Vehicle Sharing Systems: Does demand forecasting yield a better service?

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Outline

1. Introduction
   - Proposed framework
2. Methodology
   - The idea
   - Simulation
   - Mathematical model
3. Computational experiments
   - Parameter settings
   - Scenarios
   - Results
4. Conclusion

What is a Vehicle Sharing System (VSS)?

A VSS enables users to use the available vehicles generally for short period of time.

Challenges

These systems experience many challenges:

- Vehicle imbalance,
- Pricing,
- Demand modeling,
- etc.

The framework

To understand how these are related, we propose a management framework for VSSs (Atac et al., 2019).

- From decision maker point of view
- Applies to any kind of VSS
- Three dimensional classification
  - **Decision levels:** Strategic, Tactical, and Operational
  - **Actors:** Supply and Demand
  - **Layers:** Data, Models, and Actions
- Relations between the components

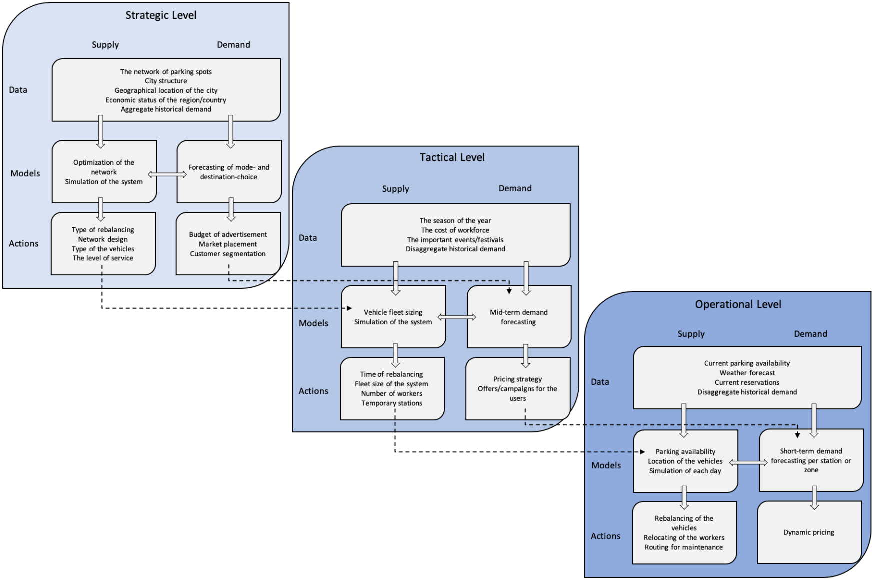


Figure: General framework and inter-relations

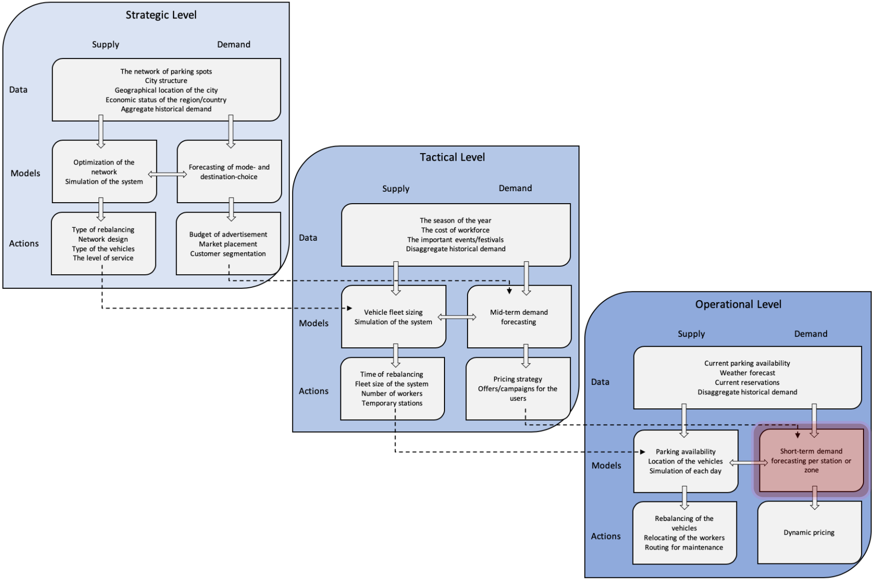
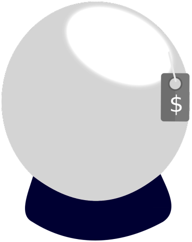


