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1 Introduction

The electrification of last mile delivery fleets presents a significant opportunity to reduce greenhouse gas (GHG) emissions and align with global sustainability goals, such as Europe's Fit for 55 initiative, which aims to cut emissions by 55 percent by 2030 compared to 1990 levels. Last-mile logistics is particularly well suited for electrification due to predictable routes, limited daily driving ranges, and the increasing capabilities of electric light commercial vehicles (LCVs), which now offer ranges exceeding 200 km.

However, transitioning to an electric fleet introduces operational challenges, including extended charging times, volatile electricity costs, and constraints on the power grid infrastructure. To remain competitive, last-mile logistics providers must optimize charging strategies to balance cost efficiency with reliability of service.

In this project, we act as consultants for Deliver-Ease, a forward-thinking last-mile logistics company committed to zero-emission deliveries with the highest service level and lowest possible cost. Our objective is to develop a smart charging algorithm that optimizes EV fleet charging schedules, considering: service-level requirements (same-day delivery, minimizing missed deliveries), cost efficiency (dynamic energy pricing, infrastructure investments, personnel costs), grid constraints (power availability, charging station capacity).

Using data-driven decision making, we aim to ensure that Deliver-Ease maximizes fleet utilization while minimizing operational expenses, ultimately supporting a seamless and sustainable transition to electrified last mile logistics.

2 Optimization and Algorithm

2.1 Depot

To find the optimal location for a single delivery depot, a weighted centroid search method is applied that minimizes the total travel distance to all demand points, with real-world road network taken into account. Instead of Euclidean distance, accurate driving distances are computed using the Open Source Routing Machine (OSRM) based on OpenStreetMap road data. A grid-based search is then performed on the area, where each candidate depot location is evaluated by computing the weighted sum of OSRM distances to all demand points. The candidate location with the lowest total weighted distance is selected as the optimal depot satisfying the following:

$$j^* = \arg\min_{j \in \mathcal{C}} \sum_{i=1}^{n} w_i \cdot D(i, j)$$

where

- w_i is the frequency of visits of demand location i,
- $D(i, j)$ is the OSRM-based driving distance from candidate depot j to demand location i,
- $\mathcal{C}$ is the set of candidate depot locations (generated from a spatial grid),
- n is the total number of demand locations.

The theoretical location is 4°42'36.00"E, 50°51'36.00"N, which is on Armand Thierylaan. Considering all the vans that come in and out every day and the high voltage of electricity that we might need, we decided to move the depot to 50 ° 51 '13.9' N, 4 ° 43 '43.6' E, an available warehouse near Researchpark Haasrode[Aximas, nd], which is 2.8 km away from the original.

2.2 Vehicle Routing

Hexaly Studio was used to determine the required fleet size and to model vehicle routes and loadings for each of the 39 days. Hexaly language (Hexaly Modeller (HXM)) was used for coding, and the input data were provided in JSON format. The input file contains the depot coordinates, the capacity, range, and price of the vans, as well as the date, ID, coordinates, size, and time windows of the deliveries. For the base scope, the time windows correspond to the working hours. For advanced customer satisfaction specialization, they are defined as a separate index for each customer.

The subproblem was formulated with two objective functions: minimizing the total distance traveled and minimizing the cost of used vans. The complete mathematical formulation of the capacitated vehicle routing problem with time windows (CVRPTW) is provided in Appendix A.

The general assumptions considered in the model are as follows:

- Each customer is visited only once during the day.
- The van capacity is reduced by 20% to account for packaging and placement inefficiencies.
- The customer service time is assumed to be identical and exactly 3 minutes.
- The vans start and end their routes at the depot.
- The vans are assumed to have a single fixed speed.
- The vans can leave the depot early to start deliveries as the working hours start, and they can return to the depot after the working hours end. In other words, only the deliveries must be completed during the given time windows.

Hexaly Studio is configured to use OpenStreetMap Geodata to compute distances, with a 15-minute time limit to run the model. The results were visualized in Hexaly Studio using dash files. These files include a map to filter routes and customers each day, a Gantt chart showing the schedules of the vans for each day, tables with the total number of customers, total distance traveled, and total number of vans used for each day, and a graph showing the van loads for each day. The van routing and Gantt chart results for the first day (12/01/2025) for all scenarios are provided in Appendix B as an example.

