Simulation-based optimization of electric truck heavy-duty freight for The Netherlands

SUSTAINABLE FREIGHT WORKSHOP 04 - 12 - 2023

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Ambitious targets for transport electrification

- **Netherlands' Emission Goals**: Targets a 55% reduction in emissions by 2030, prompting urgent actions in the transport industry (40% of global CO2 emissions in the transportation sector)

- **Zero-Emission Zones**: Several municipalities are establishing zones requiring zero-emission vehicles.

- **Government Support**: Initiatives include subsidies and tax benefits for electric trucks on specific routes.

Zero-emission zones to be introduced in many cities from 2025

This information is provided by Netherlands Enterprise Agency, RVO

Do you use a van or truck for your business that is powered by petrol or diesel? And do you deliver goods to customers in an inner city area? From 1 January 2025, a zero-emission zone may apply, meaning your company vehicle will no longer be allowed to drive into the city centre.

Albert Heijn will electrify Dutch city fleets entirely

ALBERT HEIJN | AMSTERDAM | BEV | FLEET ELECTRIFICATION | NETHERLANDS | ROTTERDAM | THE HAGUE | UTRECHT

The Dutch retailer Albert Heijn will decarbonise all deliveries in the centre of the Hague by the end of this year, including home delivery and the supply of its stores. Throughout 2023, deliveries in central Rotterdam, Utrecht, and Amsterdam are also to be made only electrically.

To this end, Albert Heijn and its transport partners plan to increase the number of e-trucks and e-delivery vans in the coming period. The retailer leaves partners and the number of vehicles unmentioned in the statement.

However, the latest press photo shows a range of vehicles from electric light trucks and a Fiat Ducato with a box body to larger distribution trucks from DAF and Mercedes-Benz. The latter is an eActros. Already previous efforts to switch to electric vehicles have seen Albert Heijn using an early Fuso eCanter, and the company has also had 25 VW Crafter converted to electric drives for use in the Amsterdam delivery fleet.

Lantz, M., & Joelsson, Y. (2023). *Electric heavy-duty trucks - Policy Outlook: Planned and implemented policies to support battery electric heavy-duty vehicles in Sweden, Austria, Germany, the Netherlands, UK and California (US)*. (IMES/EESS report ; Vol. 129). Department of Environmental and Energy Systems Studies, Lund university.

Fleet owners have incentives and pressures to go electric but also face several challenges…

- **Meeting Current Operations**
- 1300 daily trips, each about 10 tons of goods
  - **Reliability** of deliveries and minimum **waiting times**

- **Limited Charging Infrastructure**
- How **many chargers**? What **power rating**?
  - Does this depend on the trucks I buy?
  - Is my **local grid** capable of providing this power over time?

Technological Diversity
  - Navigating multiple technological options.
  - All calculations contingent on future energy prices

Key questions to address for the transition

- What are the **charging infrastructure** requirements for your operations?
  - **Number of chargers** (10 or 30?)
  - **Power rating** of the chargers (150kW or 500kW?)
  - **Total Power Demanded** on site

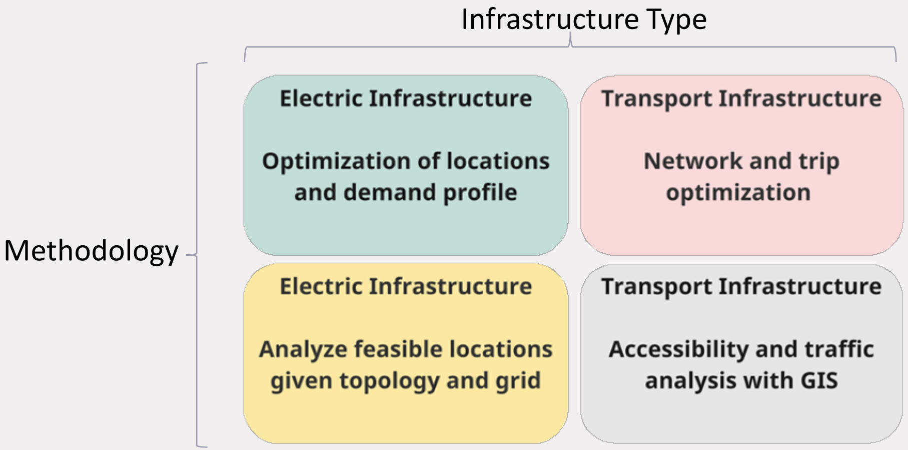
- Are e-trucks **compatible** with current operations/schedules?

- How much will the transition to electric trucks **cost**?

- How **reliable** are different solutions in the long term?

Literature approaches to the problem

There is a growing body of academic literature that develop methodologies to define the location and number of chargers



- We seek **practical, explainable models** that answer identified questions
- Trying to align as possible to existing optimized itineraries (minimal disruption)
- Ability to test **“What-if” scenarios** for different combinations on the operator side

Our proposed methodology: combining Optimization with Agent-based Simulations

- **Data Analysis**: Translate the detailed schedules of retailers' stores into a structured trip-oriented dataset

- **Optimization:** Apply optimization models to the processed dataset to obtain charging schedules and infrastructure

- **Simulation**: Utilize simulations to complement optimization, enabling robustness analysis, solution refinement, and visualization

Data Analysis: Truck characteristics

Table 1: Summary statistics by truck type

Truck Type	Battery size	Consumption (kWh/km)	Average payload (t)	Standard deviation (t)	Average roundtrip Distance (km)	Number of vehicles
City	360kWh	~1.5*	18.08	0.25	87.99	37
Euro	350kWh	~1.5*	14.47	0.15	97.18	96
Rigid	315kWh	~1.5*	9.31	0.22	70.37	23

* Approximation, actual values are taken from a simple linear regression of the form $C(w) = k \cdot w + a$ (where w is the total weight) obtained for similar trucks