Figure: General framework and inter-relations

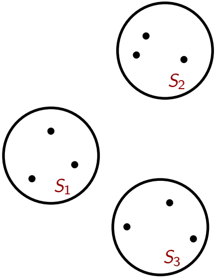
Big picture - revisited

- VSS related literature mainly focuses on rebalancing problems and their solutions by formulating them as VRP or TSP.
- Modeling the demand is also studied, but the added value of constructing such a model is not investigated.



The idea

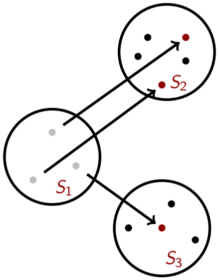
Real world



Decision center

The idea

Real world



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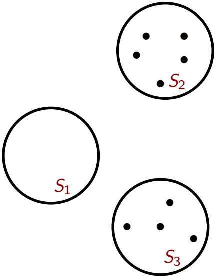

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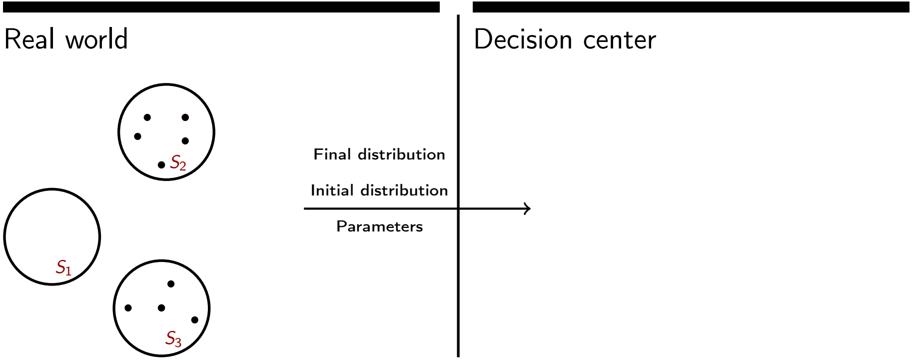
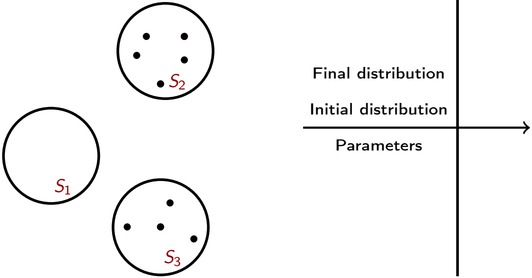

Real world
Decision center
S_2
S_1
S_3
Final distribution
Initial distribution
Parameters

The idea

Real world

Decision center

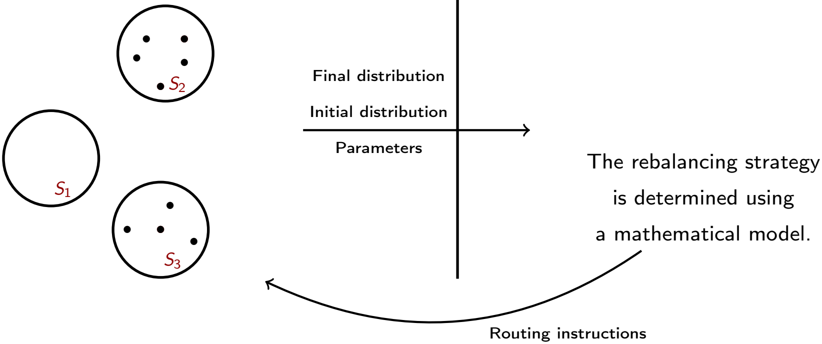


The rebalancing strategy
is determined using
a mathematical model.