2.3 Fleet

According to demand data, there were two types of van: a small type with a capacity of $3,3m^3$ and a larger one with a capacity of $4,2m^3$. Among real-life European vehicles, Citroën ë-Berlingo vans come in medium and large sizes, with capacities ranging from $3,3-3,8m^3$ and $3,9-4,4m^3$, respectively [Citroën, nd]. Since the capacities are similar, it was decided to continue with these vans.

The vehicle routing sub-problem was solved using three configurations: a combination of both types, only large vans, and only medium vans. With a customer service time of 3 minutes, the size of the vans becomes significant for most days for the base scope. On the other hand; if the customer service time increases to 5 minutes, the results showed that the delivery time windows and the van driving range were more restrictive than the loading capacities of the vans. However, since 3 minutes of customer service time was suggested, a combination of medium and large Citroën ë-Berlingo vans are used for the base scope.

The same configurations were tested for the specialization topic, and it was observed that the loading capacity of the vans was not as restrictive. Consequently, only medium-size vans were used.

The results of the van loadings for the first day (12/01/2025) from the base scope and the specialized topic are given in Appendix B to visualize the requirement of both types of van.

2.4 Charging Schedule

After determining the number of vans used every day, a charging schedule was developed. With assumptions of installation of each charging station costing 3000 €[Peng, 2025] with a yearly depreciation rate of 15%, electricity prices vary every hour[Elexys, nd] and full recharge of the van takes 30 minutes with a charger of 100 kW[Citroën, nd]. And since Dockx rental will always provide us with fully charged vans, the charging demands are proportionally reduced if the number of vans used exceeds the number of vans we have. In addition, all charging is assumed to take place between 10:00 PM and 8:00 AM.

The optimization problem is formulated to choose the best number of charging stations and charging time schedule to minimize the total cost of the charging stations and the energy cost. The mathematical model of the scheduling problem is provided in Appendix A. The algorithm provides a detailed schedule in an excel file for all 39 days. The output includes the date, time, cost, period of charge, and number of vans used.

3 Base scope

The algorithmic results indicate that van loads often exceed the capacity of the medium van, suggesting that van capacity is a limiting factor. The use of two different van types proves beneficial in optimizing the total cost of the fleet. On the busiest day, a total of 12 vans are required, while the average number is 5 daily. Their operating hours extend from 7:00 AM to 10:30 PM, ensuring that their schedules remain compatible with the charging windows.

3.1 Assets set-up

The purchase price for a medium-sized Citroën ë-Berlingo is 36,940€, whereas the large model costs 38,180€ [Belgium, 2025a]. For daily electric van rentals, a fully charged medium van is available at 71€ per day, while a large van costs 82€ per day [Rental, 2025]. During a 5-year period, accounting for a yearly depreciation rate of 15% and insurance and maintenance costs, the total cost of van usage is 35,552€ for the medium van and 36,350€ for the large van. Based on these factors, the optimal decision is to purchase 2 medium-sized vans and 5 large vans. Since the rented vans come fully charged from Dockx rental, a maximum of 7 vans will require charging each day, necessitating the installation of a single charging station at the depot. Table 1 summarizes the total amounts of vans purchased and rented, as well as the number of charging stations installed.

Table 1: Total Set-up Cost Breakdown for the Base Scope

Category	**Price (€/piece)**	**Quantity**	**Total Cost (€)**
Van (Medium)	36 940	2	73 880
Van (Large)	38 180	5	190 900
Medium Van Rent	71	5	355
Large Van Rent	82	16	1312
Charging Station	3000	1	3000
Total Cost			**269 447**

3.2 Energy prices

According to the charging schedule, the total energy cost is 436.3€, with the majority charging occurring between 3-5 am.

3.3 Personnel cost

According to Indeed Belgium(2025), a part-time van driver's salary is 150€ per day, while for a full-time driver the number is 130€[Belgium, 2025b]. Considering all the drivers we need on all days, 2 full-time drivers should be hired, and the rest of the drivers will be hired as part-time workers. Table 2 summarizes the total cost of personnel.

