Albert Heijn Delivery Case

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Contents

1 Management Summary

As a leading food retailer in the Netherlands, Albert Heijn (AH) must deliver various food products multiple times a week from their distribution centers (DC) to different stores to satisfy customer demands. AH plans to implement a new delivery schedule that incorporates more electric trucks to enhance sustainability. However, the current cost per hour per kilometer for electric trucks is high, creating a trade-off between sustainability and total delivery cost, as AH also aims to be a sustainable company for the future. Significant losses due to electric delivery would deter AH from choosing this option.

This project aims to find a new delivery schedule for AH that enhances sustainability by incorporating more electric trucks. The expected outcome is to achieve a balance between low cost and sustainability. The methodology involves running multiple scenarios and identifying the best proposal. The objectives are: 1) to minimize the overall delivery cost; and 2) to increase the use of electric trucks.

Based on priority, we suggest that the best solution is scenario 3, which balances cost and emissions efficiently. At the end of the report, we provide the details of the proposed schedule (in Excel), including information such as the truck type, loading time, and more.

Based on these results, we recommend using more advanced clustering methods, such as K-means, to cluster nearby stores together to optimize the 2-store route model and enhance overall efficiency.

2 Data Analytics

2.1 Scope of the Data

Based on the database, we obtained the following information:

- The priorities of the schedule are: Service, Cost, and Sustainability.
- Docks for fresh food and ambient food are separate, with two docks for each type at the DC.
- There are 49 stores with various food demands. Fresh food needs to be delivered every day, while ambient food can be delivered one day in advance. The demand is assumed to be independent of the delivery day.
- The schedule covers 6 days, from Monday to Saturday.
- Loading and unloading times are included in truck delivery times.
- Each store requires direct delivery from the DC, and all trucks must return to the DC after delivery.
- There are no time limits for the DC, which operates 24/7, but unloading must occur within the stores' opening times.
- Some stores cannot be reached by large trucks, and each store has truck-type limitations.

2.2 Assumptions

Supply chain models are always approximations. In this case, we ignore certain realistic limitations, such as peak time interruptions during delivery. Additionally, we assume that:

- Different scenarios refer to various soft constraints and delivery methods.
- Any damage loss during delivery is ignored; we only ensure that delivery numbers meet store demands.
- We have data on the distance and driving time from the DC to stores, but we also need data for distances and driving times different stores. In some scenarios, trucks are assumed to visit multiple stores in one trip to reduce costs. Considering truck capacity and store demands (most demands exceed 20 units), we assume one truck can visit at most two stores each time. This reduces optimality but increases efficiency. We use the Google Maps API to estimate distances and driving times between stores.
- Loading time at the DC is always 30 minutes. Assuming the loading time starts precisely on the hour (e.g., 5 am), we define the loading time decision variable as numbers from 0 to 23.5 with 0.5-hour intervals. Driving time is converted to fractions.

2.3 Methodology

To address this project, we build a supply chain model and implement it using Python and Gurobi. Subsequently, we simulate different scenarios considering various constraints to explore the correlation between delivery costs and CO2 emissions. Initially, we investigate the worst-case scenario, or the 1-store route model, in which each store is delivered separately. Subsequently, we adjust other constraints based on this fundamental model.

3 Build Supply Chain Model

3.1 Define the Model

To clearly define our model, below is a list of basic notations for this problem:

Name	**Set**	**Index**	**Content**
Distribution Center	DC	DC	DC
Stores	S	s	{1004, ..., 1222} (49 stores)
Truck Types	V	v	{Small, ..., Electric big} (6 types)
Day of The Week	W	w	{Mon, Tue, Wed, Thur, Fri, Sat}
Times	T	t	[5, 23]
Product Types	P	p	{ambient, fresh}
Docking Station	Q	q	{1, 2}

