		**Tuning Value**
$\omega_{restart}$	Restart Period	100, **500**, 1000, 10000
ω_{large}	Large Removal Occurrence	100, 250, 500, 750, 1000, **1500**
ω_{LNS}	LNS Iteration	**250**,500,750,1000,1250
ζ_{small}^{UB}	Upper Bound Small Removal	0.1, 0.15, **0.2**, 0.25, 0.3
ζ_{large}^{LB}	Lower Bound Large Removal	0.5, 0.55, **0.6**, 0.65, 0.7
ζ_{large}^{UB}	Upper Bound Large Removal	**0.7**, 0.75, 0.8, 0.85, 0.9
υ	Decay/reaction rate	**0.1**, 0.2, 0.3, 0.4, 0.5
σ_1	Score 1 (Best solution)	(33,9,13), (60,30,20), (30,30,0), (18,10,4), **(9,5,2)**
σ_2	Score 2 (Better solution)	
σ_3	Score 3 (Accepted Solution)	
c_{rate}	Cooling rate	0.99975, 0.99990, 0.99995, 0.99999, **0.99950**
η	Initial Acceptance Probability	**50%**, 45%, 30%, 25%, 20%

Bold values represent initial values of the tuning process.

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Table A.8: Parameters Final Value

Parameters	**Value 100K (30K)**
$\omega_{restart}$	10000 (3000)
ω_{large}	1500 (750)
ω_{LNS}	250
ζ_{small}^{UB}	0.25
ζ_{large}^{LB}	0.6
ζ_{large}^{UB}	0.7
υ	0.1
σ_1	9
σ_2	5
σ_3	2
c_{rate}	0.99975
w	0.05
η	50%