Table 2: Total Personnel Cost Breakdown for the Base Scope

Category	**Price (€/Person/Day)**	**Number**	**Total Cost (€)**
Full-time	130	2 (for 39 days)	10 140
Part-time	150	110	16 500
Total Cost (€)			**26 640**

4 Specialization with preferred delivery windows

People prefer delivery time windows to fit their schedules, avoid missed deliveries, and ensure package security. The weighted time slot system is proportionally estimated using survey data from Zhu et al. (2019) and

Oyama et al. (2024), ensuring that each location expecting deliveries on a given day is assigned one time slot[Zhu et al., 2019][Oyama et al., 2024]. However, in reality some people may care less about the time of their deliveries, so a version with only 50% demand locations with specific time windows was applied later. This version will be called "partial time windows" for the rest of the paper, and the following results in this section focus mainly on this scenario with a comparison with the full time windows at the end of the section.

4.1 Assets set-up

Calculated in the same way as discussed in the base scope section, the asset set-up costs are as follows:

Table 3: Total Set-up Cost Breakdown for Partial Time Windows

Category	**Price (€/piece)**	**Number**	**Total Cost (€)**
Van (Medium)	36 940	34	1 255 960
Medium Rent/Day	71	83	5893
Charging Station	3000	1	3000
Total Cost			**1 264 853**

Although now a lot more vans are used, each van travels relatively shorter distances compared to the base scope, thus shorter periods are required for charging, so, still only one charging station satisfies the demand.

4.2 Energy prices

The total energy cost would be 831.7€.

4.3 Personnel cost

With more trucks needed every day to accommodate all the specific time windows, more drivers are needed.

Table 4: Total Personnel Cost Breakdown for the Partial Time Windows

Category	**Price (€/Person/Day)**	**Number**	**Total Cost (€)**
Full-time	130	7 (for 39 days)	10 140
Part-time	150	747	112 050
Total Cost (€)			**147 540**

4.4 Full Time Windows

The cost implications become even more pronounced when every customer is assigned a preferred time window on a daily basis. In this scenario, the optimized solution requires one charging station and incurs energy costs of €1,118.61. The fleet expands to 43 medium vans, supported by 13 full-time personnel and a total of 829 part-time personnel over the 39-day period.

5 Conclusion

Compared to the base solution, the introduction of specific time windows for half of the customers significantly increases operational demands. The fleet size grows to over three times that of the base scenario, while personnel costs rise to 4.5 times the original amount, and the total travel distance more than doubles. Similarly, the size of the fleet continues to increase as more customers are assigned a specific time window for the Full Time Windows. The total cost of this scenario is 5.6 times the base-scope amount. This surge comes from the need to accommodate concentrated demand within narrower delivery windows. In other words, as customer satisfaction increases, the size of the fleet increases as well. Figure 1 shows the increase in the number of vans required daily. As a consequence of this increase, related operational costs such as hiring and training more part-time workers, increase proportionally, as summarized in Table 5.

This escalating cost trend underscores a fundamental trade-off in last-mile logistics: tighter time windows enhance customer satisfaction but at the expense of higher operational expenses. Strategic prioritization is needed to handle this trade-off. One potential solution is to impose higher charges on customers who select specific time windows, helping to offset the increased operational burden.