Data Analysis: Departure and arrival times by Day

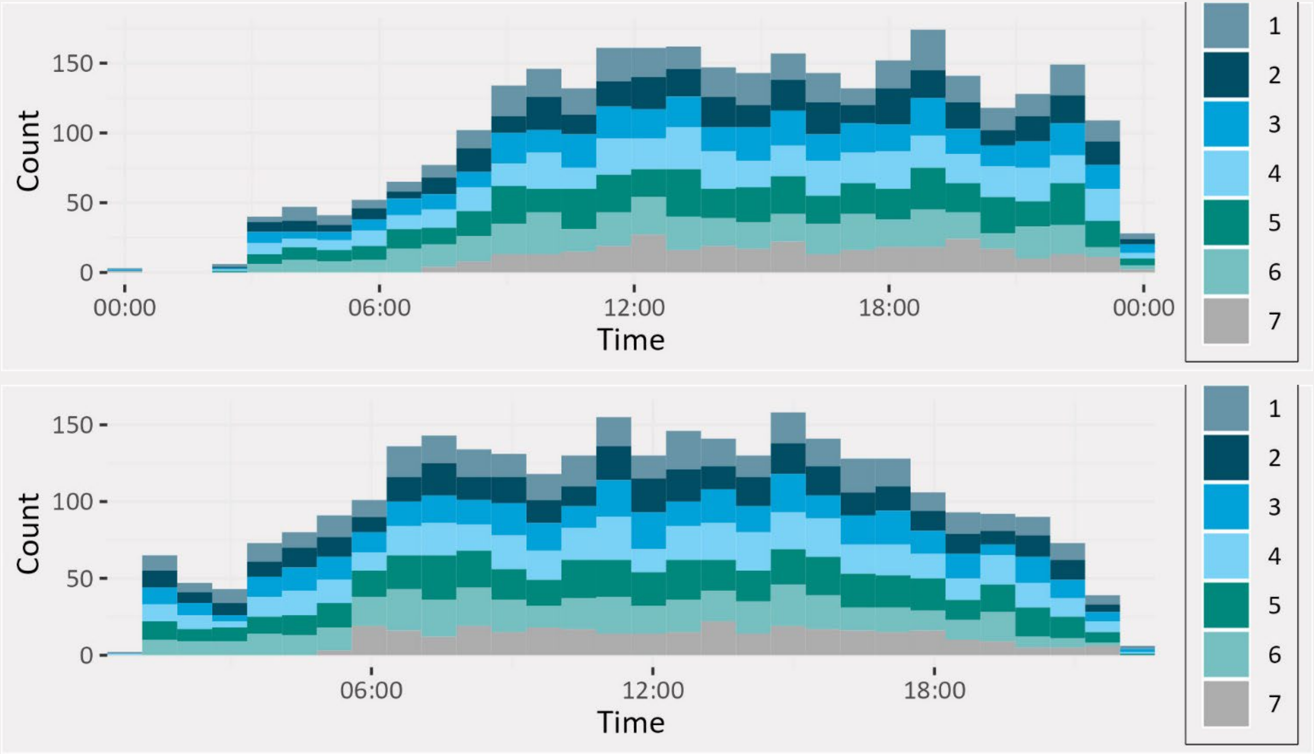


Figure 1: Scheduled arrival and departure times of trucks

Data Analysis: Distribution center and retailers

A complex logistics network in the north of The Netherlands:

- 314 locations
- 27 tons average daily deliveries to each location
- One main regional distribution center

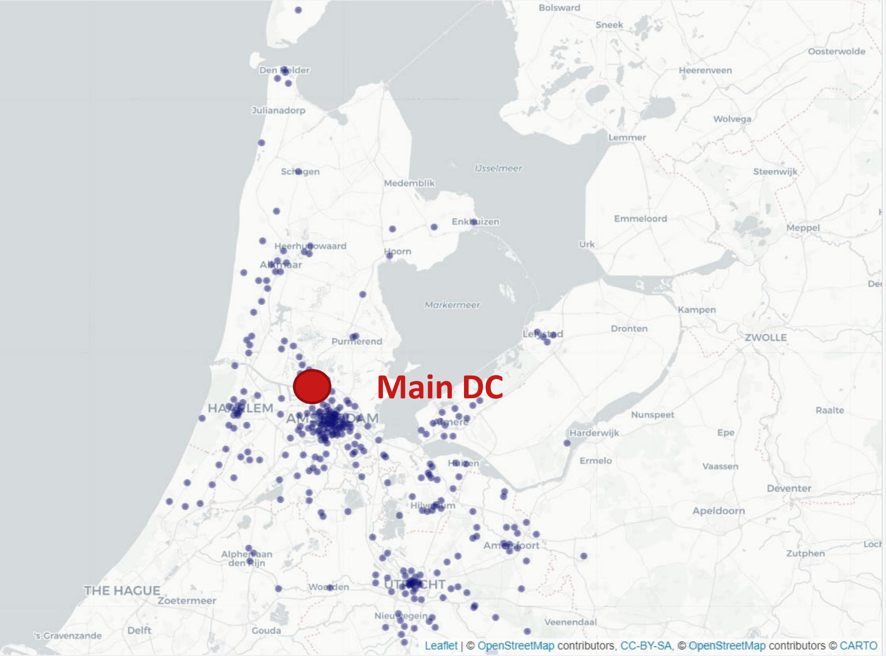


Figure 2: Locations of the 314 locations of interest (Zandaam in Red)

OPT: Set Definitions

Table 2: Summary set definitions

element	set	Description
k	K	Set of trucks
i	I	Set of Origins
j	J	Set of destinations
r	R	Set of charger Types
t	T	Set of time blocks
p	P_r^t	Set of energy costs (for each charger type and time block)
l	L^k	Set of itineraries (for each truck)

- Each l^k is a tuple holding the origin, destination, time of arrival $t_{k,l}^{\mathrm{arr}}$ and time of departure $t_{k,l}^{\mathrm{dep}}$
- We discretize day-time into units of a size τ (fraction of hour) , such that for each day we have $\frac{24}{\tau}$ time blocks t

OPT: Decision Variables

$\boldsymbol{Y_{k,l}^{r,t}} \in \{0,1\}$ Binary variable representing the **decision to charge** (for a truck k, in its itinerary leg l, at a charger type r, at the time block t)

$\boldsymbol{X_i^r} \in \mathbb{N}$ Integer Variable representing the **number of chargers** to be situated at location i, of type r

OPT: Constraints: Trip Energy Requirements

The **energy expenditure** of performing trip $d_{i,j}^{k}$ can be written equivalently (in terms of itinerary legs)

$$e_{k,l}^{\text{cons}} = d_l^k c_k \qquad (1)$$

We write the **energy charged** before a departure:

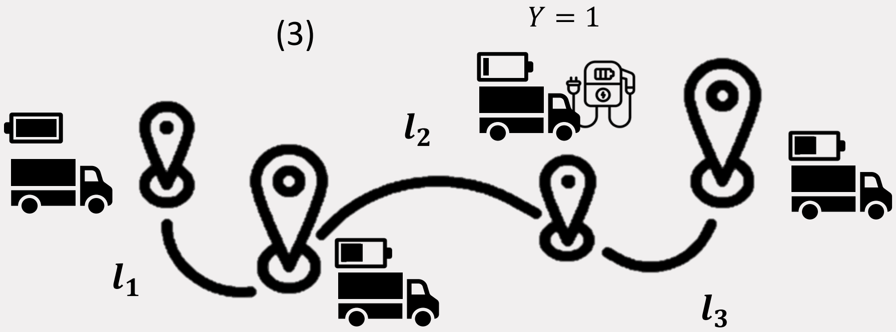
$$e_{k,l}^{\text{char}} = \sum_{t \in T_s^l, r \in R} Y_{k,l}^{t,r} \cdot c_r^{\text{char}} \qquad (t_{k,l}^{\text{arr}}, t_{k,l}^{\text{dep}}) \text{ span a subset of T: } T_s^l \qquad (2)$$

First inequality to **ensure trip legs** can be fulfilled (energy-wise):

$$E_{k,l}^{\text{arr}} \geq E_{k,l}^{\text{dep}} - e_{k,l}^{\text{cons}} + e_{k,l}^{\text{ch}} \quad \forall k \in K, l \in L^k \qquad (3)$$

We limit the **state of charge** of any vehicle to the battery capacity

$$E_{k,l}^{\text{dep}} \leq B_k \qquad (4)$$



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OPT: Constraints: Available Infrastructure

The **number of vehicles charging simultaneously** is limited by the **total number of chargers available** at each origin location

$$X_i^r \geq \sum_{k \in K, l \in L^k} Y_{k,l}^{t,r} \quad \forall t \in T, r \in R, i \in I \tag{5}$$

We **restrict each truck to be charging at one charger** only at any given time t:

$$\sum_{r \in R} Y_{k,l}^{t,r} \leq 1 \quad \forall t \in T, k \in K, l \in L^k \tag{6}$$