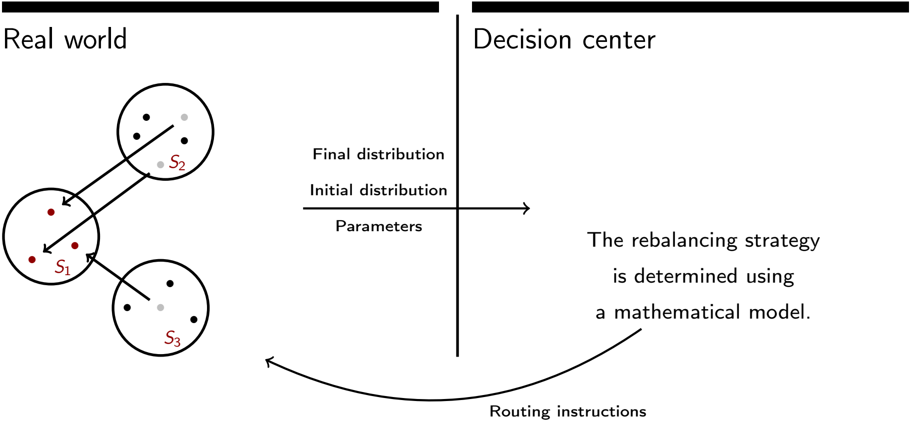
The idea

Real world

Decision center



The idea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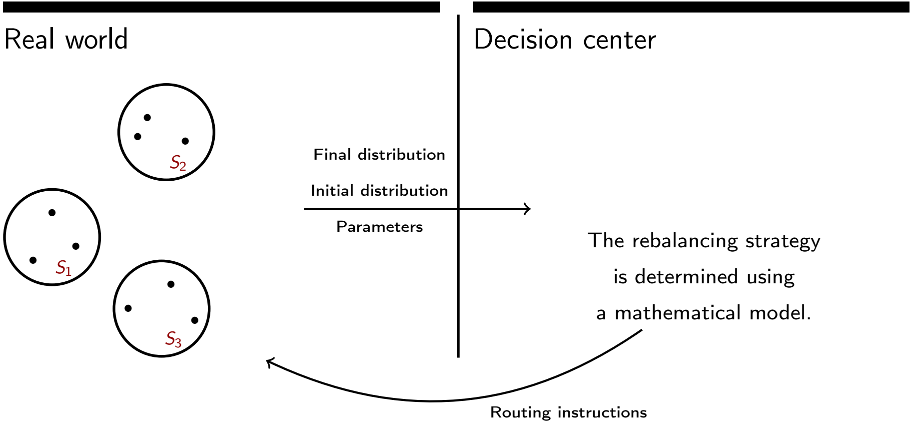
The idea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The idea

Real world

Discrete event simulations:

1- the daily demand

2- the rebalancing operations

Modeling flexible and

stochastic system behavior

Decision center

Mathematical models

to determine the routing of

rebalancing operations

More specific and

sometimes unrealistic decisions

The cases

Two cases are investigated:

- **Unknown demand:** we rebalance the system to the same initial state every day.
- **Known demand:** we assume that we perfectly know the trip demand of the following day. The initial state of the next day is determined by considering the pick-up and drop-offs at a station throughout the time horizon of the following day.

The main idea is to see how the cost of rebalancing operations and the number of lost demand differ between the two cases.

Real world - Simulation

State variables:

- t: time,
- Current vehicle availability at each station,
- Location of the orders in the system.

Parameters:

- T: the time horizon,
- N: the number of stations,
- P: number of time windows,
- C_i: the capacity of a station i, $i = 1, ..., N$,
- c_{ij}^k: the distance from station i to station j with mode k, $i = 1, ..., N$, $j = 1, ..., N$, and $k = \{\text{'walking'}, \text{'bicycle'}, \text{'car'}\}$,
- TW_p: the p^{th} time window, $p = 1, ..., P$,
- λ_p: the number of O-D pair requests per hour for time window p, $p = 1, ..., P$.