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Appendix B. Insertion Types

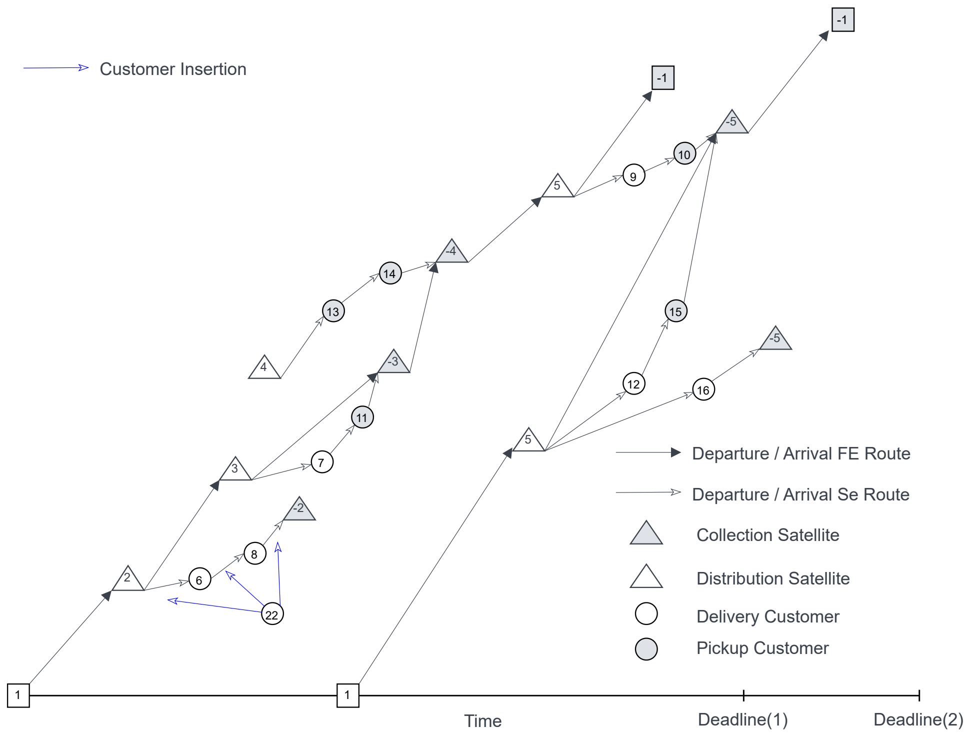

Figure B.9: Type 1 Customer Insertion

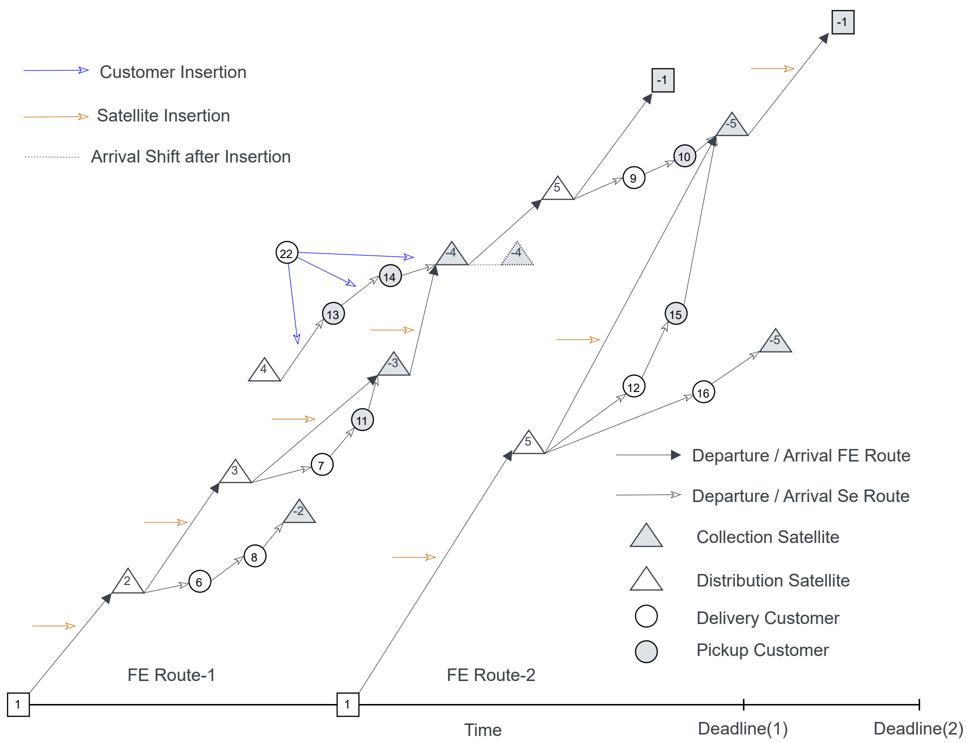

Figure B.10: Type 2 Customer Insertion

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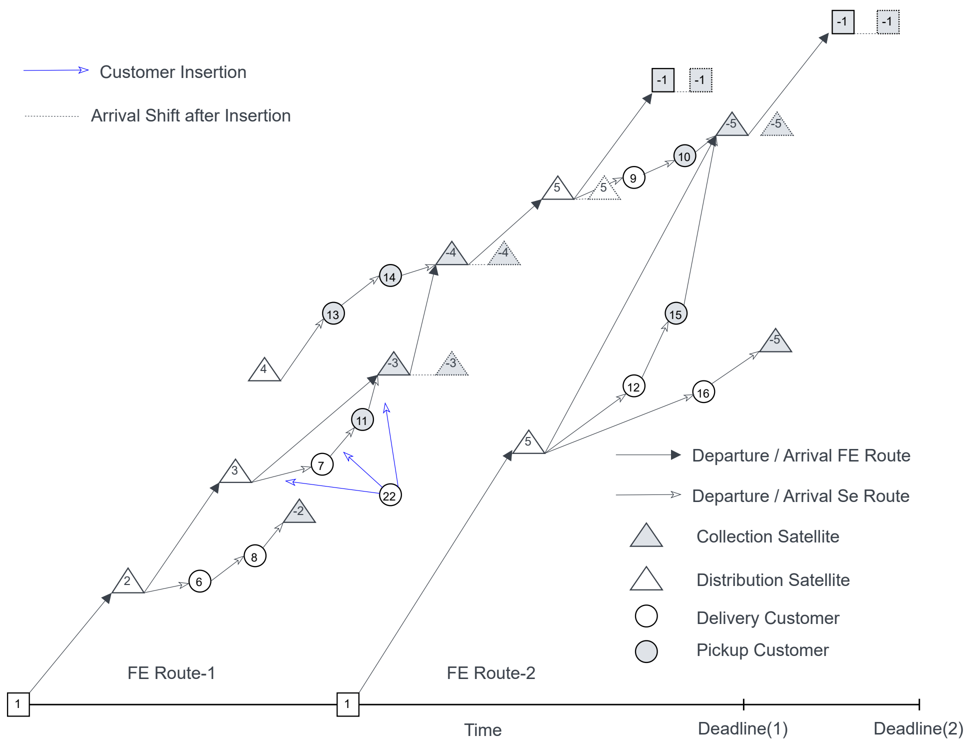