OPT: Time Constraints

To have charging schedules that are coherent with the final logistic schedules, we need to enforce that the **time of departure is posterior to the latest charging block of trip leg l**.

$$t_{k,l}^{dep.act} \geq t \cdot \sum_{r \in R} Y_{k,l}^{r,t} \qquad \forall t \in T_s^l, k \in K, l \in L^k \tag{7}$$

The time of departure chosen and **travel time to the next destination has to be consistent with the time window allowed** between the actual arrival time from the previous leg (l−1) and the departure time during the current leg l

$$t_{k,l}^{dep} + \beta \geq t_{k,l}^{dep.act} \geq t_{k,\,l-1}^{dep.act} + t_{k,\,l-1}^{travel} \qquad \forall, k \in K, l \in L^k \tag{8}$$

OPT: Cost Functions

The time spent charging for each vehicle is given the number of time blocks used for charging, summating over this the **total power charged** is given by:

$$C_{k,i}^{\text{char}} = \tau \cdot \sum_{t \in T_s^l, l \in L, r \in R} Y_{k,l}^{t,r} \cdot p_r^t \cdot c_{r,t}^{\text{pow}} \tag{9}$$

The **infrastructure costs** are given by the number of chargers required at each location:

$$C_i^{\text{infra}} = \sum_{r \in R} c_r^{\text{infra}} \cdot X_i^r \tag{10}$$

The **peak energy costs** are given by the total power being charged at a certain

$$C_{t,i}^{\text{peak}} = \alpha \sum_{k \in K, l \in L^k, r \in R} Y_{k,l}^{r,t} \cdot c_r^{\text{char}} \tag{11}$$

OPT: Objective

- We define the logistic operator's optimization problem to be centered around minimizing the **total costs of operation**.

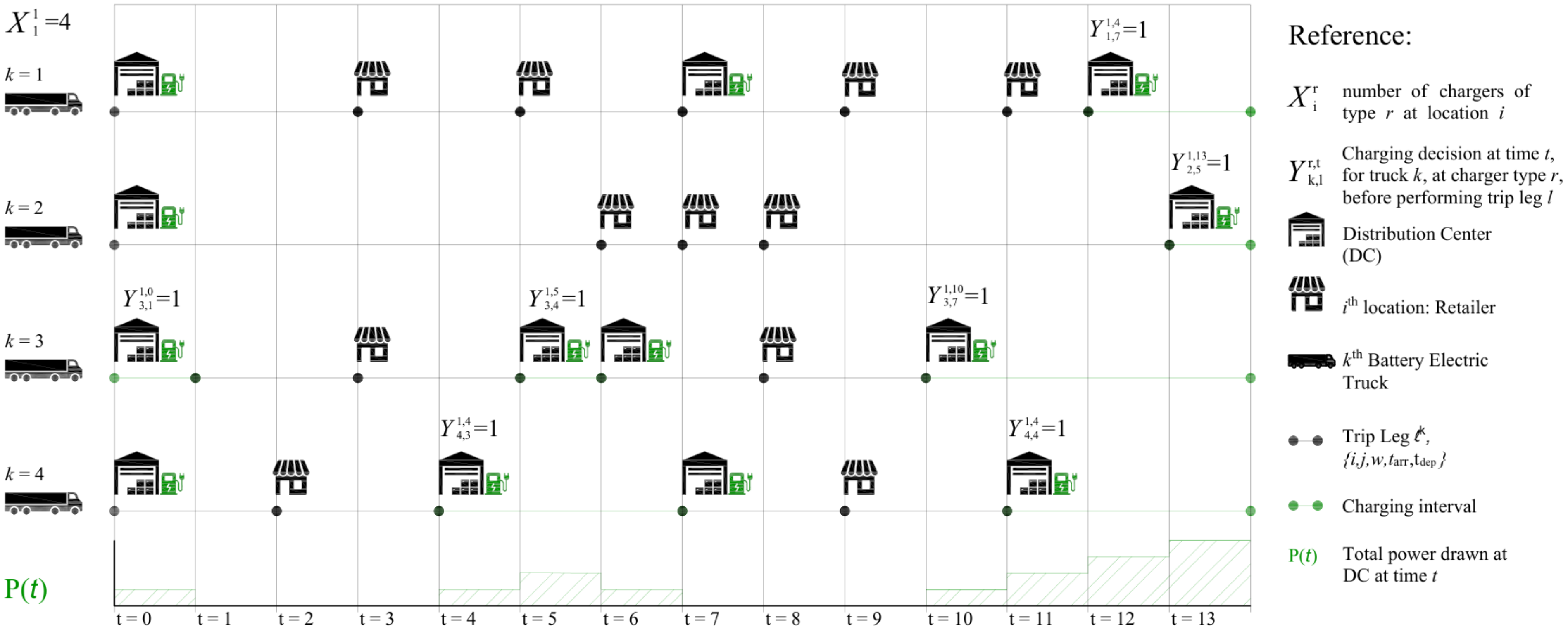
- This is comprised of the global operation costs (**charging costs**) and facility costs (**number and type of chargers by location**).

Putting eqs (9)-(11) together we build the objective function (12):

$$J(\boldsymbol{X},\boldsymbol{Y}) = \sum_{i\in I} C_i^{\text{infra}} + \sum_{i\in I, k\in K} C_{k,i}^{\text{char}} + \sum_{i\in I, t\in T_S} C_{t,i}^{\text{peak}} \tag{12}$$

Solving for this objective subject to constraints (3)-(8) yields jointly the **optimal locations, number and power ratings of the chargers** and **charging schedule of each truck**.

In a nutshell..



Parameters for Experiment 1: Infrastructure Co-Design

Parameter	Value
Days	4
τ	0.15hr (9min)
R	5 types {min:60 max:1080kW}
k	130
Locations	314
Gurobi Optimality Gap (Yalmip parser)	Abs gap <1%
$\boldsymbol{Time\ slack\ \beta}$	$\{\mathbf{10, 30}\}$
$\boldsymbol{Peak\ factor\ \alpha}$	$\{\mathbf{1, 2}\}$

Table 3: Main parameters of the simulation

We optimize schedules and infrastructure jointly, varying two parameters:

- “Tighter” Schedules (lower time slack $\boldsymbol{\beta}$ parameter)
- Increased cost of peak power $\boldsymbol{\alpha}$ surcharge

For each combination we present **final charging infrastructure, charging schedule power use, and total costs**

We contrast to a proposed project , called here “Rule-based”