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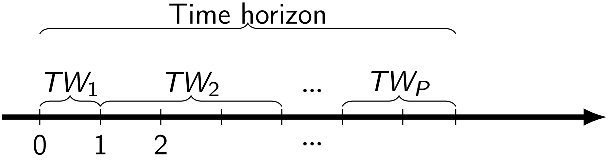

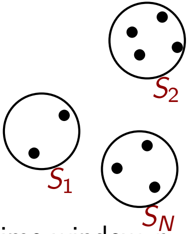

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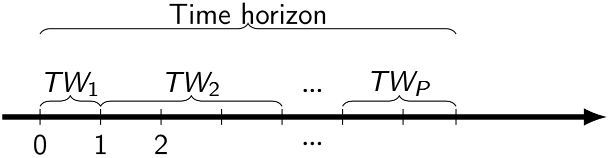

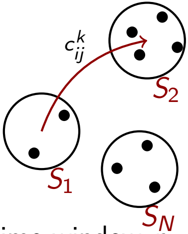

- λ_p: the number of O-D pair requests per hour for time window p, $p = 1, ..., P$.

Real world - Simulation

Indicators:

- The travel time from origin to destination and from pick-up station to drop-off station,
- Number of users using the system,
- The number of lost demand.

Assumptions:

- After T, only the events in the system are served and no new requests are accepted.
- Reserving a vehicle is not possible.
- The O-D pair requests are spatially and temporally uniformly distributed.

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Decision center

Set:

- V: the set of stations, $V = \{0, ..., N\}$, where $\{0\}$ is the depot.

Parameters:

- m: the number of relocation vehicles available,
- Q: the capacity of a relocation vehicle,
- c_{ij}: the length of the shortest path between i and j, $\forall i, j \in V$,
- q_i: the difference between the number of bikes at station i at the end of the previous day and the number of bikes desired at the beginning of the next day, $\forall i \in V$.

Decision variable:

$$x_{ij} = \begin{cases} 1, & \text{if arc } (i,j) \text{ is used by a relocation vehicle} \\ 0, & \text{otherwise} \end{cases} \quad \forall i, j \in V, \qquad (1)$$

Decision center - Modified model (Dell'Amico et al., 2013)

$$\min \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \tag{2}$$

$$\text{s.to} \quad \sum_{i \in V} x_{ij} = 1 \qquad \forall j \in V \setminus \{0\} \tag{3}$$

$$\sum_{i \in V} x_{ji} = 1 \qquad \forall j \in V \setminus \{0\} \tag{4}$$

$$\sum_{j \in V} x_{0j} \leq m \tag{5}$$

$$\sum_{j \in V \setminus \{0\}} x_{0j} = \sum_{j \in V \setminus \{0\}} x_{j0} \tag{6}$$

$$u_i - u_j + n * x_{ij} \leq n - 1 \qquad \forall i, j \in V \setminus \{0\} \tag{7}$$

$$1 \leq u_i \leq n \qquad \forall i \in V \tag{8}$$

$$\min\{Q, Q + q_j\} \geq \theta_j \geq \max\{0, q_j\} \qquad \forall j \in V \tag{9}$$

$$\theta_j - \theta_i + M(1 - x_{ij}) \geq q_j \qquad \forall i \in V, j \in V \setminus \{0\} \tag{10}$$

$$\theta_i - \theta_j + M(1 - x_{ij}) \geq q_j \qquad \forall i \in V \setminus \{0\}, j \in V \tag{11}$$

$$x_{ij} + \sum_{h \in S(i,j)} x_{jh} \leq 1 \qquad \forall i, j \in V \setminus \{0\}, h \in S(i,j) \tag{12}$$

$$\sum_{h \in S(i,j)} x_{hi} + x_{ij} \leq 1 \qquad \forall i, j \in V \setminus \{0\}, h \in S(i,j) \tag{13}$$

$$x_{ii} = 0 \qquad \forall i \in V \tag{14}$$

$$x_{ij} \in \{0, 1\} \qquad \forall i, j \in V \tag{15}$$

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Parameter settings

- This case study assumes bike sharing systems (BSSs).
- Station locations and the total number of vehicles available are obtained from PubliBike.
- We assume that there are 175 bikes in total and are distributed uniformly among the stations at the beginning of the time horizon. The rest of the parameters are set as follows:
  - T: 1 day,
  - N: 35,
  - C_i is set to infinity for each station $i \in V$,
  - λ_p depends on the scenario,
  - m: 2,
  - Q: 40.