Figure B.11: Type 3-d Customer Insertion

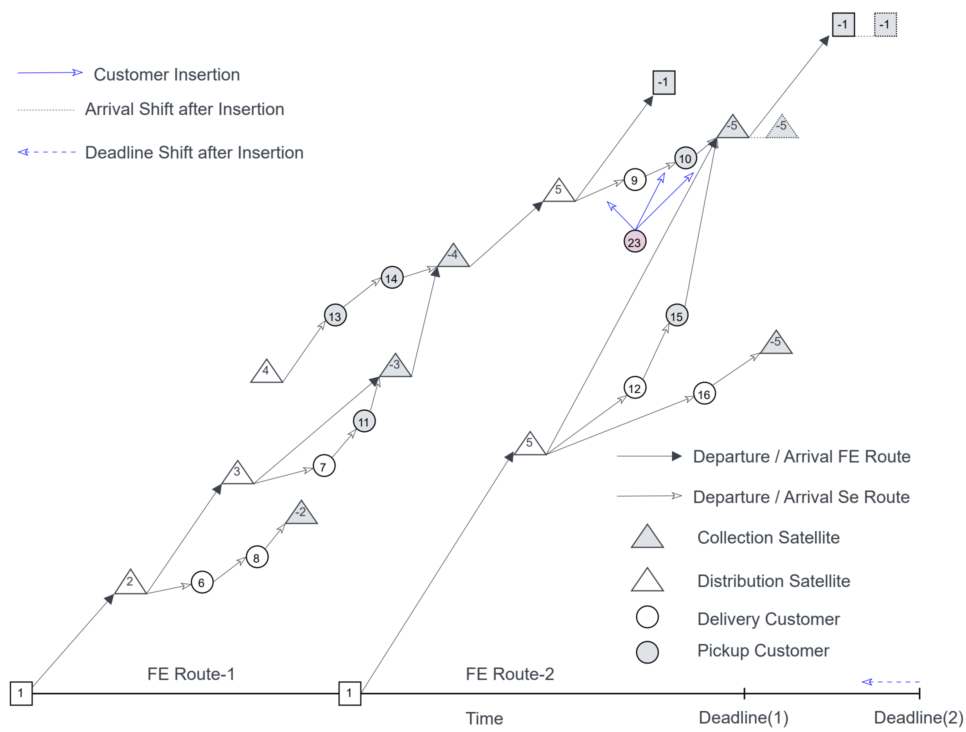

Figure B.12: Type 3-p Customer Insertion

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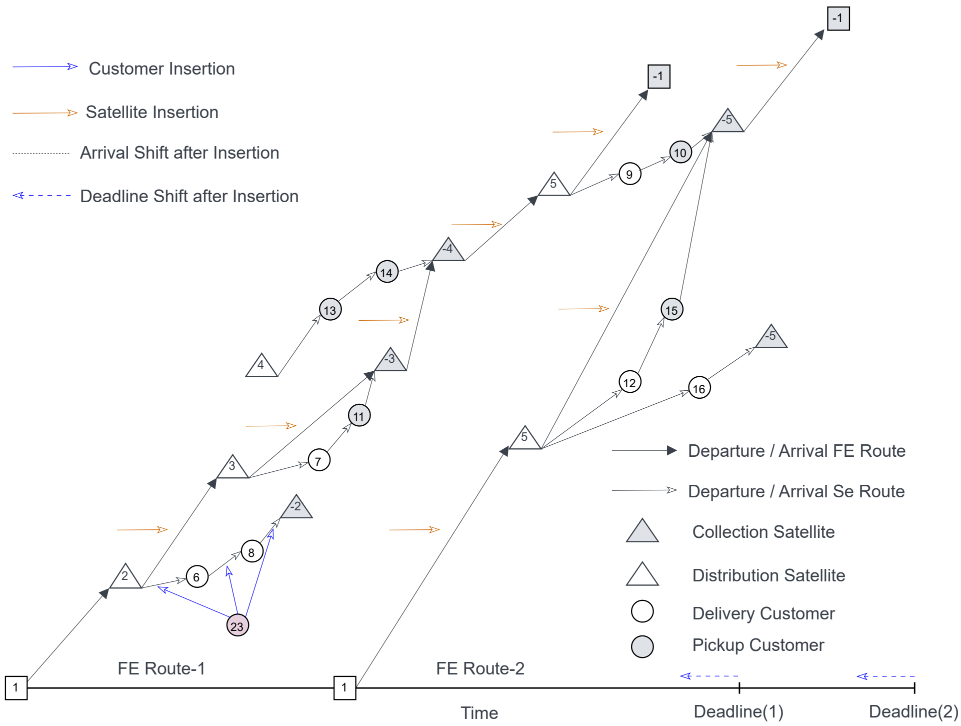

Figure B.13: Type 4 Customer Insertion

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Appendix C. Benchmark Detailed Results

Table C.9: Detailed result for 2E-VRP benchmark: Set 2a

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
E-n22-k4-s10-14	371.50	371.50	371.50	0.0	0.00	37	0
E-n22-k4-s11-12	427.22	427.22	427.22	0.0	0.00	38	4
E-n22-k4-s12-16	392.78	392.78	392.78	0.0	0.00	36	1
E-n22-k4-s6-17	417.07	417.07	417.07	0.0	0.00	36	0
E-n22-k4-s8-14	384.96	384.96	384.96	0.0	0.00	37	1
E-n22-k4-s9-19	470.60	470.60	470.60	0.0	0.00	35	1
E-n33-k4-s1-9	730.16	730.16	730.16	0.0	0.00	53	2
E-n33-k4-s14-22	779.05	779.05	779.05	0.0	0.00	61	0
E-n33-k4-s2-13	714.63	714.63	714.63	0.0	0.00	53	11
E-n33-k4-s3-17	707.48	707.48	709.17	0.0	0.24	57	2
E-n33-k4-s4-5	778.74	778.74	778.74	0.0	0.00	59	9
E-n33-k4-s7-25	756.85	756.85	756.85	0.0	0.00	54	0

Table C.10: Detailed result for 2E-VRP benchmark: Set 2b

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
E-n51-k5-s11-19-27-47	527.63	527.63	527.63	0.0	0.00	91	7
E-n51-k5-s11-19	581.64	581.64	581.64	0.0	0.00	88	17
E-n51-k5-s2-17	597.49	597.49	599.66	0.0	0.36	93	12
E-n51-k5-s2-4-17-46	530.76	530.76	530.76	0.0	0.00	101	7
E-n51-k5-s27-47	538.22	538.22	538.36	0.0	0.03	98	50
E-n51-k5-s32-37	552.28	552.28	552.28	0.0	0.00	94	53
E-n51-k5-s4-46	530.76	530.76	530.76	0.0	0.00	92	21
E-n51-k5-s6-12-32-37	531.92	531.92	537.07	0.0	0.97	103	42
E-n51-k5-s6-12	554.81	554.81	558.41	0.0	0.65	91	27

Table C.11: Detailed result for 2E-VRP benchmark: Set 2c

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
E-n51-k5-s11-19-27-47	530.76	530.76	530.76	0.0	0.00	106	53
E-n51-k5-s11-19	617.42	617.42	617.42	0.0	0.00	93	5
E-n51-k5-s2-17	601.39	601.39	601.39	0.0	0.00	97	9
E-n51-k5-s2-4-17-46	601.39	601.39	601.39	0.0	0.00	102	23
E-n51-k5-s27-47	530.76	530.76	530.76	0.0	0.00	106	15
E-n51-k5-s32-37	752.59	752.59	753.16	0.0	0.08	99	8
E-n51-k5-s4-46	702.33	702.33	702.33	0.0	0.00	94	13
E-n51-k5-s6-12-32-37	567.42	567.42	569.03	0.0	0.28	100	32
E-n51-k5-s6-12	567.42	567.42	569.96	0.0	0.45	95	34

Table C.12: Detailed result for 2E-VRP benchmark: Set 3

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
E-n22-k4-s13-14	526.15	526.15	526.15	0.00	0.00	35	1
E-n22-k4-s13-16	521.09	521.09	521.09	0.00	0.00	36	0
E-n22-k4-s13-17	496.38	496.38	496.38	0.00	0.00	35	0
E-n22-k4-s14-19	498.80	498.80	498.80	0.00	0.00	36	1
E-n22-k4-s17-19	512.81	512.80	512.80	0.00	0.00	36	1
E-n22-k4-s19-21	520.42	520.42	520.42	0.00	0.00	36	2
E-n33-k4-s16-22	672.17	672.17	672.17	0.00	0.00	51	4
E-n33-k4-s16-24	666.02	666.02	666.02	0.00	0.00	50	3
E-n33-k4-s19-26	680.36	680.36	680.36	0.00	0.00	61	14
E-n33-k4-s22-26	680.37	680.36	680.36	0.00	0.00	58	16
E-n33-k4-s24-28	670.43	670.43	670.43	0.00	0.00	51	5
E-n33-k4-s25-28	650.58	650.58	650.58	0.00	0.00	51	5
E-n51-k5-s12-18	690.59	692.56	695.20	0.29	0.67	128	14
E-n51-k5-s12-41	683.05	697.59	697.59	2.13	2.13	189	58
E-n51-k5-s12-43	710.41	710.41	710.41	0.00	0.00	261	48
E-n51-k5-s13-19	560.73	564.45	564.86	0.66	0.74	131	17
E-n51-k5-s13-42	564.45	564.45	564.45	0.00	0.00	166	6
E-n51-k5-s13-44	564.45	564.45	564.45	0.00	0.00	246	4
E-n51-k5-s39-41	728.54	728.54	729.10	0.00	0.08	103	14
E-n51-k5-s40-41	723.75	723.75	726.75	0.00	0.41	152	45
E-n51-k5-s40-42	746.31	746.31	748.28	0.00	0.26	102	25
E-n51-k5-s40-43	752.15	752.15	754.73	0.00	0.34	118	46
E-n51-k5-s41-42	771.56	771.56	771.84	0.00	0.04	162	11
E-n51-k5-s41-44	802.91	802.91	820.04	0.00	2.13	124	30