Charging Infrastructure Results

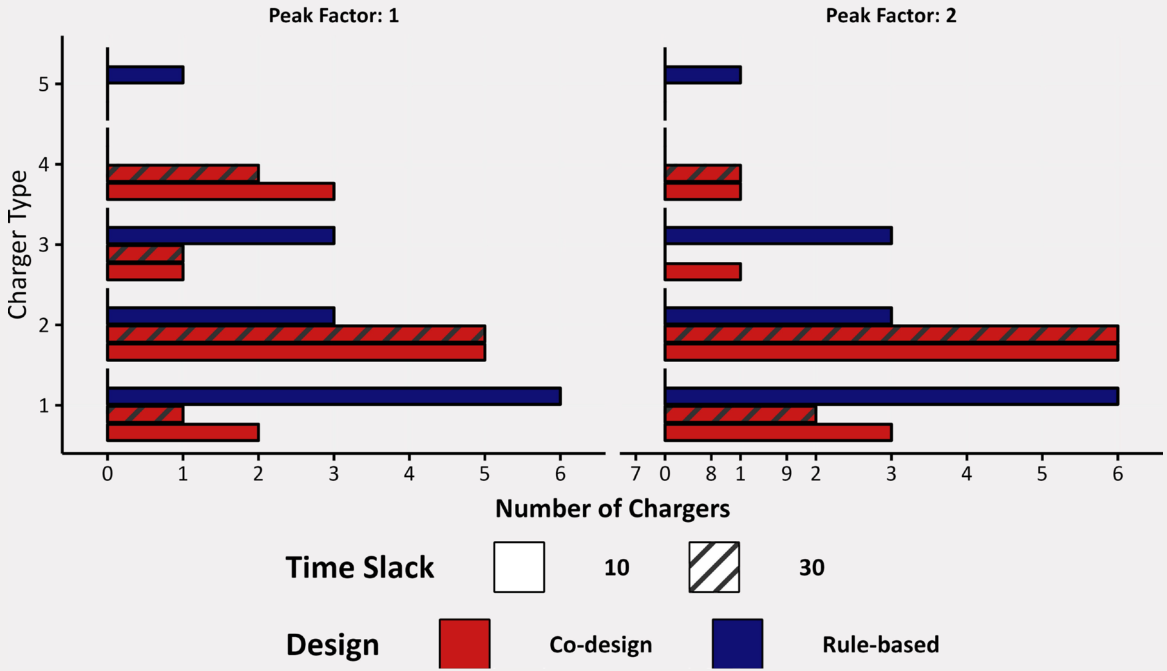


Figure 6: Number of chargers by type, for different peak and time-slack values

- Higher peak penalization leads to a design with lower powered chargers.
- Tighter schedule constraints induce the use of more chargers
- Co-design shifts use of type 1 chargers to type 2 chargers, and from type 5 to type 4.

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Average Power Consumption (Co-Design)

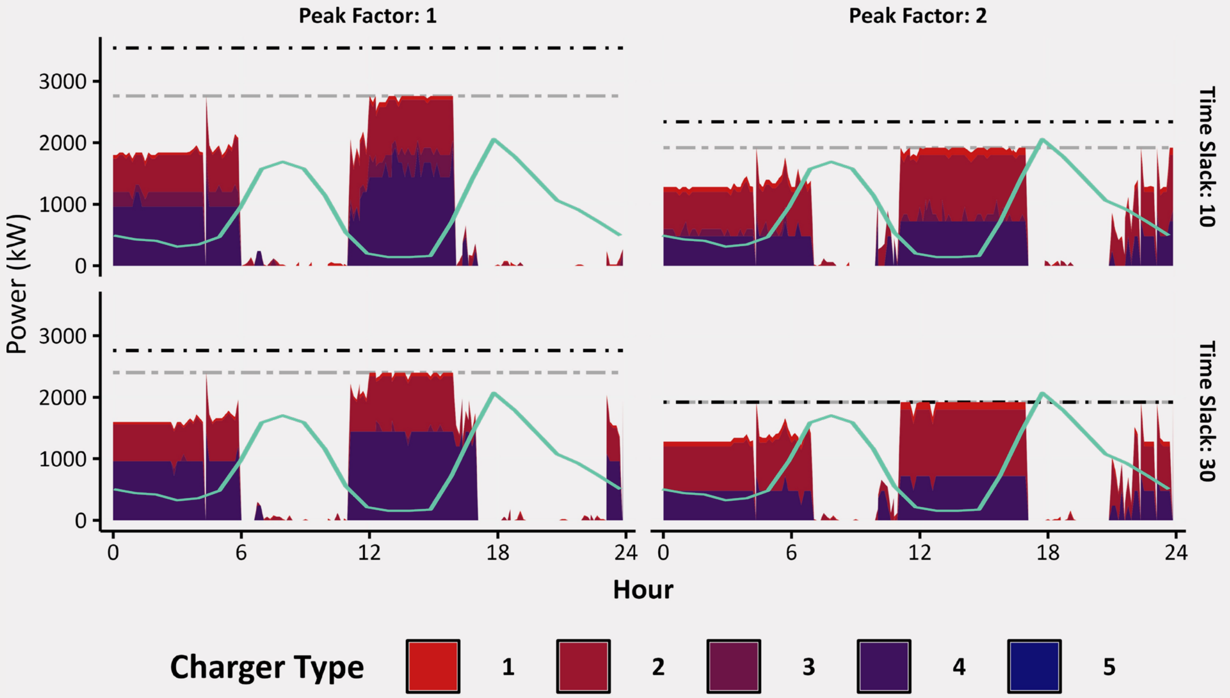

Figure 9: Power load curves for the optimal planning schedules obtained (co-design), average price curve in green

- With **less time slack** for operations then more power is drawn from higher speed chargers- yielding more peaks.
- Higher **peak factors** reduce peak charging power used and decrease alignment to lower energy prices.
- Higher time slack allows a higher gap between maximum installed power and peak power used.

Average Consumption curves (Rule-based design)

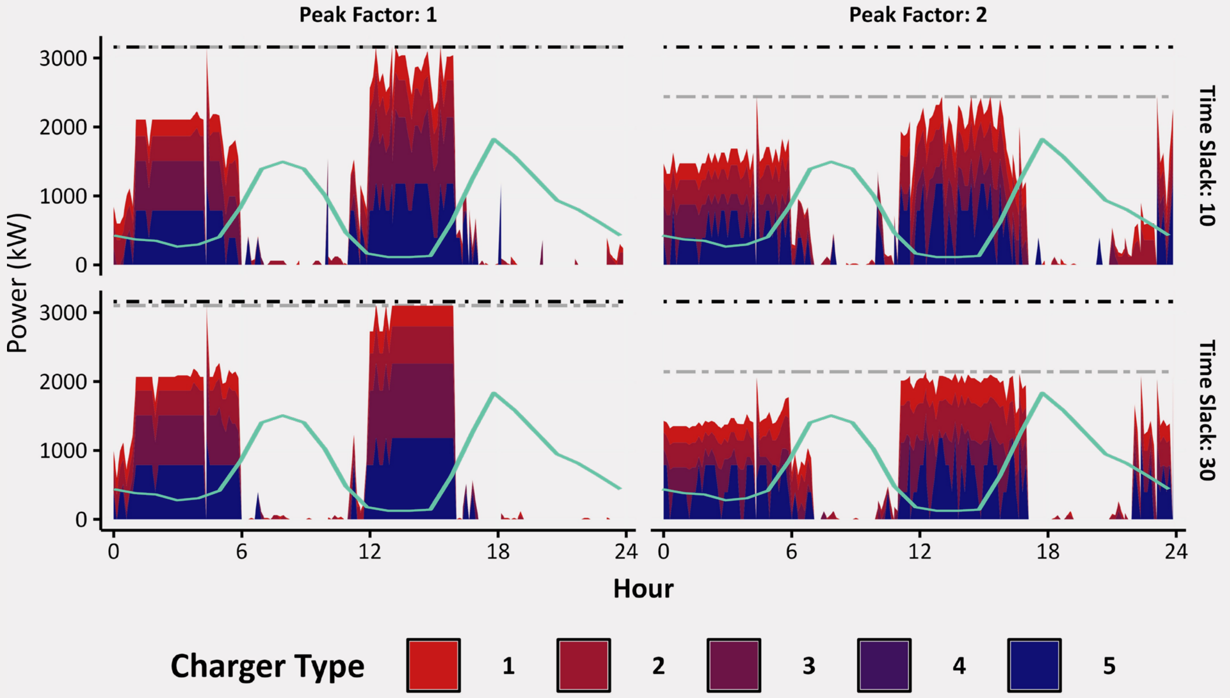

Figure 9: Power load curves for the optimal planning schedules obtained (rule-based) , average price curve in green