Table 1: Sets

Parameter	**Size**	**Index**
distance from DC to store s	$S \times 1$	$dist_s$
driving time from DC to store s	$S \times 1$	τ_s
opening time of store s	$S \times 1$	$open_s$
closing time of store s	$S \times 1$	$close_s$
demand of store s of food type p at day w	$S \times P \times W$	$D_{s,p,w}$
truck capacity of type v for food type p	$P \times V$	$cap_{v,p}$
truck range for type v	$V \times 1$	ran_v
truck type v limited by store s	$S \times V$	$\Phi_{s,v}$
truck cost per km of type v	$V \times 1$	$Cdist_v$
truck cost per hour of type v	$V \times 1$	$Chour_v$
truck emissions per km of type v	$V \times 1$	E_v
loading time	1×1	$lt = 0.5h$
unloading time	1×1	$ult = 0.5h$

Table 2: Parameters

To clearly define the decision variables, we must specify the following:

- at which time t AH utilizes which truck type v.
- when AH begins to load and deliver which product p to which store s.
- the number of replenishment deliveries made at each instance.

Index	**Range**	**Explanation**
y_{wtpqs}	binary	1 if a truck is loaded on day w at time t for product type p at dock q going to store s, or 0 otherwise
ϕ_{wtpqv}	binary	1 if a truck is loaded on day w at time t for product type p at dock q by truck type v, or 0 otherwise
z_{wtpqsv}	binary	1 if a truck is loaded on day w at time t for product type p at dock q going to store s with truck type v, or 0 otherwise
R_{wtpqs}	$\mathbb{N}^+$	replenishment amount of product type p delivering to store s by truck z

Table 3: Decision Variables

3.2 Constraints

3.2.1 DC constraints

- y_{wtpqs} is binary:

$$y_{wtpqs} \in \{0, 1\}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S \tag{1}$$

- ϕ_{wtpqv} is binary:

$$\phi_{wtpqv} \in \{0, 1\}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall v \in V \tag{2}$$

- z_{wtpqsv} is binary:

$$z_{wtpqsv} \in \{0, 1\}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S, \forall v \in V \tag{3}$$

- at any given time t, there should be a maximum of one truck in loading:

$$\sum_{s \in S} y_{wtpqs} \leq 1, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q \tag{4}$$

- only if when $y = 1$ and $\phi = 1$, z can be 1:

$$z_{wtpqsv} = y_{wtpqs} \cdot \phi_{wtpqv}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S, \forall v \in V \tag{5}$$

3.2.2 Truck constraints

- electric trucks cannot travel exceed 100km:

$$z_{wtpqsv} \cdot dist_s \cdot 2 \leq ran_v, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S, \forall v \in V, \tag{6}$$

- any truck going to any store s should satisfy the truck-type limitation:

$$z_{wtpqsv} \leq \Phi_{s,v}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S, \forall v \in V \tag{7}$$

- replenishment number should be always limited by truck capacity:

$$R_{wtpqs} \leq z_{wtpqsv} \cdot cap_{v,p}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S, \forall v \in V \tag{8}$$

3.2.3 Store constraints

- arrival and unloading should occur within working hours:

$$t + lt + \tau_s \geq open_s \cdot y_{wtpqs}, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S \tag{9}$$

$$(t + lt + \tau_s + ult) \cdot y_{wtpqs} \leq close_s, \quad \forall w \in W, \forall t \in T, \forall p \in P, \forall q \in Q, \forall s \in S \tag{10}$$

3.2.4 Demand constraints

- all replenishment at day w should be larger than this day's demand:

$$\sum_{t \in T} \sum_{q \in Q} \sum_{v \in V} R_{wtpqs} \geq D_{w,p,s}, \quad \forall w \in W, \forall p \in P, \forall s \in S \tag{11}$$

3.3 Objective Function

- the total cost for distance is the cost per km per truck · truck type · (distance from DC to s + from s to DC):

$$Cdist_{cost} = \sum_{w \in W} \sum_{t \in T} \sum_{p \in P} \sum_{q \in Q} \sum_{s \in S} \sum_{v \in V} z_{wtpqsv} \cdot Cdist_v \cdot (2 \cdot dist_s) \tag{12}$$