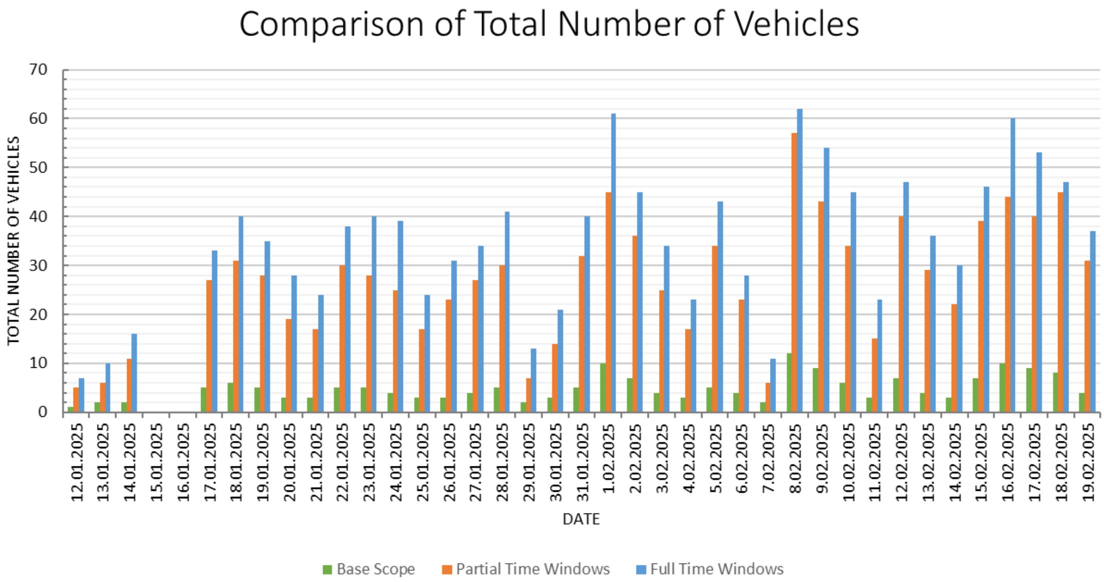

Figure 1: Comparison of Total Number of Vans Required Daily

Table 5: Comparison of Scenarios

Category	Base	Partial Time Windows	Full Time Windows
Van (Medium)	2	34	43
Van (Large)	5	0	0
Medium Van Rent	5	83	88
Large Van Rent	16	0	0
Charging Station	1	1	1
Full-Time Personnel	2	7	13
Part-Time Personnel	110	747	829
Total Cost (€)	296 523.3	1 413 224.7	1 664 697.6

In the specialization scenarios, the Gantt charts reveal idle periods where vans pause mid-route to adhere to time windows, an inefficiency that could be repurposed for charging if roadside infrastructure was available, potentially extending van range without compromising schedules. In addition, this increase in range may accommodate more volumes of deliveries and bring capacity back as an active constraint. In addition, the large number of part-time workers may increase the operational cost as training and recruitment are needed.

In conclusion, high customer satisfaction significantly impacts setup and operational costs by affecting fleet size and staffing. Relaxing the time windows should be carefully evaluated considering the trade-off between service quality and customer satisfaction.

6 Generative AI

Generative AI, especially ChatGPT and Copilot, was used to proofread the final report and to help with the LaTeX structure.

7 References

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Appendix

Appendix A: Mathematical Models

Model 1: Capacitated Vehicle Routing Problem with Time Windows (CVRPTW)

Sets

- D: Set of planning days ($D = \{1, 2, ..., 39\}$)
- T: Set of trucks
- C_d: Set of customers on day $d \in D$

Parameters

- $q_{c,d}$: Demand of customer $c \in C_d$ on day d (in m^3)
- Q_t: Capacity of truck $t \in T$
- A_t: Maximum range of truck $t \in T$
- s: Service time per customer
- $[e, l]$: Delivery time window ($[08{:}00, 22{:}00]$)
- c_t: Fixed usage cost of truck $t \in T$
- d_{ij}^d: Distance between customer i and j on day d
- d_{0i}^d, d_{i0}^d: Distance from/to depot and customer i on day d
- $\mathrm{dur}(\cdot)$: Function mapping distance to travel time
- e_{id}: Earliest time customer i can be served on day d (time windows for the specialization)
- l_{id}: Latest time customer i can be served on day d (time windows for the specialization)

Decision Variables

- $x_{ijt}^d \in \{0, 1\}$: 1 if truck t travels from customer i to j on day d, 0 otherwise
- $u_{it}^d \in \{0, 1\}$: 1 if truck t serves customer i on day d, 0 otherwise
- $s_{it}^d \in R_+$: Arrival time of truck t at customer i on day d
- $z_t^d \in \{0, 1\}$: 1 if truck t is used on day d, 0 otherwise