- Rule-based design has always the same maximum installed power.
- Same tradeoff between maximum peak charging power used and alignment to lower energy prices.
- Inability to adapt infrastructure forces usage of type 5 chargers and yields higher peaks

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Energy, Infrastructure, Peak and Total Costs

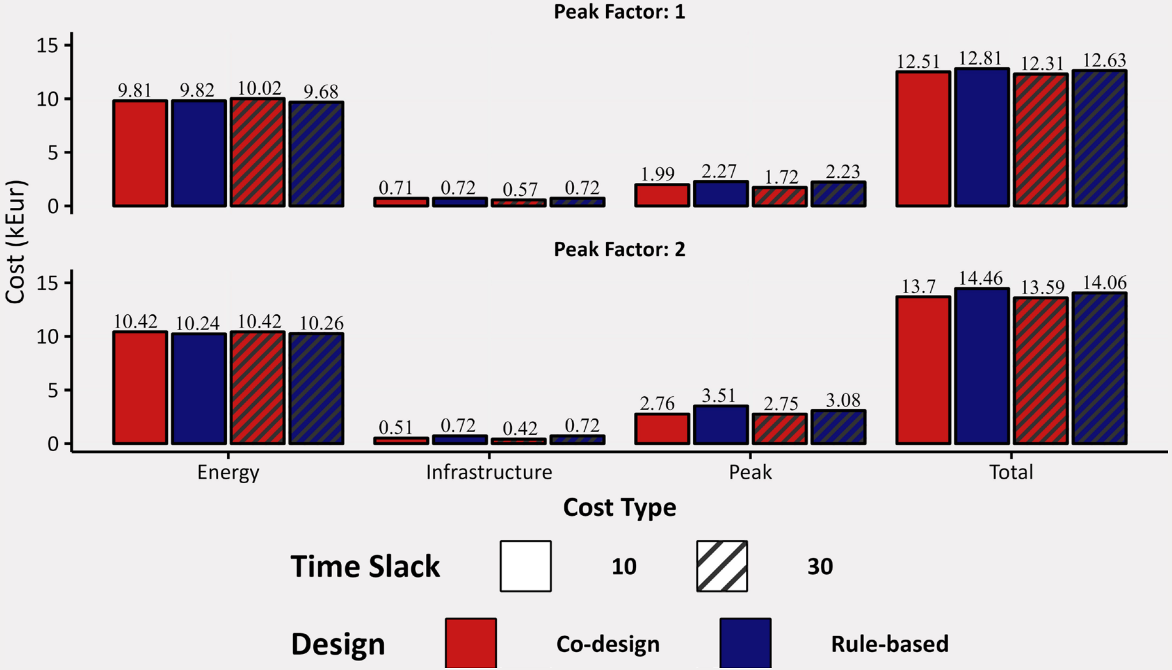

Figure 10: Total solution costs obtained from the optimization algorithm

- Co-design focuses on the reduction of infrastructure and peak power costs in lieu of energy costs
- The infrastructure costs for rule-based design are fixed, co-design costs are lower or equal (-14.23% and -55.72%)
- Co-design has higher energy costs (1.67% and 1.69%), but lower peak costs (-21.88% and -19.51%)
- Total costs are lower in co-design (-2.51% and -4.51%)

Higher values of peak factor may suggest chargers outside the main DC

Peak Factor 10, Time Slack = **5** | Peak Factor 10, Time Slack = **10** | Peak Factor 10, Time Slack = **30**

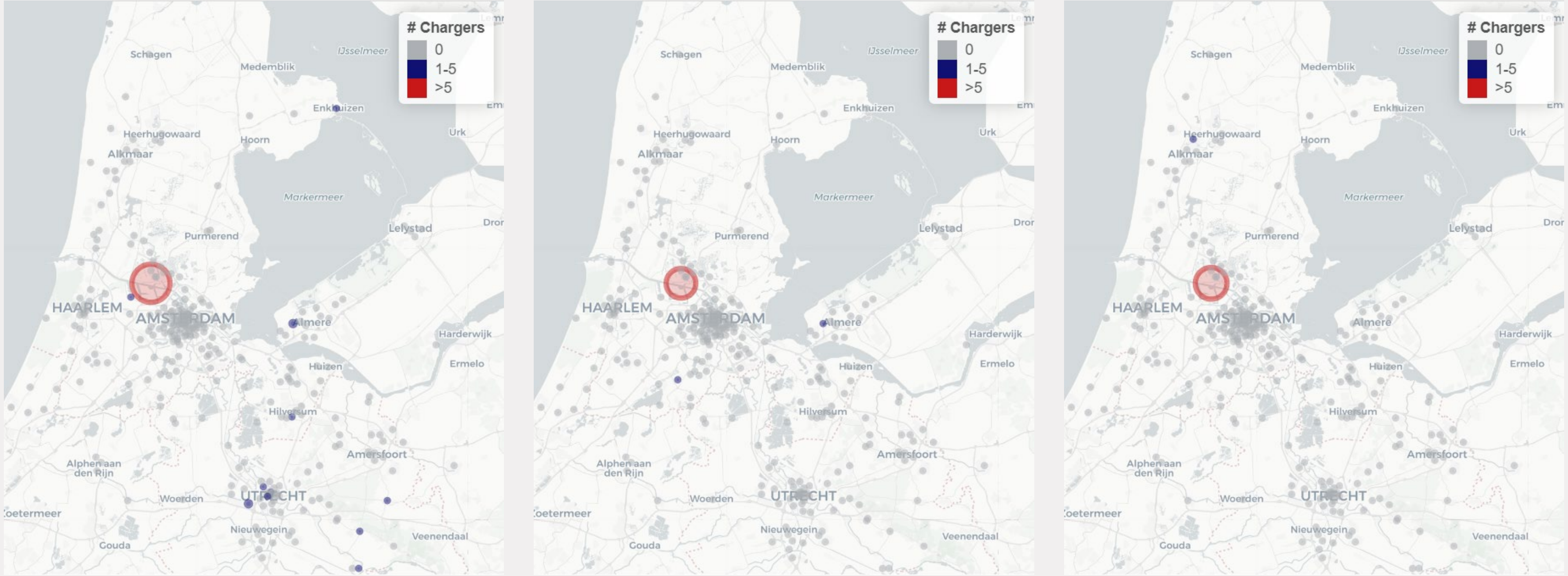

Figure 11: Number of chargers by location. (Aggregated all types) Peak Factor = 10

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Why Agent Based Simulation ?

