ECOLOGICAL & PROFITABLE CARSHARING BUSINESS: EMISSION LIMITS & HETEROGENEOUS FLEETS

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Research paper

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Abstract

Carsharing is a mobility concept that addresses the world’s growing interest in sustainability. It reduces CO\textsubscript{2} emissions, traffic congestion, and noise in cities. Including electric and hybrid vehicles in the carsharing fleet supports these aspects even more. For a station-based carsharing organization (CSO), the distribution and availability of vehicles play a crucial role to satisfy the customers’ needs as well as to obtain profits. We developed a tactical optimization model to determine the size and composition of a heterogeneous carsharing fleet while considering different emission limits with time-dependent demand profiles. Different propulsion modes and vehicle classes represent the heterogeneity of the fleet. Using the application example of the city of San Francisco, results are presented, discussed, and analyzed. Our benchmarks for two different demand scenarios reveal the strong influence of a preset maximum level of CO\textsubscript{2} emissions on fleet composition and monthly net profit. The optimization model allows CSOs to provide a sustainable and profitable mobility concept; city planners are supported to evaluate influences of CO\textsubscript{2} emission thresholds on CSOs. The model thereby represents a Green IS approach, as it contributes to supporting a society’s path towards a low emission and noise-reduced environment in urban areas where carsharing is feasible.

Keywords: Carsharing, Emission Limits, Decision Support, Green IS.

1 Introduction and Motivation

A growing level of eco-consciousness in both public and business sectors, combined with an increasing percentage of the world living in cities, evokes a rethinking of car usage and personal vehicle ownership (Dedrick, 2010; Shaheen and Cohen, 2013). According to estimates for the year 2030, it is expected that approximately 60 % of the world’s population is living in cities (Shaheen and Cohen, 2013). Besides these factors, economic uncertainty, rising energy costs, and the wish to reduce CO\textsubscript{2} emissions are reasons why the means of transportation are being widely reconsidered. A comparatively new mobility concept that addresses this question is carsharing (Shaheen and Cohen, 2013). Carsharing means that individuals gain access to a fleet of shared-use vehicles in an urban area and pay on an as-needed basis (Shaheen et al., 2005). The development of the mobility market in general seems to be faster than ever before, which is reasonable especially due to technological progress and modern information and communication technologies. These facts also apply to the carsharing development. The availability, location, and status of each carsharing vehicle can be checked online at any time and any place. This greatly simplified carsharing services in recent years. Today a high service level can be offered to the customers (Hayashi et al., 2014; Kaspi et al., 2014). Owing to these circumstances, the number of people using carsharing is rising rapidly, which is observable all over the world. For example zipcar, which is one of...
the leading organizations in terms of carsharing, serves 950,000 members in seven countries by providing 12,000 vehicles on different vehicle types (Zipcar, 2016).

Regarding the environment, carsharing services can reduce negative impacts of vehicle usage, such as energy consumption, emissions, congestion, and inefficient land use (Shaheen and Cohen, 2008). In particular, the effects of reduced emissions and energy consumption from limited resources can be reinforced by including vehicles with alternative propulsion modes in the carsharing fleet. Vehicles with low fuel consumption and low emissions, in many cases hybrid or electric vehicles, are already used to meet requirements of different environmental labelling programs, which are mostly voluntary nowadays (Millard-Ball et al., 2005). To satisfy the demand for carsharing trips and to benefit from advantages of vehicles with alternative propulsion modes simultaneously, the task of planning carsharing fleets is crucial to success. In general, carsharing can be distinguished between station-based and free floating services. Station-based services provide a defined number of stations, which customers can access. Free floating systems operate without fixed stations and vehicles are accessible in the operating area. While offering increased flexibility to customer, this approach is disadvantageous when using electric vehicles, which require charging infrastructures. Our article therefore focuses on station-based carsharing. The respective planning process can be structured in three different planning stages (Boyaci et al., 2015). First, the strategic planning focuses on the establishment of stations in terms of number, location, and size. Second, the tactical planning assigns vehicles to the stations. Lastly, the operational level deals with elements such as pricing or relocation approaches.