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Table C.13: Detailed result for 2E-VRP benchmark: Set 4b

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
Instance50-1	1569.42	1569.42	1571.85	0.00	0.15	154	18
Instance50-2	1438.33	1438.32	1444.39	0.00	0.42	157	9
Instance50-3	1570.34	1570.43	1572.17	0.01	0.12	107	48
Instance50-4	1424.04	1424.04	1424.04	0.00	0.00	140	11
Instance50-5	2193.52	2193.52	2193.52	0.00	0.00	110	20
Instance50-6	1279.87	1279.89	1279.89	0.00	0.00	136	35
Instance50-7	1408.57	1408.58	1408.58	0.00	0.00	159	94
Instance50-8	1360.32	1360.32	1360.32	0.00	0.00	128	19
Instance50-9	1403.53	1403.53	1403.53	0.00	0.00	151	13
Instance50-10	1360.56	1360.54	1360.54	0.00	0.00	144	4
Instance50-11	2047.46	2053.64	2058.23	0.30	0.53	100	14
Instance50-12	1209.42	1209.46	1210.33	0.00	0.08	113	14
Instance50-13	1450.93	1450.94	1450.94	0.00	0.00	134	11
Instance50-14	1393.61	1393.64	1395.50	0.00	0.14	114	18
Instance50-15	1466.83	1466.84	1466.84	0.00	0.00	119	10
Instance50-16	1387.83	1387.85	1387.85	0.00	0.00	217	30
Instance50-17	2088.49	2088.48	2089.30	0.00	0.04	96	42
Instance50-18	1227.61	1227.68	1227.68	0.01	0.01	84	15
Instance50-19	1546.28	1546.28	1546.28	0.00	0.00	102	36
Instance50-20	1272.97	1272.98	1272.98	0.00	0.00	90	13
Instance50-21	1577.82	1577.82	1578.92	0.00	0.07	94	35
Instance50-22	1281.83	1281.83	1281.83	0.00	0.00	114	6
Instance50-23	1652.98	1652.98	1652.98	0.00	0.00	88	13
Instance50-24	1282.68	1282.69	1282.69	0.00	0.00	102	4
Instance50-25	1408.57	1408.58	1409.12	0.00	0.04	134	54
Instance50-26	1167.46	1167.47	1167.47	0.00	0.00	96	1
Instance50-27	1444.50	1444.49	1450.66	0.00	0.43	100	47
Instance50-28	1210.44	1210.46	1214.34	0.00	0.32	111	25
Instance50-29	1552.66	1552.66	1553.26	0.00	0.04	120	27
Instance50-30	1211.49	1212.68	1212.68	0.10	0.10	130	11
Instance50-31	1440.86	1440.85	1442.87	0.00	0.14	113	47
Instance50-32	1199.00	1199.05	1199.05	0.00	0.00	91	8
Instance50-33	1478.86	1478.87	1478.87	0.00	0.00	85	12
Instance50-34	1233.92	1233.96	1233.96	0.00	0.00	82	1
Instance50-35	1570.72	1570.73	1570.73	0.00	0.00	91	19
Instance50-36	1228.89	1228.95	1228.95	0.00	0.00	101	34
Instance50-37	1528.73	1528.73	1528.73	0.00	0.00	96	36
Instance50-38	1163.07	1163.07	1163.07	0.00	0.00	89	15
Instance50-39	1520.92	1520.92	1520.92	0.00	0.00	90	13
Instance50-40	1163.04	1163.04	1177.59	0.00	1.25	91	3
Instance50-41	1652.98	1652.98	1655.98	0.00	0.18	109	8
Instance50-42	1190.17	1190.17	1191.19	0.00	0.09	90	32
Instance50-43	1406.11	1408.58	1409.67	0.18	0.25	134	45
Instance50-44	1035.03	1035.05	1035.05	0.00	0.00	85	7
Instance50-45	1401.87	1401.87	1404.38	0.00	0.18	99	45
Instance50-46	1058.11	1058.10	1064.68	0.00	0.62	91	14
Instance50-47	1552.66	1552.66	1554.38	0.00	0.11	152	44
Instance50-48	1074.50	1074.51	1074.51	0.00	0.00	91	0
Instance50-49	1434.88	1440.85	1441.52	0.42	0.46	106	31
Instance50-50	1065.25	1065.30	1065.30	0.00	0.00	83	4
Instance50-51	1387.51	1387.51	1395.93	0.00	0.61	86	11
Instance50-52	1103.42	1103.47	1108.11	0.00	0.43	89	39
Instance50-53	1545.73	1545.76	1545.76	0.00	0.00	101	33
Instance50-54	1113.62	1113.66	1113.66	0.00	0.00	85	13

Table C.14: Detailed result for 2E-VRP benchmark: Set 5

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
100-5-1	1564.46	1564.46	1590.20	0.00	1.65	345	206
100-5-1b	1099.35	1099.35	1104.64	0.00	0.48	235	138
100-5-2	1016.32	1016.45	1023.51	0.01	0.71	424	232
100-5-2b	782.25	782.78	791.88	0.07	1.23	248	100
100-5-3	1045.29	1047.01	1060.71	0.16	1.48	312	209
100-5-3b	828.54	828.54	830.03	0.00	0.18	264	139
100-10-1	1124.93	1124.93	1134.23	0.00	0.83	387	188
100-10-1b	911.80	911.95	920.38	0.02	0.94	341	103
100-10-2	985.40	1001.03	1004.09	1.59	1.90	393	198
100-10-2b	766.28	769.85	774.78	0.47	1.11	312	223
100-10-3	1042.63	1054.24	1062.27	1.11	1.88	347	226
100-10-3b	848.16	853.65	856.55	0.65	0.99	317	149
200-10-1	1537.52	1552.56	1572.09	0.98	2.25	1094	804
200-10-1b	1173.07	1183.71	1191.24	0.91	1.55	940	632
200-10-2	1352.87	1371.02	1378.06	1.34	1.86	1588	992
200-10-2b	985.99	993.16	1002.54	0.73	1.68	908	575
200-10-3	1777.49	1800.79	1810.97	1.31	1.88	1530	1082
200-10-3b	1192.35	1207.20	1209.80	1.25	1.46	954	663