- the total cost for time is the cost per hour per truck · truck type · (loading time + time from DC to s + unloading time at s + time from s to DC):

$$Chour_{cost} = \sum_{w \in W} \sum_{t \in T} \sum_{p \in P} \sum_{q \in Q} \sum_{s \in S} \sum_{v \in V} z_{wtpqsv} \cdot Chour_v \cdot (lt + 2 \cdot dist_s + ult) \tag{13}$$

- the CO2 emissions is emission per km per truck · truck type · (distance from DC to s + from s to DC):

$$Emission = \sum_{w \in W} \sum_{t \in T} \sum_{p \in P} \sum_{q \in Q} \sum_{s \in S} \sum_{v \in V} z_{wtpqsv} \cdot E_v \cdot (2 \cdot dist_s) \tag{14}$$

The objective of this project is to reduce costs and CO2 emissions simultaneously. Therefore, an ideal method is to reduce both together and compare results from different scenarios. The objective function is:

$$\min \quad Cdist_{cost} + Chour_{cost} + Emission, \tag{Q}$$

To preserve flexibility regarding the prioritization of sustainability versus cost minimization, we adjust the objective to represent a weighted average of both costs and emissions. The weighted objective function is:

$$\min \quad \alpha \cdot (Cdist_{cost} + Chour_{cost}) + (1 - \alpha) \cdot Emission, \tag{Q*}$$

Here, α indicates the weight given to each objective. We explore 3 different values of α: $\alpha = 0$, $\alpha = 0.5$, and $\alpha = 1$, and compare the results.

4 Results and Recommendations

From the model, we compare 3 different scenarios: minimizing the cost, minimizing the emissions, and minimizing both. the results are as follows:

Scenarios	Objective	Hour Cost	Distance Cost	The Total Cost(€)	CO2 Emissions(kg)	Number of Electric trucks	Number of All trucktypes	Ratio
1	minimize Cost only	81903	32905	114808	53653	0	677	0.00%
2	minimize Emissions only	99218	38011	137229	36530	502	779	64%
3	minimize both	87342	34690	122032	43263	226	677	33%