Real world - Data

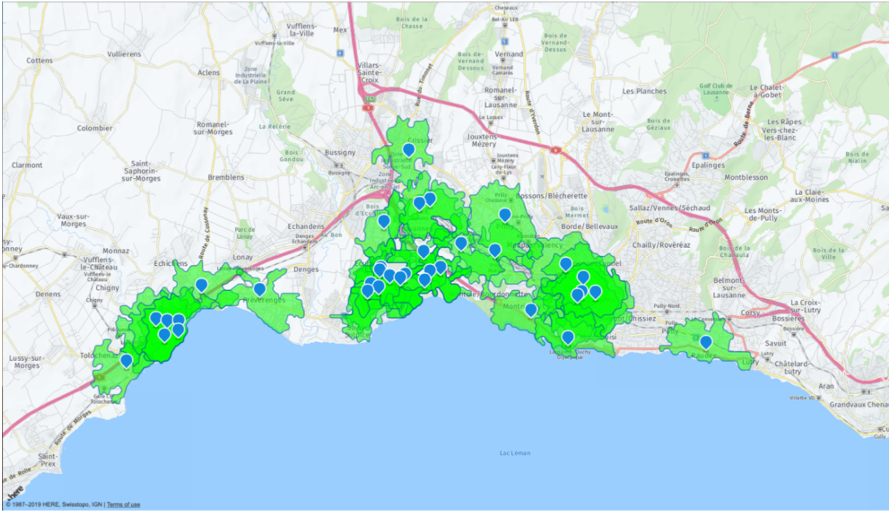


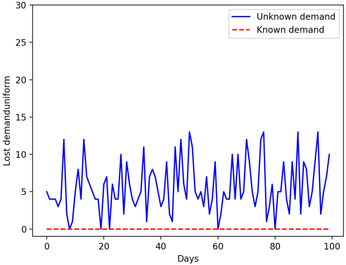
Figure: PubliBike stations and corresponding isoline polygons

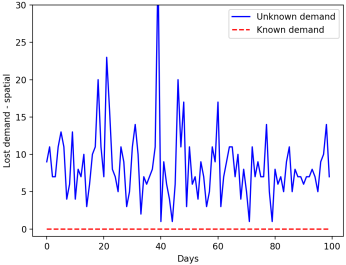
The scenarios

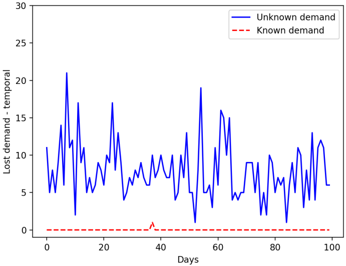
For each case we test four scenarios:

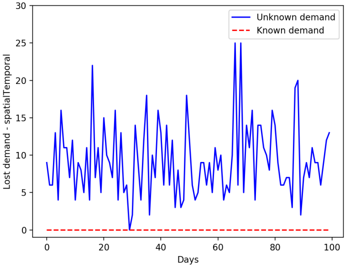
- **Uniform:** $\lambda_p = 20,\ \forall p \in P$ and demand is spatially uniformly distributed.
- **Temporal differences:** The day is divided into 5 time windows, each window has a different λ_p, and demand is spatially uniformly distributed.
- **Spatial differences:** $\lambda_p = 20,\ \forall p \in P$ but altitude differences are taken into account.
- **Spatial and temporal differences:** Both the spatial and temporal differences mentioned above are taken into account.