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Table C.15: Detailed result for 2E-VRP benchmark: Set 6

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
A-n101-4	1194.17	1194.17	1196.76	0.00	0.22	247	149
A-n101-5	1211.38	1213.49	1215.95	0.17	0.38	262	156
A-n101-6	1155.89	1155.96	1161.78	0.01	0.51	236	93
A-n51-4	652.00	652.00	652.00	0.00	0.00	85	6
A-n51-5	663.41	663.41	663.41	0.00	0.00	94	6
A-n51-6	662.51	662.51	662.51	0.00	0.00	105	22
A-n76-4	985.95	985.95	985.99	0.00	0.00	131	27
A-n76-5	979.15	979.15	982.17	0.00	0.31	149	82
A-n76-6	970.20	970.20	972.73	0.00	0.26	157	82
B-n101-4	939.21	939.21	940.77	0.00	0.17	228	101
B-n101-5	967.82	969.07	971.07	0.13	0.34	229	73
B-n101-6	960.29	963.09	964.94	0.29	0.48	243	30
B-n51-4	563.98	563.98	564.15	0.00	0.03	88	16
B-n51-5	549.23	549.23	551.09	0.00	0.34	92	9
B-n51-6	556.32	556.32	562.44	0.00	1.10	104	46
B-n76-4	792.73	792.73	795.65	0.00	0.37	136	45
B-n76-5	783.93	783.93	784.08	0.00	0.02	141	64
B-n76-6	774.17	774.17	777.62	0.00	0.45	160	80
C-n101-4	1292.04	1299.86	1302.8	0.61	0.83	266	140
C-n101-5	1304.86	1305.82	1307.18	0.07	0.18	264	147
C-n101-6	1284.48	1296.03	1299.92	0.90	1.20	264	139
C-n51-4	689.18	689.18	689.18	0.00	0.00	87	11
C-n51-5	723.12	723.12	723.12	0.00	0.00	86	14
C-n51-6	697.00	697.00	697.00	0.00	0.00	100	31
C-n76-4	1054.89	1054.89	1055.61	0.00	0.07	143	65
C-n76-5	1115.32	1115.32	1122.5	0.00	0.64	152	60
C-n76-6	1060.52	1060.52	1063.56	0.00	0.29	150	61

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Table C.16: Detailed result for 2E-VRP benchmark: Set 7

Instance	BKS	Best 5	Avg. 5	Δ best (%)	Δ avg (%)	t(s)	t*(s)
2e-100-5-1c	1284.59	1321.66	1325.0	2.89	3.15	352	170
2e-100-5-2c	821.42	830.67	834.04	1.13	1.54	413	83
2e-100-5-3c	841.17	850.56	850.57	1.12	1.12	346	206
2e-100-5-4a	895.37	908.5	909.84	1.47	1.62	278	141
2e-100-5-4b	560.25	562.77	563.16	0.45	0.52	219	71
2e-100-10-1c	961.61	975.82	983.14	1.48	2.24	337	87
2e-100-10-2c	860.66	865.49	869.50	0.56	1.03	316	140
2e-100-10-3c	815.32	837.63	838.21	2.74	2.81	341	176
2e-100-10-4a	886.61	893.12	894.19	0.73	0.85	346	107
2e-100-10-4b	594.70	595.81	595.81	0.19	0.19	322	110
2e-200-10-1c	1513.95	1569.14	1579.93	3.65	4.36	1571	1191
2e-200-10-2c	1370.65	1395.05	1398.93	1.78	2.06	1488	1255
2e-200-10-3c	1793.82	1857.28	1866.04	3.54	4.03	1527	1325
2e-200-10-4a	1411.80	1441.85	1471.23	2.13	4.21	1428	1112
2e-200-10-4b	906.28	913.70	922.27	0.82	1.76	864	384
2e-200-15-1a	1535.11	1570.10	1580.56	2.28	2.96	1483	1337
2e-200-15-1b	1000.53	1015.89	1021.86	1.54	2.13	1106	691
2e-200-15-1c	1461.80	1481.53	1506.89	1.35	3.08	1521	940
2e-200-15-2a	1493.41	1541.03	1548.87	3.19	3.71	1790	1335
2e-200-15-2b	916.78	924.41	929.15	0.83	1.35	914	406
2e-200-15-2c	1275.75	1305.73	1313.33	2.35	2.95	1821	1474
2e-200-15-3a	1569.77	1603.67	1611.77	2.16	2.68	1432	1023
2e-200-15-3b	972.28	976.57	981.04	0.44	0.90	1091	893
2e-200-15-3c	1330.52	1342.48	1358.45	0.90	2.10	1643	1381
2e-200-15-4a	1352.70	1374.71	1387.82	1.63	2.60	1671	1099
2e-200-15-4b	879.66	887.35	896.80	0.87	1.95	1065	747
2e-200-15-4c	1403.50	1449.10	1452.83	3.25	3.51	1732	1614
2e-300-10-1a	4223.34	4328.79	4395.39	2.50	4.07	3573	3013
2e-300-10-1b	2592.16	2612.69	2651.93	0.79	2.31	1840	1502
2e-300-10-1c	4862.91	4973.68	5002.91	2.28	2.88	5306	4830
2e-300-10-2a	4060.08	4165.71	4181.63	2.60	2.99	5373	4484
2e-300-10-2b	2329.41	2355.47	2368.14	1.12	1.66	2010	1597
2e-300-10-2c	3613.03	3734.34	3757.71	3.36	4.00	3339	2976
2e-300-10-3a	4008.59	4122.31	4142.18	2.84	3.33	4812	4337
2e-300-10-3b	2378.62	2390.98	2413.05	0.52	1.45	1740	1243
2e-300-10-3c	4688.70	4814.88	4856.54	2.69	3.58	3811	3187
2e-300-10-4a	4094.94	4186.74	4210.68	2.24	2.83	4474	3622
2e-300-10-4b	2390.00	2434.02	2459.76	1.84	2.92	1898	1645
2e-300-10-4c	3938.17	4038.78	4053.37	2.55	2.93	3261	3028
2e-300-15-1a	4021.42	4066.83	4149.51	1.13	3.19	3565	2920
2e-300-15-1b	2523.98	2572.09	2603.16	1.91	3.14	2255	1891
2e-300-15-1c	4219.51	4331.90	4369.89	2.66	3.56	3155	2525
2e-300-15-2a	3671.50	3732.00	3795.18	1.65	3.37	5566	5188
2e-300-15-2b	2196.96	2216.30	2235.79	0.88	1.77	2393	2028
2e-300-15-2c	3563.77	3664.26	3681.84	2.82	3.31	3591	3178
2e-300-15-3a	3491.35	3548.44	3585.75	1.64	2.70	3247	2595
2e-300-15-3b	2162.50	2186.15	2206.37	1.09	2.03	1783	1367
2e-300-15-3c	3911.00	3983.01	4038.87	1.84	3.27	2762	2215
2e-300-15-4a	3813.33	3913.47	3958.68	2.63	3.81	2331	2247
2e-300-15-4b	2229.98	2253.13	2278.38	1.04	2.17	1808	1529
2e-300-15-4c	3600.79	3654.34	3688.81	1.49	2.44	2103	1839