Objective Functions

$$\min \sum_{d \in D} \sum_{t \in T} \left(\sum_{i,j \in C_d} d_{ij}^d \cdot x_{ijt}^d + \sum_{i \in C_d} (d_{0i}^d + d_{i0}^d) \cdot u_{it}^d \right) \tag{1}$$

$$\min \sum_{d \in D} \sum_{t \in T} c_t \cdot z_t^d \tag{2}$$

Constraints

$$\sum_{t \in T} u_{it}^d = 1 \qquad \forall i \in C_d,\ \forall d \in D \quad \text{(each customer is served once)} \tag{3}$$

$$\sum_{i \in C_d} q_{i,d} \cdot u_{it}^d \leq Q_t \qquad \forall t \in T,\ \forall d \in D \quad \text{(capacity)} \tag{4}$$

$$\sum_{i,j \in C_d} d_{ij}^d \cdot x_{ijt}^d + \sum_{i \in C_d} (d_{0i}^d + d_{i0}^d) \cdot u_{it}^d \leq A_t \qquad \forall t \in T,\ \forall d \in D \quad \text{(range)} \tag{5}$$

$$e \leq s_{it}^d \leq l \qquad \forall i \in C_d,\ \forall t \in T,\ \forall d \in D \quad \text{(time windows)} \tag{6}$$

$$s_{jt}^d \geq s_{it}^d + \mathrm{dur}(d_{ij}^d) + s \qquad \text{if } x_{ijt}^d = 1 \quad \text{(route continuity)} \tag{7}$$

$$z_t^d \geq u_{it}^d \qquad \forall i \in C_d,\ \forall t \in T,\ \forall d \in D \quad \text{(truck usage flag)} \tag{8}$$

$$s_{it}^d + s \leq l \qquad \forall i \in C_d,\ \forall t \in T,\ \forall d \in D \quad \text{(no lateness)} \tag{9}$$

$$e_{id} \leq s_{it}^d \leq l_{id} \qquad \forall i \in C_d,\ \forall t \in T,\ \forall d \in D \quad \text{(time windows for the specialization)} \tag{10}$$

Model 2: Charging Schedule
Sets

- D: Set of planning days ($D = \{1, 2, ..., 39\}$)
- $\mathcal{H}_d$: Set of valid charging hours for day d ($\mathcal{H}_d = \{22, 23, 0, 1, 2, \ldots, 7\}$)

Parameters

- C_{infra}: Depreciation of the charging station in 39 days (€48.1)
- $p_{d,h}$: Electricity price at hour h of day d (€/kWh)
- P_{rate}: Charger power rating (100 kW)
- k_d: Total daily mileage (km)
- n_d: Number of vehicles used
- n: Number of vehicles bought
- 0.0875 kWh/km: Energy consumption rate

Decision Variables

- $x_{d,h}$: Charging time at hour h of day d (continuous variable, hours)
- N: Number of chargers (integer decision variable)
- Z: Total cost (€)

Objective Function

$$\min Z = C_{\text{infra}} \cdot N + \sum_{d \in D} \sum_{h \in \mathcal{H}_d} p_{d,h} \cdot x_{d,h} \cdot 100$$

Constraints

$$\sum_{h \in \mathcal{H}_d} x_{d,h} \geq \frac{0.0875 \cdot \min(n_d, n) \cdot k_d}{60 \cdot n_d} \qquad \forall d \in \{1, \ldots, D\} \quad \text{(energy demand)} \tag{11}$$

$$x_{d,h} = 0 \qquad \forall d \in \{1, \ldots, D\},\ h \notin \{22, 23\} \text{ of day } d \cup \{0, \ldots, 7\} \text{ of day } d+1 \quad \text{(night charging)} \tag{12}$$

$$x_{d,h} \leq N \qquad \forall d \in \{1, \ldots, D\},\ h \in \{0, \ldots, 23\} \quad \text{(charger capacity)} \tag{13}$$

$$N \in Z_+ \quad \text{and} \quad x_{d,h} \geq 0 \qquad \forall d \in \{1, \ldots, D\},\ h \in \{0, \ldots, 23\} \quad \text{(non-negativity and integer constraints)} \tag{14}$$