We follow a design science research approach to develop an optimization approach for tactical fleet planning based on an existing carsharing network, fixed in number, location, and size of stations. The model as resulting artifact is classified as nascent design theory (Gregor and Hevner, 2013); an applicability check serves as instantiation to evaluate the model and its results. Regarding to Green IS, this approach supports solution-oriented research in the field of sustainable transportation. We contribute to Green IS in providing decision support to optimize a two-way carsharing system with a heterogeneous fleet and a time-dependent demand to determine the optimal fleet size and composition, while fulfilling pre-defined emission limits. This leads us to the following research question:

**RQ:** How can a heterogeneous carsharing fleet be optimized while considering emission limits and demand variations?

The remainder of this article is structured as follows; first, we describe carsharing and provide an overview of related research. In section 3 we present our research. In the following section we explain and note our developed optimization model. Subsequently, we performed benchmarks for an application example. Also, we show and further discuss our results and observed sensitivities. In section 6 we describe limitations and recommendations of our approach. Finally, we provide conclusion and outlook.

## 2 Carsharing and Related Work

“Never before has world opinion been so united on a single goal as it is on achieving sustainable development” (Watson et al., 2010). Watson et al. (2010) appeal to the academic Information System (IS) community to use the “transformative power” of IS to ensure and enhance environmental sustainability and address the resulting challenges (Watson et al., 2010). The importance of IS to improve sustainability across the economy, defined as Green IS, is growing exponentially (Dedrick, 2010). The Green IS concept supports interactions of IT and humans with the prime goal of conserving resources and the environment (Watson et al., 2010; Butler, 2011). High-level modeling systems for mathematical programming and optimization represent a foundation for a variety of solver and provide user interfaces to solve complex optimization models related to environmental issues. However, studies examining Green IS research by Malhotra et al. (2013) and Gholami et al. (2016) reveal that conceptualization and analyses are overrepresented while the design and impact oriented research is lacking. With our solution-oriented research, we aim to react to these findings contributing to a further improvement of a green
transportation concept. Our optimization model for carsharing fleets meets ecological and profitable demands to recently established sustainable transportation businesses.

Carsharing is a transportation mode that offers the use of vehicles to people who have the necessary permits and who pay trip-dependent fees. After they have registered at a carsharing organization (CSO), they can use a vehicle from the fleet by picking it up and returning it to the same location. This is how the two-way (also called round-trip) carsharing concept, considered in our article, operates. Members can utilize any available vehicle of the fleet as long and as often as they want to satisfy their mobility needs. To ensure availability, members may reserve a vehicle in advance; however, spontaneous rides are possible as long as no reservation exists. This is in contrast to one-way services, where vehicles can be driven between dedicated stations, or free-floating carsharing, which allows a vehicle to be left anywhere within a designated operation area (Wagner et al., 2016). The reasons for the growing popularity of carsharing are diverse; yet, they can predominantly be summarized using the three types of sustainability that carsharing addresses: social equity, economic efficiency, and ecological awareness (Boudreau et al., 2009). Social equity is achieved by anti-discriminatory registration, meaning that anyone can use a CSO vehicle independent of social background or income. Economic sustainability often represents the most important criterion for joining a CSO, as members can achieve tremendous savings with very calculable costs per ride when compared to a private vehicle. Costs, such as procurement or leasing, fueling, depreciation, residential parking, insurance, registration fees, maintenance, repair, and car-dependent taxes simply do not affect a carsharer (Duncan, 2011). The usage of low (or even zero) emission vehicles in particular, further leads to the third type of sustainability: ecological awareness. For instance, in North America a carsharing vehicle removes approximately 15 private cars from the road (Cohen et al., 2008). An online survey by Martin and Shaheen (2011) showed a decrease in the number of vehicles per household from 0.47 to 0.24 vehicles when becoming a carsharing member.

Carsharing vehicles are newer, create less pollution, and are much more fuel-efficient than most private ones; often hybrid or electrical vehicles are used to reduce the pollution even more (Millard-Ball et al., 2005; Barth and Todd, 1999). Moreover, the typical way people use cars changes; members usually use the shared vehicle less than they would use a private one. Instead they take more trips by walking, biking, or using local public transportation systems. When carsharing is integrated into the public transportation of a city, there is a large increase in potential customers and the concept of sustainable mobility can be realized. Resulting advantages affect the whole community, which profits due to less traffic, less pollution, and less noise. In addition, it frees up parking spaces, which can be replaced with green areas (Millard-Ball et al., 2005).