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Appendix D. Instances Detailed Results

Table D.17: Detailed results for the 2E-VRP-PDD instances: 50 Customers

	ALNS 30K				MIP			ALNS 100K				
Instance	*Avg 5*	*Best 5*	*t*	*t**	*Avg 5*	*Best 5*	*t*	*Avg 5*	*Best 5*	*t*	*t**	BKS
A-50-1-D	1345.46	1341.17	54	25	1338.80	1329.32	122	1337.18	1329.78	138	89	1329.32
A-50-2-D	1357.10	1333.95	72	50	1335.00	1333.95	66	1335.25	1333.95	193	67	1333.95
A-50-3-D	1436.83	1430.99	60	45	1430.68	1429.61	29	1431.77	1429.61	147	99	1429.61
A-50-4-D	1564.50	1555.50	67	40	1550.03	1549.43	1077	1560.24	1552.83	197	138	1549.43
A-50-5-D	1584.97	1574.37	57	29	1574.02	1569.89	2926	1580.52	1574.37	176	106	1569.89
A-50-6-D	1702.72	1676.89	41	27	1688.71	1674.71	2779	1690.47	1674.71	139	51	1674.71
A-50-7-D	1410.55	1395.09	93	41	1396.67	1395.09	50	1407.79	1403.03	208	95	1395.09
A-50-8-D	1373.59	1370.59	54	24	1370.59	1370.59	97	1370.73	1369.31	138	38	1369.31
A-50-9-D	1668.69	1660.43	99	40	1660.43	1660.43	135	1660.43	1660.43	268	103	1660.43
A-50-10-D	1380.30	1364.97	75	37	1374.86	1363.50	1654	1364.37	1351.90	175	65	1351.90
B-50-1-D	1601.19	1580.92	130	89	1587.82	1574.74	3646	1593.93	1573.50	287	244	1573.50
B-50-2-D	1555.82	1533.76	91	57	1555.18	1533.76	3104	1571.30	1554.64	215	122	1533.76
B-50-3-D	1413.95	1402.47	75	52	1410.03	1401.93	5234	1388.98	1375.29	247	138	1375.29
B-50-4-D	1248.03	1245.38	104	75	1244.28	1243.31	41	1244.86	1243.31	295	111	1243.31
B-50-5-D	1374.10	1354.00	98	46	1354.18	1337.90	648	1337.68	1307.99	248	175	1307.99
B-50-6-D	1414.89	1399.51	92	56	1398.85	1393.18	219	1410.32	1399.51	243	95	1393.18
B-50-7-D	1235.20	1235.20	109	69	1235.20	1235.20	80	1235.20	1235.20	327	60	1235.20
B-50-8-D	1432.84	1421.18	78	57	1416.04	1414.75	568	1424.92	1414.75	237	168	1414.75
B-50-9-D	1479.64	1472.37	107	49	1469.96	1460.88	942	1473.86	1464.08	356	225	1460.88
B-50-10-D	1344.73	1333.88	116	49	1340.67	1328.23	1828	1329.30	1315.75	300	62	1315.75
C-50-1-D	1353.78	1337.15	157	79	1349.31	1337.15	4522	1358.29	1337.15	441	236	1337.15
C-50-2-D	1380.70	1364.64	233	170	1374.98	1364.64	3277	1380.13	1364.64	572	271	1364.64
C-50-3-D	1279.42	1267.03	196	62	1277.37	1267.03	4047	1286.92	1277.99	596	221	1267.03
C-50-4-D	1312.30	1287.45	136	78	1291.79	1281.56	2149	1282.26	1270.90	497	185	1270.90
C-50-5-D	1351.56	1339.40	205	80	1348.69	1336.76	241	1365.58	1339.40	651	357	1336.76
C-50-6-D	1404.52	1378.21	215	125	1393.54	1367.43	3511	1395.52	1366.57	623	204	1366.57
C-50-7-D	1225.27	1215.09	268	223	1211.66	1195.97	2348	1223.46	1205.60	619	264	1195.97
C-50-8-D	1300.62	1292.41	235	130	1300.62	1292.41	1966	1308.90	1294.30	657	309	1292.41
C-50-9-D	1339.91	1309.66	168	80	1331.25	1309.66	814	1332.41	1309.66	512	319	1309.66
C-50-10-D	1276.88	1225.75	231	105	1266.39	1211.29	2473	1283.24	1239.98	671	449	1211.29