Lost demand vs days









Lost demand - comparing the scenarios

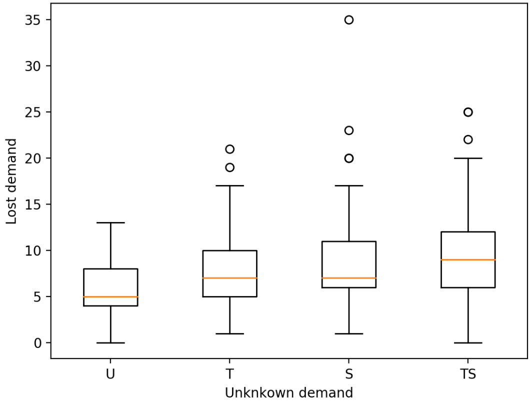
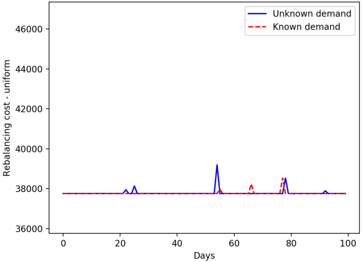
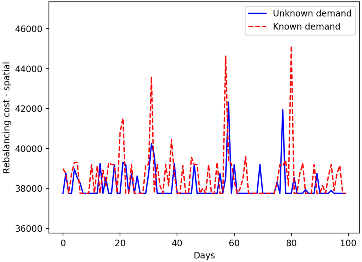
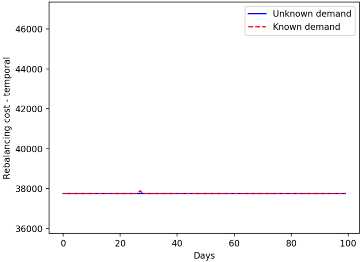


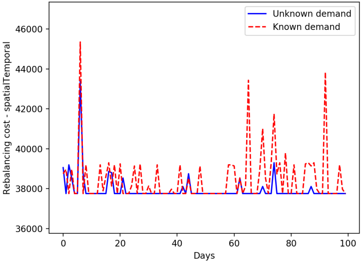
Figure: Lost demand over 100 days (Unknown demand case)

Rebalancing cost vs days









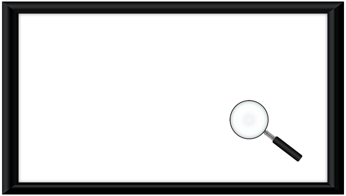
Results obtained so far

- The main structure of the framework is completed.
- The discrete-event simulator of the VSS daily demand is developed.
- A mathematical model for rebalancing operations is selected from the literature and it is modified so that it can solve the problem with 35 stations.
- A small case study showed promising results.

Future work

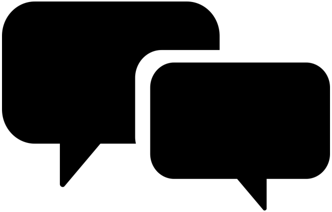
The future work includes

- The development of rebalancing simulation
- The consideration of different scenarios
- Application on real data[1]



[1] https://bikeshare-research.org

Questions and discussion



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Simulation events

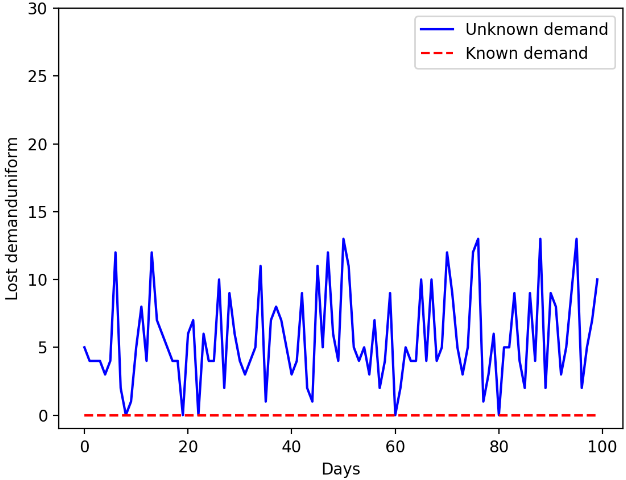
- Station-based configuration is assumed.
- Reservations are not possible.