Appendix B: Instances of Results

Instances of Truck Loadings

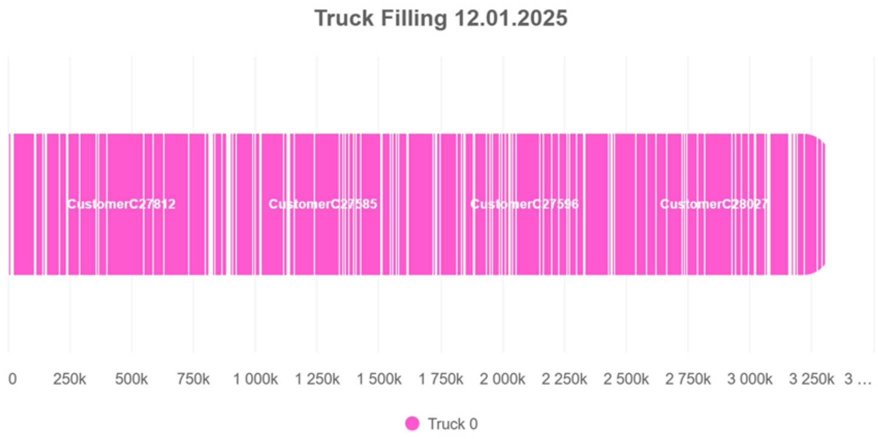

Figure 2: Truck Filling for the First Day in Base Scope

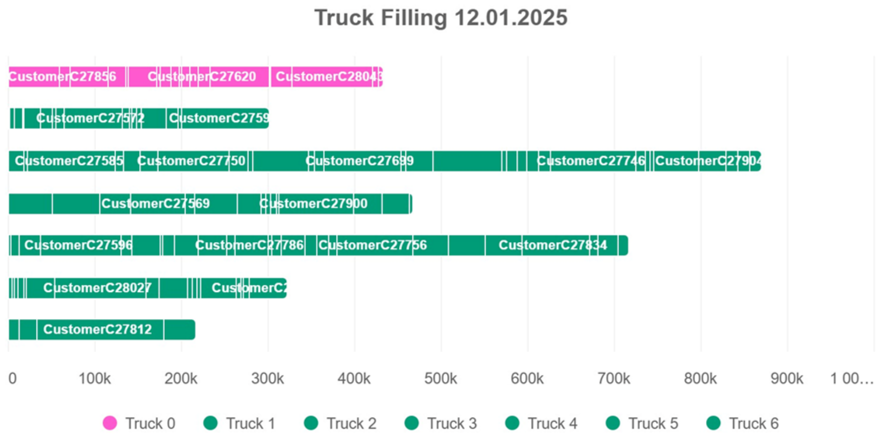

Figure 3: Truck Filling for the First Day in Full Time Windows

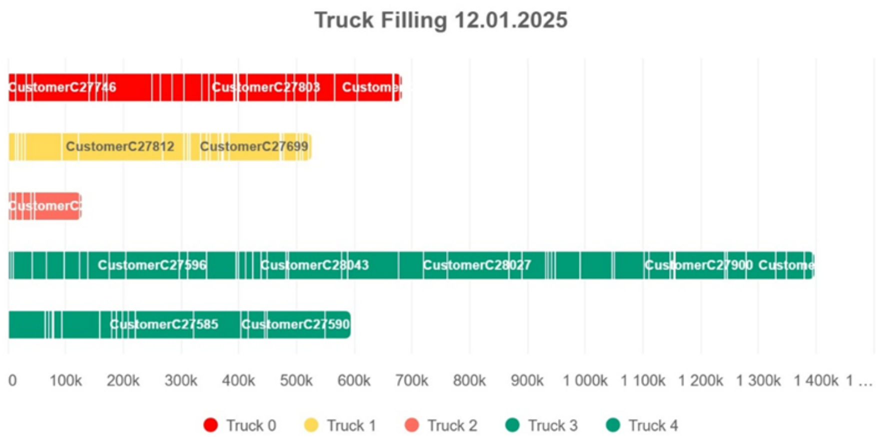

Figure 4: Truck Filling for the First Day in Partial Time Windows