- Allows **inclusion of details that would make optimization too computationally expensive**
  e.g.: battery degradation, charge acceptance curve, minute resolution
- Easy introduction and propagation of **uncertainty**
  e.g.: truck speed, traffic jams, downtime of a charger
- **Decision logic** attached to individual agents
  e.g: individual Decision of where to charge, limitation of power provided
- **Feedback loops and queueing mechanics** are easily included
- In specific platforms, allows easy implementation into java app that can be **interacted with** and produce **online visualizations**

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Agent Based Simulation : Overview

- Agents: Distribution Center, Trucks, Coordinating Agent, Chargers

- Environment: GIS environment of Northern Netherlands

- Timeseries data for the cost of energy

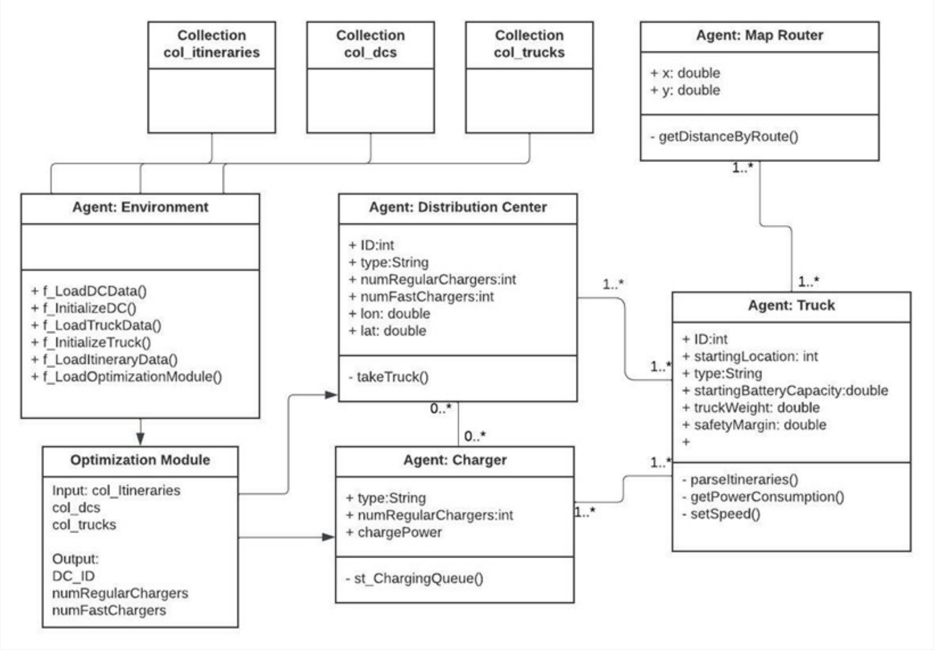


Figure 3: UML diagram for the Agent-Based Model

Agent Based Simulation: Truck Agent

- **Reads Daily itinerary and loads**, travels to required destination, records its arrival time, decides on charging.
- **Power consumption model**: Physical or given by regression.
- **Non cooperative behavior**: every truck tries to charge at the fastest available charger

Description	Symbol	Distribution
Consumption Coefficient	c_k	$N(c_k, 0.05c_k)$
Payload	w_p	$N(w_p, 0.05w_p)$
Loading/Unloading Times	t_u	$N(t_u, 0.05t_u)$

Table 4: Stochastic variables affecting truck behavior in simulations

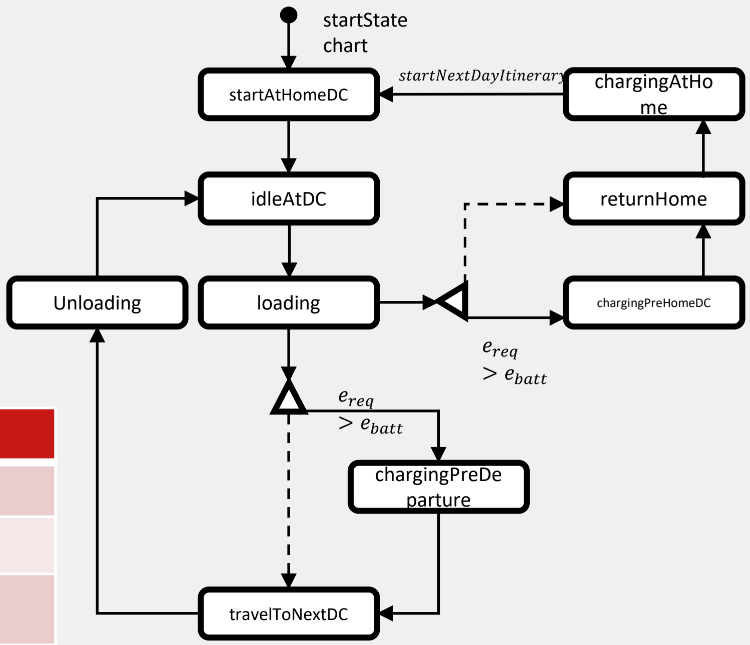


Figure 13: Statechart (simplified) for a truck agent

Agent Based Simulation: Distribution Centre

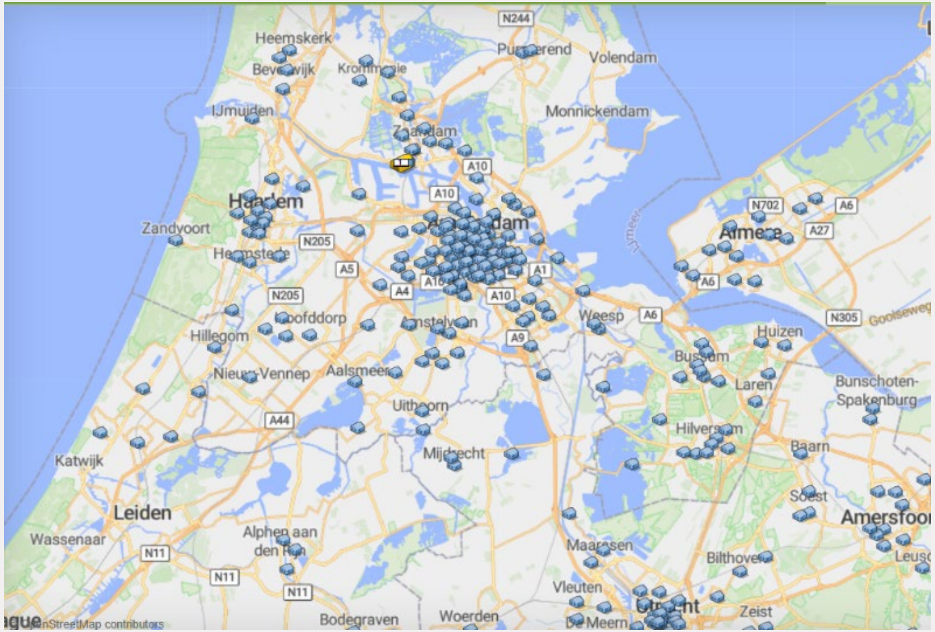


Figure 13: Screenshot of the GIS location of the 314 points of interest

- Takes its spatial location and receives trucks for loading/unloading and charging (queue)