Event	Triggered Event	Queue
`Sim Start`	`REQUEST`, `Sim End`	-
`REQUEST`	`REQUEST` (if $t < T$), `PICKUP` (if an available station is in 20 min walk)	$ns = ns + 1$ -
`PICKUP`	`DROPOFF` (if there are available vehicles)	$nu = nu + 1$
`DROPOFF`	`DROPOFF` (if no parking available), `COMPLETED`	- $nu = nu - 1$
`COMPLETED`		$ns = ns - 1$
`Sim End`		-

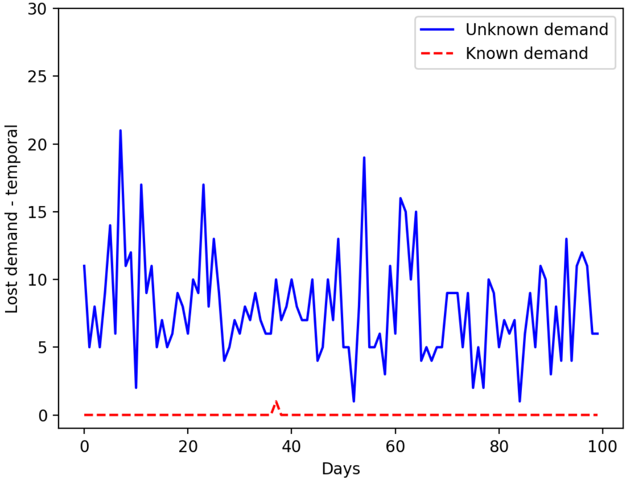
Mathematical model - The base model (Dell'Amico et al., 2013)

$$
\begin{aligned}
(F3)\ \min \quad & \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} & \\
\text{s.to} \quad & \sum_{i \in V} x_{ij} = 1 & \forall j \in V \setminus \{0\} \\
& \sum_{i \in V} x_{ji} = 1 & \forall j \in V \setminus \{0\} \\
& \sum_{j \in V} x_{0j} \leq m & \\
& \sum_{j \in V \setminus \{0\}} x_{0j} = \sum_{j \in V \setminus \{0\}} x_{j0} & \\
& \sum_{i \in S} \sum_{j \in S} x_{ij} \leq |S| - 1 & \forall S \subseteq V \setminus \{0\}, S \neq \emptyset \\
& \min\{Q, Q + q_j\} \geq \theta_j \geq \max\{0, q_j\} & \forall j \in V \\
& \theta_j - \theta_i + M(1 - x_{ij}) \geq q_j & \forall i \in V, j \in V \setminus \{0\} \\
& \theta_i - \theta_j + M(1 - x_{ij}) \geq q_j & \forall i \in V \setminus \{0\}, j \in V \\
& x_{ij} \in \{0, 1\} & \forall i, j \in V
\end{aligned}
$$