Instances of Routings

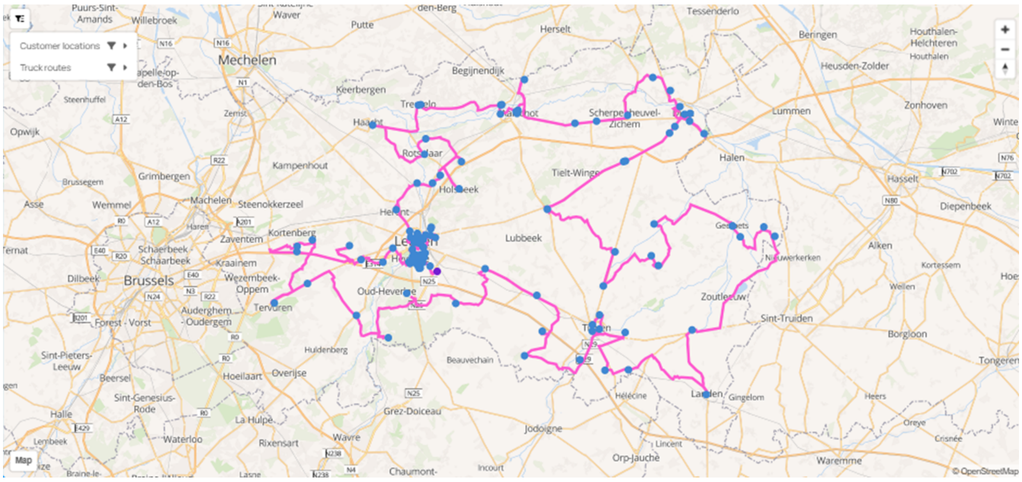

Figure 5: Routings for the First Day in Base Scope

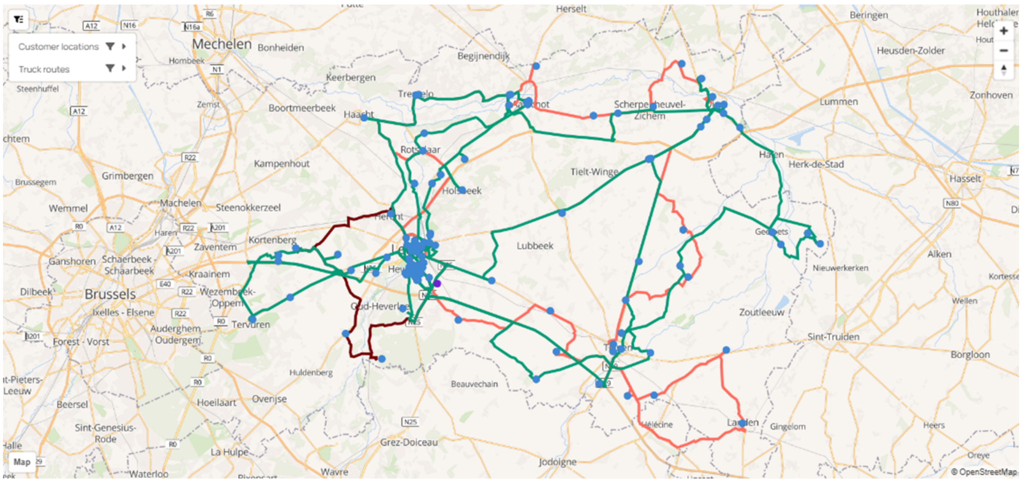

Figure 6: Routings for the First Day in Full Time Windows

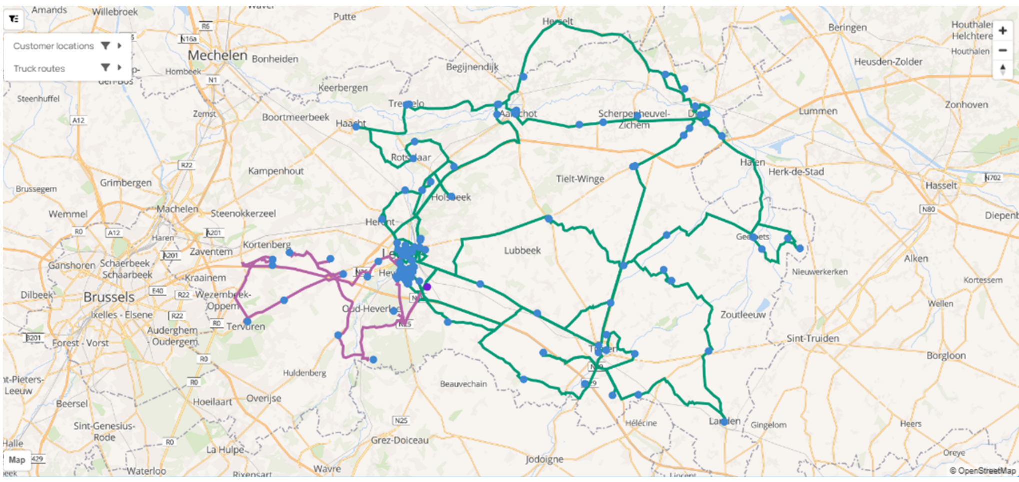

Figure 7: Routings for the First Day in Partial Time Windows

