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

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Outline

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   - Proposed framework

2. Methodology
   - The idea
   - Simulation
   - Mathematical model

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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.
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
Introduction

Proposed framework

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

\[ S_1, S_2, S_3 \]

Decision center
The idea

Real world

Decision center

$S_1$ $S_2$ $S_3$
The idea

Real world

- $S_1$
- $S_2$
- $S_3$

Decision center
The idea

Real world

\[ S_1, S_2, S_3 \]

Decision center

Final distribution

Initial distribution

Parameters
The idea

Real world

- $S_1$
- $S_2$
- $S_3$

Decision center

- Initial distribution
- Final distribution
- Parameters

The rebalancing strategy is determined using a mathematical model.
The idea

Real world

Decision center

The rebalancing strategy is determined using a mathematical model.

Routing instructions

Initial distribution

Final distribution

Parameters

SA, NO, MB (TRANSP-OR/EPFL)
The idea

Real world

Decision center

The rebalancing strategy is determined using a mathematical model.

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Initial distribution

Parameters
The idea

Real world

- \( S_1 \)
- \( S_2 \)
- \( S_3 \)

Decision center

- Initial distribution
- Final distribution
- Parameters

Routing instructions

The rebalancing strategy is determined using a mathematical model.
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 $i$, $i = 1, \ldots, N$,
- $c_{ij}^k$: the distance from station $i$ to station $j$ with mode $k$, $i = 1, \ldots, N$, $j = 1, \ldots, N$, and $k = \{'walking','bicycle','car'\}$,
- $TW_p$: the $p^{th}$ time window, $p = 1, \ldots, P$,
- $\lambda_p$: the number of O-D pair requests per hour for time window $p$, $p = 1, \ldots, P$. 
Real world - Simulation

State variables:
- $t$: time,
- Current vehicle availability at each station,
- Location of the requests in the system.

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

![Diagram of Time horizon and stations](image)
Real world - Simulation

State variables:
- $t$: time,
- Current vehicle availability at each station,
- Location of the requests in the system.

Parameters:
- $\lambda_p$: the number of O-D pair requests per hour for time window $p$, $p = 1, \ldots, P$. 
- $TW_1$, $TW_2$, ..., $TW_P$: time windows.
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.
Real world - Simulation

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- The travel time from origin to destination and from pick-up station to drop-off station,
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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:
\[
x_{ij} = \begin{cases} 
1, & \text{if arc } (i,j) \text{ is used by a relocation vehicle} \\
0, & \text{otherwise} 
\end{cases} \quad \forall i, j \in V, \quad (1)
\]
Decision center - Modified model (Dell’Amico et al., 2013)

\[
\begin{align*}
\text{min} \quad & \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \\
\text{s.to} \quad & \sum_{i \in V} x_{ij} = 1 \quad \forall j \in V \setminus \{0\} \\
& \sum_{i \in V} x_{ji} = 1 \quad \forall j \in V \setminus \{0\} \\
& \sum_{j \in V} x_{0j} \leq m \\
& \sum_{j \in V \setminus \{0\}} x_{0j} = \sum_{j \in V \setminus \{0\}} x_{j0} \\
& u_i - u_j + n \times x_{ij} \leq n - 1 \quad \forall i, j \in V \setminus \{0\} \\
& 1 \leq u_i \leq n \quad \forall i \in V \\
\end{align*}
\]
Decision center - Modified model (Dell’Amico et al., 2013)

\[ \min \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij} \]  \hspace{1cm} (2)

s.to \[ \sum_{i \in V} x_{ij} = 1 \] \hspace{1cm} \forall j \in V \setminus \{0\} \hspace{1cm} (3)

\[ \sum_{j \in V} x_{ji} = 1 \] \hspace{1cm} \forall j \in V \setminus \{0\} \hspace{1cm} (4)

\[ \sum_{j \in V} x_{0j} \leq m \] \hspace{1cm} (5)

\[ \sum_{j \in V \setminus \{0\}} x_{0j} = \sum_{j \in V \setminus \{0\}} x_{j0} \] \hspace{1cm} (6)

\[ u_i - u_j + n \cdot x_{ij} \leq n - 1 \] \hspace{1cm} \forall i, j \in V \setminus \{0\} \hspace{1cm} (7)

\[ 1 \leq u_i \leq n \] \hspace{1cm} \forall i \in V \hspace{1cm} (8)

\[ \min \{Q, Q + q_j\} \geq \theta_j \geq \max \{0, q_j\} \] \hspace{1cm} \forall j \in V \hspace{1cm} (9)