Table D.18: Detailed results for the 2E-VRP-PDD instances: 100 Customers

	ALNS 30K				MIP			ALNS 100K				
Instance	*Avg 5*	*Best 5*	*t*	*t**	*Avg 5*	*Best 5*	*t*	*Avg 5*	*Best 5*	*t*	*t**	BKS
A-100-1-D	2381.11	2303.78	256	217	2493.21	2274.73	5401	2365.13	2340.46	661	551	2274.73
A-100-2-D	2801.43	2760.72	270	248	2881.19	2753.21	5401	2735.40	2705.26	764	615	2705.26
A-100-3-D	2287.27	2271.03	215	176	2252.77	2227.66	5401	2248.21	2223.79	566	324	2223.79
A-100-4-D	2589.62	2554.37	230	186	2830.45	2514.38	5401	2595.96	2544.45	611	524	2514.38
A-100-5-D	2402.71	2364.60	202	181	2414.49	2324.92	5402	2374.19	2341.45	711	482	2324.92
A-100-6-D	2607.32	2578.36	264	201	2585.93	2547.38	5402	2581.83	2566.54	616	486	2547.38
A-100-7-D	2400.87	2367.46	231	170	2501.47	2378.93	5401	2382.47	2360.01	616	368	2360.01
A-100-8-D	2596.04	2572.90	235	159	2827.19	2532.40	5402	2544.80	2509.01	601	486	2509.01
A-100-9-D	2358.12	2316.84	199	170	2308.16	2299.17	3021	2341.50	2316.70	508	337	2299.17
A-100-10-D	2226.06	2210.01	234	176	2192.60	2142.78	5402	2226.83	2220.60	628	422	2142.78
B-100-1-D	2213.74	2199.16	447	373	2300.75	2175.57	5401	2209.16	2197.93	1172	813	2175.57
B-100-2-D	2376.11	2327.54	347	295	2330.68	2309.96	5403	2361.18	2326.23	877	592	2309.96
B-100-3-D	2293.5	2282.47	359	307	2328.73	2267.99	5402	2286.36	2271.55	970	630	2267.99
B-100-4-D	2160.00	2141.01	369	298	2184.58	2134.67	5402	2180.87	2164.36	1086	850	2134.67
B-100-5-D	2371.08	2329.50	380	325	2498.35	2293.09	5402	2342.58	2315.74	1106	756	2293.09
B-100-6-D	2191.71	2136.44	290	245	2568.34	2141.41	5402	2163.90	2134.79	758	443	2134.79
B-100-7-D	2399.37	2364.00	357	264	2440.88	2347.11	5402	2377.74	2333.61	904	637	2333.61
B-100-8-D	2026.76	1963.02	270	229	2059.90	1954.02	5402	1978.01	1958.13	804	560	1954.02
B-100-9-D	2338.23	2284.76	444	348	3035.22	2486.62	5401	2288.27	2232.30	941	656	2232.30
B-100-10-D	2148.27	2101.74	399	285	2194.17	2095.52	5401	2125.94	2098.17	711	558	2095.52
C-100-1-D	2110.20	2030.68	588	515	2140.38	2026.77	4674	2078.01	2035.06	1488	1206	2026.77
C-100-2-D	2030.08	1998.57	836	546	2025.52	1982.33	5402	2004.19	1991.05	2111	1364	1982.33
C-100-3-D	2014.91	2009.72	516	451	1996.76	1986.23	5401	2010.19	1993.00	1424	1093	1986.23
C-100-4-D	2146.17	2098.71	623	506	2196.51	2086.99	5402	2146.43	2101.08	1543	1309	2086.99
C-100-5-D	1994.14	1968.82	866	626	2020.12	1962.72	5402	1956.90	1892.19	1912	1253	1892.19
C-100-6-D	2074.07	2042.19	792	507	2078.42	1994.15	5402	2073.49	2044.33	2398	2035	1994.15
C-100-7-D	1907.07	1876.82	562	475	1901.24	1867.25	5402	1910.95	1894.31	1671	1286	1867.25
C-100-8-D	2212.98	2176.80	703	630	2308.27	2143.39	5402	2170.99	2164.88	2020	1263	2143.39
C-100-9-D	2080.83	2060.88	688	526	2215.19	2039.16	5401	2069.59	2039.59	2021	1395	2039.16
C-100-10-D	2152.17	2121.70	640	524	2117.14	2092.58	5403	2154.83	2107.43	1747	1256	2092.58

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Table D.19: Detailed results for the deadline impact in 2E-VRP-PDD : 50 Customers (ALNS 30K)

	Without Deadline		Loose Deadline		Deadline		Tight Deadline	
Instance	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*
A-50-1-D	1245.17	1228.34	1294.49	1275.79	1345.46	1341.17	1376.41	1359.90
A-50-2-D	1294.51	1288.36	1354.64	1351.17	1357.10	1333.95	1472.67	1464.47
A-50-3-D	1404.94	1404.22	1503.52	1489.55	1436.83	1430.99	1514.61	1500.60
A-50-4-D	1469.73	1456.49	1577.46	1557.55	1564.50	1555.50	1563.75	1554.33
A-50-5-D	1509.18	1500.39	1556.03	1521.75	1584.97	1574.37	1599.19	1595.48
A-50-6-D	1574.53	1568.99	1575.21	1568.99	1702.72	1676.89	1730.58	1722.57
A-50-7-D	1376.49	1361.32	1387.67	1376.67	1410.55	1395.09	1421.23	1415.66
A-50-8-D	1255.62	1246.73	1375.42	1372.66	1373.59	1370.59	1458.82	1445.67
A-50-9-D	1537.64	1527.05	1595.53	1565.33	1668.69	1660.43	1667.02	1657.74
A-50-10-D	1295.18	1275.46	1350.24	1335.23	1380.30	1364.97	1384.82	1366.58
B-50-1-D	1395.23	1357.49	1511.44	1507.11	1601.19	1580.92	1552.91	1536.31
B-50-2-D	1401.64	1375.46	1537.58	1536.75	1555.82	1533.76	1570.97	1534.73
B-50-3-D	1231.27	1231.27	1374.24	1359.78	1413.95	1402.47	1421.59	1418.82
B-50-4-D	1232.15	1229.81	1312.49	1310.64	1248.03	1245.38	1371.84	1316.40
B-50-5-D	1274.76	1274.76	1371.25	1354.22	1374.10	1354.00	1498.59	1494.18
B-50-6-D	1300.48	1284.74	1374.93	1370.34	1414.89	1399.51	1434.29	1420.99
B-50-7-D	1196.75	1196.54	1248.20	1245.65	1235.20	1235.20	1264.06	1255.19
B-50-8-D	1345.98	1293.30	1401.29	1394.10	1432.84	1421.18	1442.15	1424.48
B-50-9-D	1376.66	1361.30	1426.97	1411.60	1479.64	1472.37	1503.10	1481.48
B-50-10-D	1197.29	1188.18	1355.33	1335.33	1344.73	1333.88	1351.35	1333.74
C-50-1-D	1236.93	1222.06	1292.12	1283.59	1353.78	1337.15	1343.99	1325.06
C-50-2-D	1211.72	1208.22	1391.91	1343.39	1380.70	1364.64	1395.07	1354.44
C-50-3-D	1138.78	1111.23	1222.73	1207.23	1279.42	1267.03	1328.67	1310.96
C-50-4-D	1167.10	1145.34	1212.25	1197.79	1312.30	1287.45	1364.75	1361.76
C-50-5-D	1305.97	1293.70	1337.04	1331.51	1351.56	1339.40	1444.15	1441.97
C-50-6-D	1216.47	1211.70	1330.96	1322.65	1404.52	1378.21	1365.80	1338.29
C-50-7-D	1159.30	1140.05	1156.15	1136.58	1225.27	1215.09	1252.93	1241.08
C-50-8-D	1272.19	1249.03	1345.32	1334.89	1300.62	1292.41	1356.99	1330.91
C-50-9-D	1266.78	1237.50	1272.47	1248.15	1339.91	1309.66	1368.73	1346.80
C-50-10-D	1200.81	1168.19	1246.70	1232.95	1276.88	1225.75	1257.39	1248.19