Instances of Gantt Charts

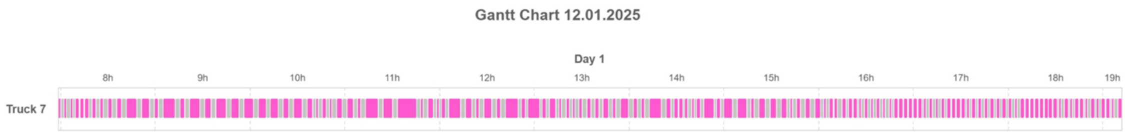

Figure 8: Gantt Chart for the First Day in Base Scope

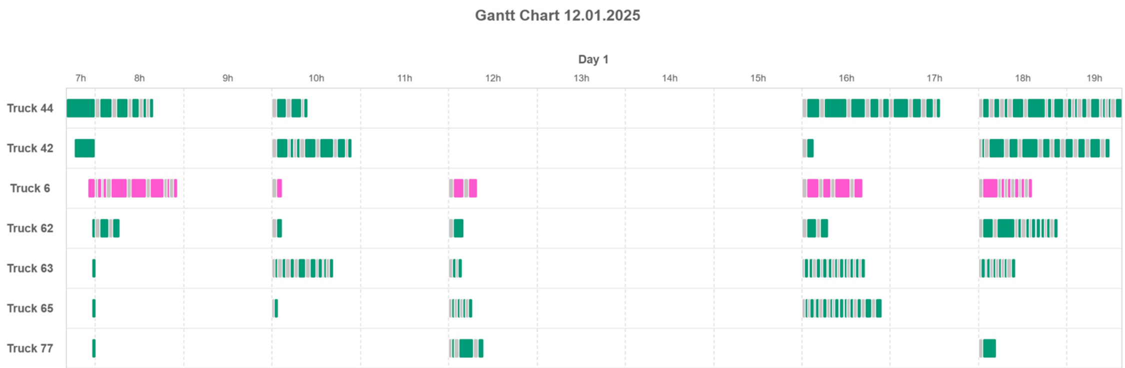

Figure 9: Gantt Chart for the First Day in Full Time Windows

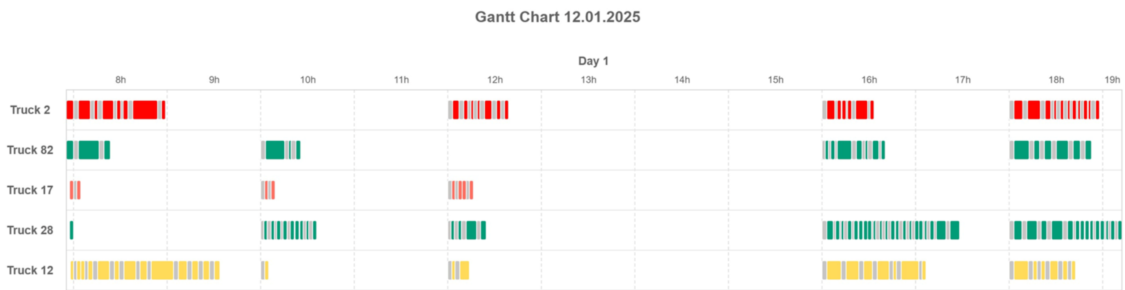

Figure 10: Gantt Chart for the First Day in Partial Time Windows