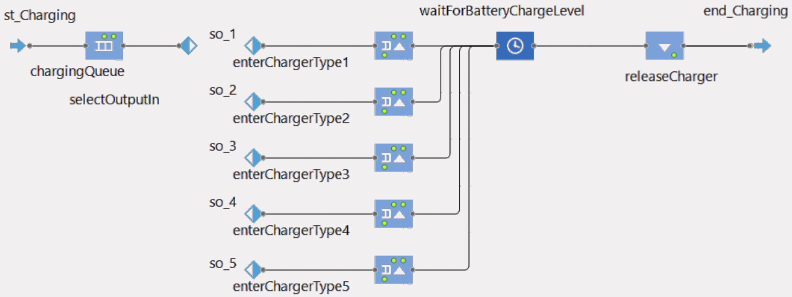
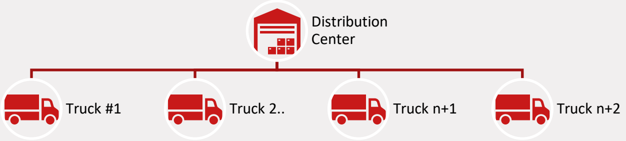


Figure 14: Queuing bock (Simplified) of the charging process at a POI

- Simple communication protocol with trucks according to charger queueing



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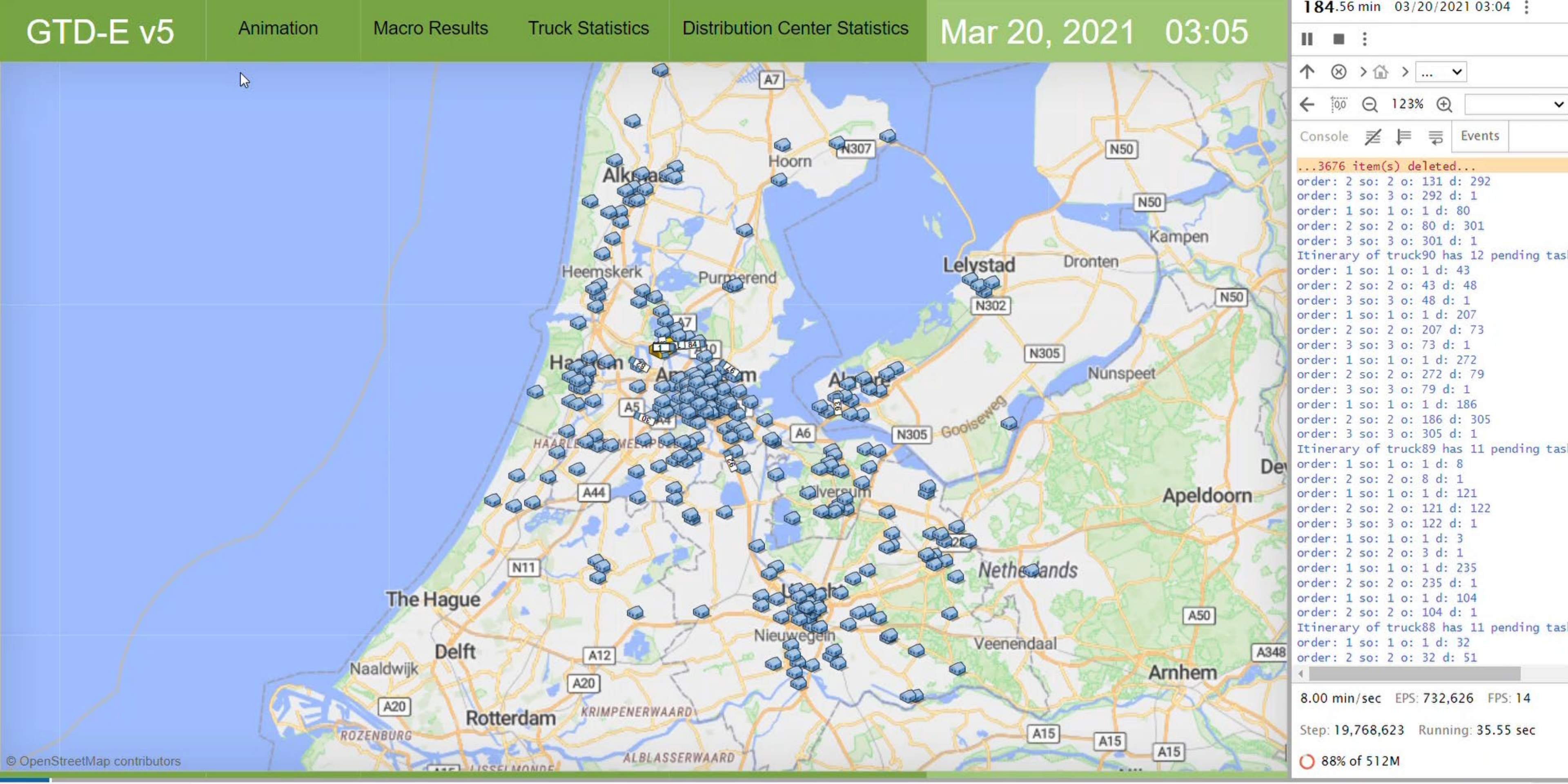
GTD-E v5
Animation
Macro Results
Truck Statistics
Distribution Center Statistics
Mar 20, 2021 03:05
184.56 min 03/20/2021 03:04
123%
Console
Events
...3676 item(s) deleted...
order: 2 so: 2 o: 131 d: 292
order: 3 so: 3 o: 292 d: 1
order: 1 so: 1 o: 1 d: 80
order: 2 so: 2 o: 80 d: 301
order: 3 so: 3 o: 301 d: 1
Itinerary of truck90 has 12 pending tas
order: 1 so: 1 o: 1 d: 43
order: 2 so: 2 o: 43 d: 48
order: 3 so: 3 o: 48 d: 1
order: 1 so: 1 o: 1 d: 207
order: 2 so: 2 o: 207 d: 73
order: 3 so: 3 o: 73 d: 1
order: 1 so: 1 o: 1 d: 272
order: 2 so: 2 o: 272 d: 79
order: 3 so: 3 o: 79 d: 1
order: 1 so: 1 o: 1 d: 186
order: 2 so: 2 o: 186 d: 305
order: 3 so: 3 o: 305 d: 1
Itinerary of truck89 has 11 pending tas
order: 1 so: 1 o: 1 d: 8
order: 2 so: 2 o: 8 d: 1
order: 1 so: 1 o: 1 d: 121
order: 2 so: 2 o: 121 d: 122
order: 3 so: 3 o: 122 d: 1
order: 1 so: 1 o: 1 d: 3
order: 2 so: 2 o: 3 d: 1
order: 1 so: 1 o: 1 d: 235
order: 2 so: 2 o: 235 d: 1
order: 1 so: 1 o: 1 d: 104
order: 2 so: 2 o: 104 d: 1
Itinerary of truck88 has 11 pending tas
order: 1 so: 1 o: 1 d: 32
order: 2 so: 2 o: 32 d: 51
8.00 min/sec EPS: 732,626 FPS: 14
Step: 19,768,623 Running: 35.55 sec
88% of 512M
Hoorn
Heemskerk
Purmerend
Lelystad
Dronten
Kampen
Nunspeet
Apeldoorn
Netherlands
The Hague
Delft
Naaldwijk
Rotterdam
Veenendaal
Arnhem
Nieuwegein
ROZENBURG
KRIMPENERWAARD
ALBLASSERWAARD
Gooiseweg
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Experimental setup for validation

