1 Introduction

Research has shown that one-way carsharing systems tend to suffer from spatial imbalance in the distribution of vehicles across stations. Such imbalance occurs even in idealized cities where origins and destinations are uniformly distributed over the network (Daganzo et al., 2013; Barrios and Doig, 2014). Carsharing Organizations (CSOs) are thus constantly seeking strategies to mitigate the costly vehicle stock imbalance problem.

Relocation strategies are to date the most prevalent approach to mitigate the shortage problem. Operator-based strategies, which involve using trucks or personnel to carry out the relocation, have been investigated by means of a discrete event simulations based on queuing theory (Barth and Todd, 2014), heuristic algorithms based on likelihood of minimizing shortage possibilities (Duron et al., 2000), and stochastic MIP to minimize relocation costs (Nair and Miller-Hooks, 2011). Previous work has also focused on user-based strategies using the prize model (Weikl and Bogenberger, 2014; Pfrommer et al., 2014; Febbraro et al., 2012), which consists of financially incentivizing users to drop-off the vehicle at an alternative destination that suffers from vehicle shortage.

This work explores mixing relocation strategies (user- and operator- based) as a solution to the imbalance problem, and highlights the resulting potential environmental benefits in terms of reduction in Vehicle Miles Traveled (VMT) as opposed to purely maximizing profit. To this end, we first explore the environmental benefits of pairing the strategies using an agent-based simulation model and heuristic algorithm in a city with uniformly distributed demand. Next, we proceed to studying the benefits of the mixed strategy using a generalized form of the demand and optimize the relocation strategy by
means of mixed-integer linear programming (MILP).

2 Agent-Based Simulation Model

An agent-based simulation is used to simulate the carsharing operations, as previously done in the literature (Barrios and Doig, 2014), for its desirable property of modeling individual entities and capturing their interactions. The agents are the vehicles, users, and operators.

2.1 Simulation Setup

We extend the model in (Barrios and Doig, 2014) to include user-based relocation strategies. The simulation is implemented using the NETLOGO agent-based simulation model (Wilensky, 1999) and uses parameters calibrated in (Barrios and Doig, 2014) for Austin’s one-way carsharing service Car2Go in 2011. The algorithm used is greedy in that it continuously maximizes the service area coverage (defined as the proportion of the city’s areas falling within walking distance of a vehicle). The simulation is run for the equivalent of 24 days of continuous operations to allow for the observation of the expected value of performance metrics (e.g. service area coverage, VMT per trip, etc.). Once the user inputs their destination of choice, the system identifies any alternative destination to which the user can be redirected that is falls within a maximum acceptable walking distance form the user’s actual destination. The user’s probability of accepting the proposed alternative is modeled as a Bernoulli trial where the probability of success is pre-determined. The operators are either idle or relocating vehicles to locations in shortage by choosing the closest area available with a surplus of vehicles.

2.2 Performance of the Combined Strategy

We plot the number of operators in each scenario versus the system-wide probability of user relocation acceptance in Figure 1. The VMT per trip are portrayed with the various shades while the service area coverage is given by the white isoquants. We find that there is a trade-off: while user-based relocations achieve lower VMT per trip, they are unable to provide high service area coverage for a realistic level of user relocation acceptance. Therefore, a combination of both user- and operator- based strategies is indispensable for reducing negative environmental impacts. We highlight the combination of strategies needed to achieve the desired level of service area coverage while minimizing VMT per trip.

Figure 1: Contour Map
3 Mixed-Integer Linear Program

We formulate the following MILP model for the general case of the demand distribution. The decision variables (relocation strategy) and parameters are described in Table 1. The lower bound on this problem (i.e. maximum VMT incurred) is equivalent to solving the problem with a fully operator based relocation strategy.

\[
\text{minimize } \sum_{u \in U} \sum_{k \in J} \sum_{j \in J} \sum_{i \in J} a_{i,j,u} y_{i,j,k,u} (1 - p_{i,j,k}) d_{ij} \\
+ \sum_{u \in U} \sum_{k \in J} \sum_{j \in J} \sum_{i \in J} a_{i,j,u} y_{i,j,k,u} p_{i,j,k} d_{jk} \\
+ \sum_{u \in U} \sum_{k \in J} \sum_{j \in J} \sum_{i \in J} a_{i,j,u} y_{i,j,k,u} (1 - p_{i,j,k})^2 d_{jk}
\]

Subject to: (1) Relocating the user only once:

\[
\sum_{k \in J} y_{i,j,k,u} = 1 \quad \forall i,j,u \quad (i \neq j)
\]

(2) Maximum walking distance:

\[
y_{i,j,k,u} d_{jk} \leq D \quad \forall i,j,k,u
\]

(3) Budget:

\[
c_{o} \sum_{u \in U} \sum_{j \in J} \sum_{k \in J} \sum_{i \in J} a_{i,j,u} y_{i,j,k,u} (1 - p_{i,j,k}) \\
+ c_{u} \sum_{u \in U} \sum_{k \in J} \sum_{j \in J} \sum_{i \in J} a_{i,j,u} y_{i,j,k,u} p_{i,j,k} \leq B
\]

(4) Threshold for change in vehicles:

\[
\sum_{u \in U} \sum_{j \in J} \sum_{k \in J} a_{j,k,u} y_{j,k,i,u} p_{j,k} + \sum_{u \in U} \sum_{j \in J} a_{j,i,u} (1 - y_{j,i,k,u}) \\
+ \sum_{u \in U} \sum_{j \in J} \sum_{k \in J} a_{j,i,u} y_{j,i,k,u} (1 - p_{i,j,k}) - \sum_{u \in U} a_{i,j,u} \leq T \quad \forall i \in J
\]

(5) Binary constraint: \( y_{i,j,k,u} \in \{0, 1\} \quad \forall i, j, k, u \)

Table 1: Decision Variables and Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
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<tbody>
<tr>
<td>( y_{i,j,k,u} )</td>
<td>Binary decision variable, matrix Y reveals the relocation strategy. Entry is 1 if user u wishing to travel from i to j is relocated to k and 0 otherwise</td>
</tr>
<tr>
<td>( a_{i,j,u} )</td>
<td>Origin Destination matrix: entry is 1 if user u wishes to travel from i to j and 0 otherwise. Example distribution: ( \sum_{i,j} a_{i,j,u} \sim \text{Poisson}(\lambda) )</td>
</tr>
<tr>
<td>( p_{i,j,k} )</td>
<td>binary variable for accepting relocation from j to k with origin i: drawn from a Bernoulli trial with predefined probability of success p</td>
</tr>
<tr>
<td>( d_{ij}, \text{ and } D )</td>
<td>distance between locations i and j, and maximum acceptable walking distance</td>
</tr>
<tr>
<td>( J, \text{ and } U )</td>
<td>set of locations, and set of users</td>
</tr>
<tr>
<td>( B )</td>
<td>budget of the CSO (found from fully operator-based strategy)</td>
</tr>
<tr>
<td>( T )</td>
<td>threshold for the change in vehicles at a station during a time horizon</td>
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</table>
Future work entails solving the above MILP for the generalized demand distribution, and comparing the results for uniform demand to the current findings from the simulation. This study is limited in that the probability of user relocation acceptance is not fully investigated: the probabilities can be estimated by means of a binomial logit model through providing a discrete choice for accepting and rejecting the relocation based on the extra walking distance incurred by the user and the financial incentive given to the user.

References