Table D.20: Detailed results for the deadline impact in 2E-VRP-PDD : 100 Customers (ALNS 30K)

	Without Deadline		Loose Deadline		Deadline		Tight Deadline	
Instance	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*	*Avg 5*	*Best 5*
A-100-1-D	2283.24	2254.59	2377.09	2317.98	2381.11	2303.78	2375.64	2343.31
A-100-2-D	2657.34	2640.01	2721.68	2694.28	2801.43	2760.72	2751.61	2722.17
A-100-3-D	2170.27	2140.60	2267.86	2242.49	2287.27	2271.03	2250.50	2214.68
A-100-4-D	2491.01	2462.44	2569.89	2490.16	2589.62	2554.37	2615.09	2594.88
A-100-5-D	2313.59	2296.60	2354.25	2317.67	2402.71	2364.60	2425.32	2377.23
A-100-6-D	2575.17	2537.58	2579.09	2527.43	2607.32	2578.36	2637.30	2562.07
A-100-7-D	2299.44	2283.27	2390.77	2366.32	2400.87	2367.46	2413.22	2387.54
A-100-8-D	2425.21	2411.71	2526.30	2480.61	2596.04	2572.90	2572.70	2515.11
A-100-9-D	2313.32	2284.94	2357.56	2310.65	2358.12	2316.84	2424.47	2336.74
A-100-10-D	2130.94	2114.63	2196.58	2179.16	2226.06	2210.01	2240.45	2220.50
B-100-1-D	2078.91	2037.70	2195.94	2125.45	2213.74	2199.16	2223.66	2210.00
B-100-2-D	2071.45	2066.08	2357.24	2340.54	2376.11	2327.54	2400.66	2361.37
B-100-3-D	2234.97	2205.35	2297.62	2252.17	2293.50	2282.47	2334.84	2319.44
B-100-4-D	1977.03	1970.16	2092.39	2070.04	2160.00	2141.01	2183.39	2156.78
B-100-5-D	2247.02	2212.59	2259.79	2230.76	2371.08	2329.50	2372.15	2357.44
B-100-6-D	2057.25	2013.79	2194.34	2154.87	2191.71	2136.44	2220.87	2194.78
B-100-7-D	2132.89	2094.68	2383.04	2318.08	2399.37	2364.00	2424.81	2397.40
B-100-8-D	1882.82	1868.78	1991.92	1969.54	2026.76	1963.02	2009.95	1987.26
B-100-9-D	2159.78	2139.42	2267.36	2217.62	2338.23	2284.76	2282.52	2265.76
B-100-10-D	1994.13	1944.99	2145.80	2083.51	2148.27	2101.74	2187.22	2130.01
C-100-1-D	1990.49	1977.28	1999.16	1971.73	2110.20	2030.68	2173.45	2144.38
C-100-2-D	1822.46	1796.17	2024.77	1996.42	2030.08	1998.57	2112.44	2082.98
C-100-3-D	1918.31	1872.28	2030.73	2012.58	2014.91	2009.72	2054.01	2041.51
C-100-4-D	1935.16	1897.26	2133.76	2093.22	2146.17	2098.71	2223.69	2172.31
C-100-5-D	1824.91	1804.89	1960.10	1953.16	1994.14	1968.82	2011.58	1993.49
C-100-6-D	1901.63	1890.41	2072.30	2034.37	2074.07	2042.19	2168.19	2136.34
C-100-7-D	1814.91	1787.56	1926.80	1901.68	1907.07	1876.82	1994.46	1937.01
C-100-8-D	2056.68	2038.29	2088.58	2040.32	2212.98	2176.80	2269.43	2235.14
C-100-9-D	1926.94	1900.26	2004.56	1969.50	2080.83	2060.88	2099.32	2061.23
C-100-10-D	1976.28	1959.10	2137.55	2082.06	2152.17	2121.70	2184.97	2146.52

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Appendix E. Case Study Detailed Results

Table E.21: Detailed results for Case Study: (ALNS 30K)

	Strategy 1			Strategy 2			Strategy 3		
Instance	*Cost*	*#FEVs*	*# SEVs*	*Cost*	*#FEVs*	*# SEVs*	*Cost*	*#FEVs*	*# SEVs*
CS-1-D	2913.35	8	56	3510.46	14	52	3614.78	16	51
CS-2-D	1836.71	9	40	2214.20	10	35	2212.75	10	35
CS-3-D	3428.93	13	58	4179.98	14	53	4296.04	13	48
CS-4-D	2290.53	10	36	2672.65	10	38	2559.42	9	38
CS-5-D	2696.73	9	52	3317.06	13	50	3359.40	12	46

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