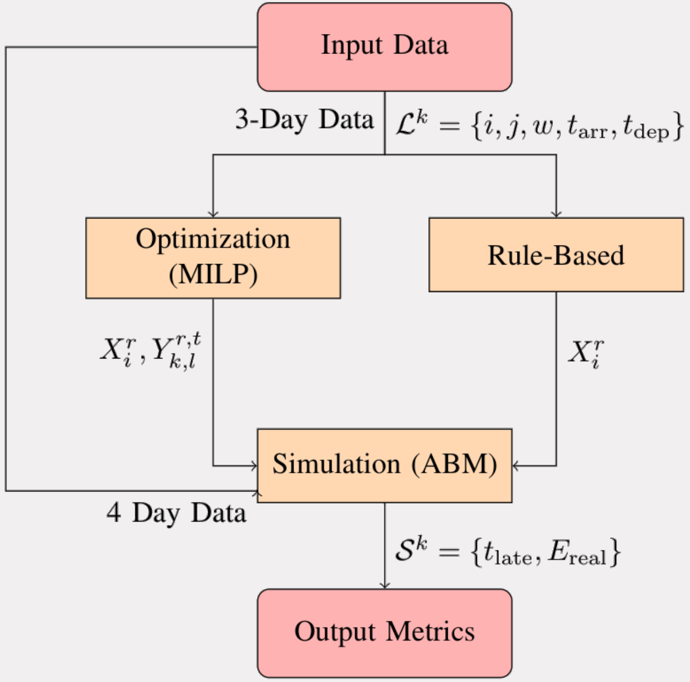


Figure 15: Framework flowchart for design validation

Table 5: Experiments defined with type of charging infrastructure and scheduling methodology

Experiment ID	Infrastructure	Scheduling
RR	Rule-based	Rule-based
RO	Rule-based	Optimized
OR	Optimized	Rule-based
OO	Optimized	Optimized

- We design for part of the total period, and then validate on an extended schedule.
- We devise 4 experiments, varying from non-optimized, to partly optimized, to fully optimized.

Results: Charging and queuing times

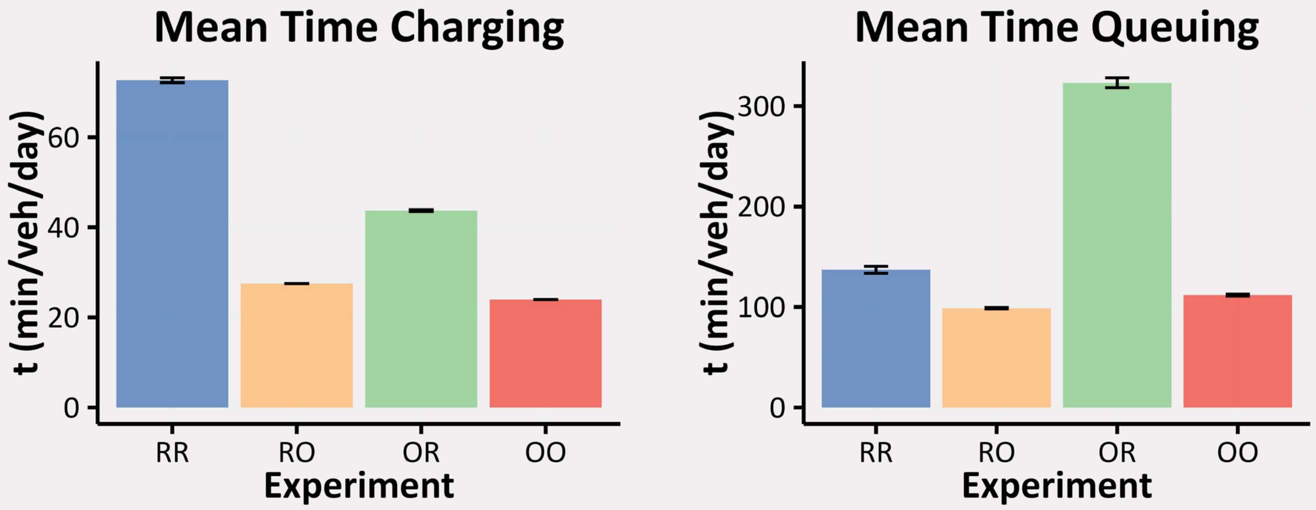
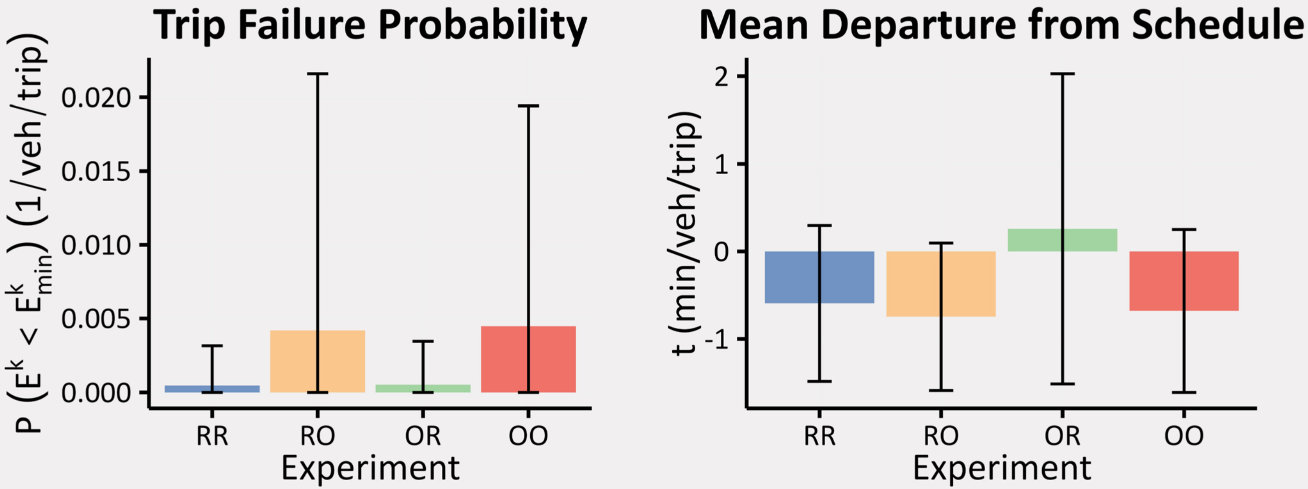


Figure 16: Charging and queuing time results for simulation (N=100)

- Optimization of schedules leads to less charging times (better allocation to faster chargers). Optimization of infrastructure too
- Optimized infrastructure falls short in terms of queuing with non optimized schedules.

Results: Probability of trip failure and deviation from scheduled delivery time



- Defining failure as the probability a state of chart for a truck k to drop below E_{min}, Optimized schedules show higher probability of failure and higher variability
- Departures from schedule are highest and most variable with the optimized infrastructure-but rule-based charging

Figure 17: Failure probability and departure from schedules results for simulation (N=100)

Discussion

A. Implications for companies considering electric vehicle adoption

- Truck range **capacity** vis-à-vis **planned operations** impacts greatly the **required infrastructure**. Tighter schedules = more fast chargers.
- This in turn affects the **patterns of consumption curves** at distribution centres.
- **Peak pricing** and **Power Infrastructure** will play a **determinant role** on final charging solutions.
- Coordination and **Energy Management Systems** are **key** in the transition to BETs

B. Optimization and simulation methodology

- Considering **jointly charging and infrastructure** can lead to improved cost designs, especially with maximum power constraints on site
- With simulation can model different **coordination strategies and obtain reliability results** for different designs, and planning for future scenarios

Figure 18: Argentina still celebrating the 2022 world cup victory

Thanks!

SUSTAINABLE FREIGHT WORKSHOP **04 - 12 - 2023**

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