Figure 1: Results

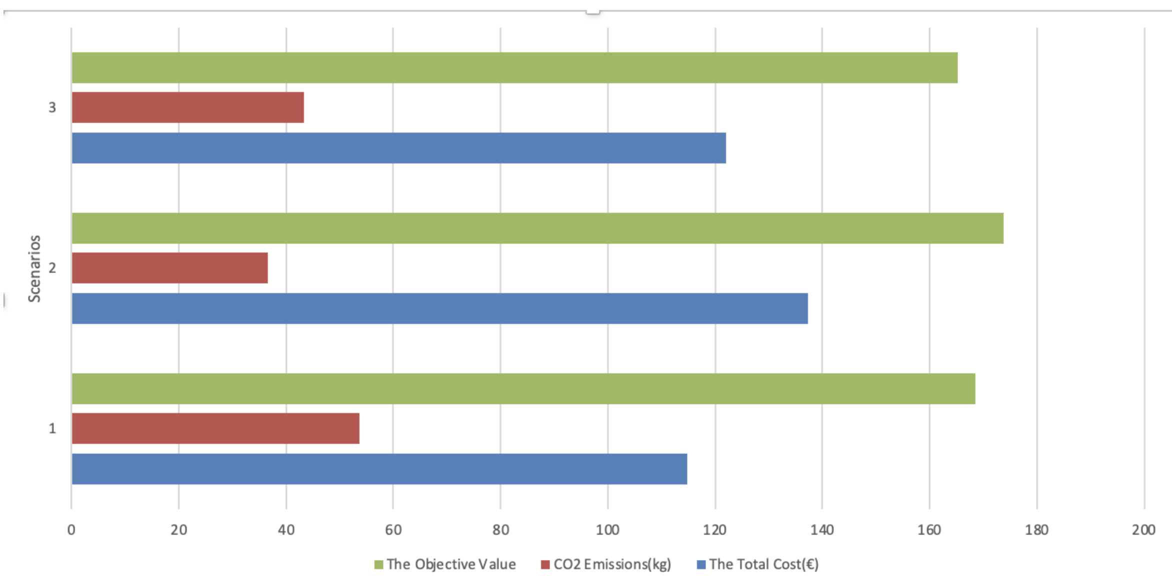

Figure 2: Comparision of 3 scenarios

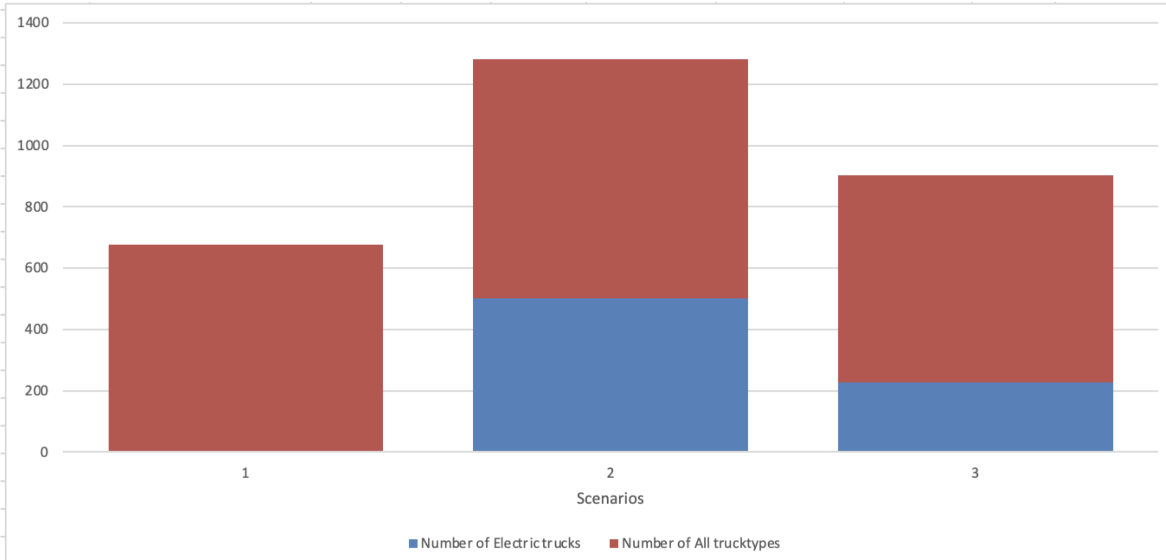

Figure 3: The number of electric trucks

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Mon, fresh, 1 | 19.5 | 1198 | Electric Big | 55.0 | 50
Mon, fresh, 1 | 14.0 | 1199 | Rigid | 34.0 | 29
Mon, fresh, 2 | 12.0 | 1205 | Electric Big | 40.0 | 32
Mon, fresh, 2 | 11.0 | 1208 | Electric Big | 40.0 | 31
Mon, fresh, 1 | 18.0 | 1219 | Electric Big | 40.0 | 22
Mon, fresh, 2 | 16.0 | 1222 | Electric Big | 55.0 | 47
```

```
Mon, fresh, 2 | 15.0 | 1198 | City | 50.0 | 50
Mon, fresh, 1 | 11.0 | 1199 | Rigid | 34.0 | 29
Mon, fresh, 1 | 16.0 | 1205 | Rigid | 34.0 | 32
Mon, fresh, 2 | 7.0 | 1208 | Electric Big | 40.0 | 31
Mon, fresh, 2 | 16.0 | 1219 | Rigid | 34.0 | 22
Mon, fresh, 2 | 11.0 | 1222 | City | 50.0 | 47
```

Figure 4: The Comparison of Electric Trucks Used for the Same Stores in Scenarios 2 and 3

From the table above, we observe that while the first scenario has the lowest cost, it results in higher emissions due to the absence of electric trucks. In comparison, scenario 2 introduces electric trucks, resulting in reduced emissions but at a slightly higher cost. However, scenario 3 strikes a balance between cost and emissions, with both factors minimized effectively. Therefore, we recommend that AH opts for scenario 3.

For further research, we suggest using advanced clustering methods such as K-means to group nearby stores together to optimize the 2-store route model.