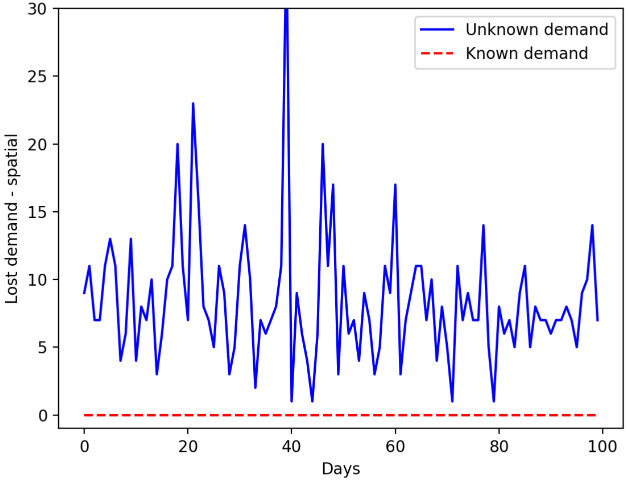
Lost demand vs days - Uniform



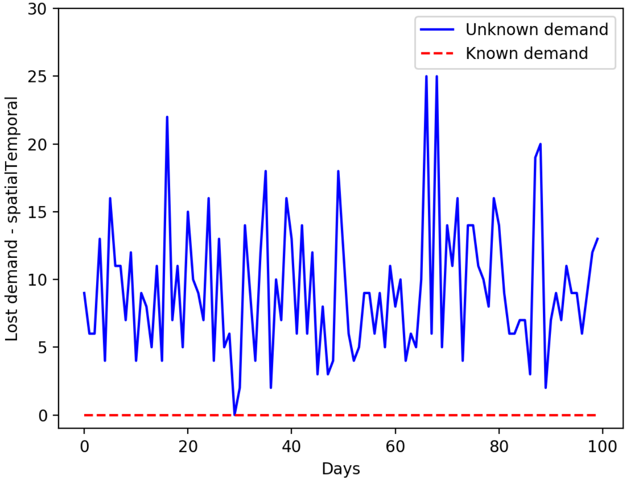
Lost demand vs days - Temporal



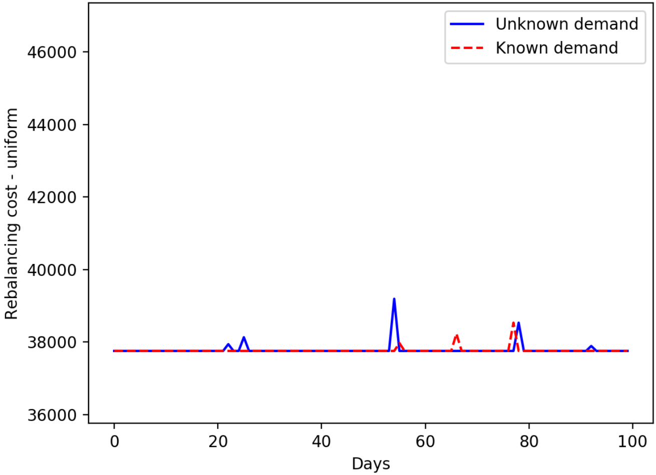
Lost demand vs days - Spatial



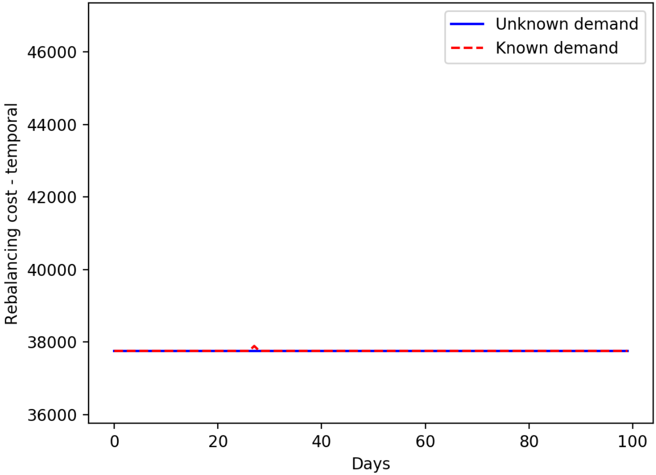
Lost demand vs days - Spatial and temporal



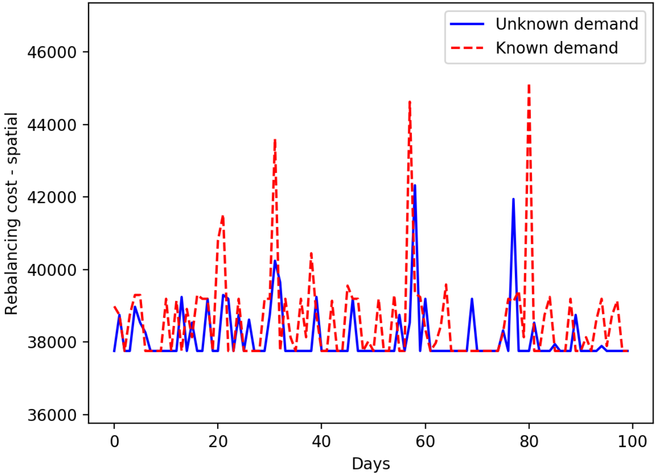
Rebalancing cost vs days - Uniform



Rebalancing cost vs days - Temporal



Rebalancing cost vs days - Spatial



Rebalancing cost vs days - Spatial and temporal