\[ \theta_j - \theta_i + M(1 - x_{ij}) \geq q_i \] \hspace{1cm} \forall i \in V, j \in V \setminus \{0\} \hspace{1cm} (10)

\[ \theta_i - \theta_j + M(1 - x_{ij}) \geq q_j \] \hspace{1cm} \forall i \in V \setminus \{0\}, j \in V \hspace{1cm} (11)

\[ x_{ij} + \sum_{h \in S(i,j)} x_{jh} \leq 1 \] \hspace{1cm} \forall i, j \in V \setminus \{0\}, h \in S(i,j) \hspace{1cm} (12)

\[ \sum_{h \in S(i,j)} x_{hi} + x_{ij} \leq 1 \] \hspace{1cm} \forall i, j \in V \setminus \{0\}, h \in S(i,j) \hspace{1cm} (13)

\[ x_{ii} = 0 \] \hspace{1cm} \forall i \in V \hspace{1cm} (14)

\[ x_{ij} \in \{0, 1\} \] \hspace{1cm} \forall i, j \in V \hspace{1cm} (15)
Decision center - Modified model (Dell’Amico et al., 2013)

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

s.to \[
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\sum_{i \in V} x_{ji} = 1 \quad \forall j \in V \setminus \{0\} \tag{4}
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\sum_{j \in V} x_{0j} \leq m \tag{5}
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\sum_{j \in V \setminus \{0\}} x_{0j} = \sum_{j \in V \setminus \{0\}} x_{j0} \tag{6}
\]

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

\[
u \leq u \leq n \quad \forall i \in V \tag{8}
\]

\[
\min \{Q, Q + q_j\} \geq \theta_j \geq \max\{0, q_j\} \tag{9}
\]

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\]

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\]

\[
x_{ij} \in \{0, 1\} \quad \forall i, j \in V \tag{15}
\]
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 $i \in V$,
- $\lambda_p$ 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 $\lambda_p$, 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

![Graph 1](result1.png)

![Graph 2](result2.png)

![Graph 3](result3.png)

![Graph 4](result4.png)
Lost demand - comparing the scenarios

**Figure:** Lost demand over 100 days (Unknown demand case)
Rebalancing cost vs days

- **Unknown demand**
- **Known demand**
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

1https://bikeshare-research.org
Questions and discussion

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References II


Simulation events

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

<table>
<thead>
<tr>
<th>Event</th>
<th>Triggered Event</th>
<th>Queue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sim Start</td>
<td>REQUEST, Sim End</td>
<td>-</td>
</tr>
<tr>
<td>REQUEST</td>
<td>REQUEST (if $t &lt; T$), PICKUP (if an available station is in 20 min walk)</td>
<td>$ns = ns + 1$</td>
</tr>
<tr>
<td>PICKUP</td>
<td>DROPOFF (if there are available vehicles)</td>
<td>$nu = nu + 1$</td>
</tr>
<tr>
<td>DROPOFF</td>
<td>DROPOFF (if no parking available), COMPLETED</td>
<td>-</td>
</tr>
<tr>
<td>COMPLETED</td>
<td></td>
<td>$nu = nu - 1$</td>
</tr>
<tr>
<td>Sim End</td>
<td></td>
<td>$ns = ns - 1$</td>
</tr>
</tbody>
</table>
Mathematical model - The base model (Dell’Amico et al., 2013)

\[(F3) \min \sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}\]

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\sum_{i \in S} \sum_{j \in S} x_{ij} \leq |S| - 1 \quad \forall S \subseteq V \setminus \{0\}, S \neq \emptyset
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\min\{Q, Q + q_j\} \geq \theta_j \geq \max\{0, q_j\} \quad \forall j \in V
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\[
x_{ij} \in \{0, 1\} \quad \forall i, j \in V
\]
Lost demand vs days - Uniform

![Graph showing lost demand vs days for Uniform distribution with blue line for unknown demand and red dashed line for known demand.](image-url)
Lost demand vs days - Temporal
Lost demand vs days - Spatial

Legend:
- Blue line: Unknown demand
- Red dashed line: Known demand
Lost demand vs days - Spatial and temporal
Rebalancing cost vs days - Uniform

[Graph showing rebalancing cost vs days for unknown and known demand]
Rebalancing cost vs days - Temporal
Rebalancing cost vs days - Spatial

![Graph showing rebalancing cost vs days]
Rebalancing cost vs days - Spatial and temporal

![Graph showing rebalancing cost vs days for spatial and temporal rebalancing](image-url)