The typical carsharing user appreciates the above advantages, and accordingly, is ecology-minded, well-educated, socially engaged, does not own a vehicle, regularly uses public transportation, and is usually between 24 and 40 years old, irrespective of gender (Martin et al., 2010). Geographic factors such as high population density, walkability, and mixed used urban areas with a good coverage of public transportation are important for the success of a CSO (Cohen et al., 2008; Celsor and Millard-Ball, 2007). The competitive conditions as well as the potential and development of carsharing has been further discussed in many articles. For example, Shaheen (2013) provides a global perspective on carsharing growth and future developments and anticipates electric vehicles in fleets of CSO in the coming years. Furthermore, many articles deal with different carsharing concepts, demand-related topics, or other analyses focusing on existent and running CSOs (Duncan, 2011; Efthymiou et al., 2013). Articles focusing on the establishment and planning of carsharing networks have been frequently discussed in recent years. Thereby, several optimization models have been developed underlying different decision levels and different optimization foci. Based on the wide range of this literature, only articles dealing with tactical decisions will be presented and discussed in following. In some of these articles, the decision models do not only include the fleet optimization but also strategical or operative elements.

For our literature review we carefully reviewed carsharing optimization articles, but also closely related topics such as bikesharing and car rental, which similarly require identification of optimal locations. Most of the research on bikesharing considers one-way modes since a relocation can be conducted more
easily compared to cars (Martinez et al., 2012; Askari et al., 2016). Several aspects are investigated such as the optimal location, number of stations, and routes of customers to optimize revenues, which can be partly applied to carsharing. Car rental is a similar service to carsharing which also needs several stations; however they mainly differ on the length of rental times, since traditional car rental organizations usually rent out their vehicles for whole days and even longer. The location of the stations can be determined through a mathematical model by analyzing the vehicle availability of existing rental companies, but the dimension of the fleet also must be considered to optimize profits (George and Xia, 2011). However, the circumstances of station-based carsharing differ from these businesses and hence the existing models can not immediately adopted. The distribution of stations and the number of vehicles is investigated by Cepolina and Farina (2012) who provide a cost minimization model for the distribution of personal intelligent city accessible vehicles (PICAVs) within the city of Genoa (Italy). A similar approach is the identification of points of interest to estimate the expected demand accurately and calculate the number of required vehicles or stations (Wagner et al., 2014).

The identification of optimal locations is a major topic of carsharing research. Awasthi et al. (2007) present a three-stage approach for the selection of carsharing stations and adjacent distribution of vehicles. They identify potential stations, assign allotted weights for each station, and then select the final stations for a case example in France. Musso et al. (2012) introduce a similar approach to extend an existing carsharing network by assigning three success factors to different regions and installing new stations and vehicles in the highest-rated regions. El Fassi et al. (2012) developed a decision support system for existing CSOs. It is based on a discrete event simulation, which determines the best expansion strategy for the desired investigation area. The optimization of carsharing stations locations can be assigned to strategic decisions, but in this article we consider the optimal fleet size, which is referred to tactical decisions (Boyaci et al., 2015). This concrete and specific research is very rarely investigated in recent articles. Rhee et al. (2014) provide a discrete event simulation for analyzing many different scenarios in terms of fleet size and its impact on acceptance ratio and utilization ratio to derive recommendations for fleet dimensions (Rhee et al., 2014). Costain et al. (2012) addresses the tactical decision level by proving an approach of operative allocation of rides to reduce the number of vehicles on the streets. Furthermore, optimization models for one-way carsharing services have been developed which combine strategical, tactical and even operational decisions by providing simplified mathematical models by satisfying the entire demand (Boyaci et al., 2015; Nourinejad and Roorda, 2015). The presented articles deal mostly with tactical problems, oftentimes for different travel mode businesses combined with other decision levels, which results in a lack of profundity regarding the fleet optimization for carsharing itself. The number and the allocation of vehicles to existing stations is the most crucial factor for meeting customers’ demands and to reach profits. Hence, our model focuses strictly on tactical decisions to optimize the fleet size where different vehicles types (e.g. gas, hybrid or electric) and classes (e.g., small, medium or large) can be implemented whereby additionally, certain emission limits has to be met.

3 Research Design

Our research methodology is based on design science research (DSR) principles as proposed by Hevner et al. (2004) visualized through three cycles (relevance, design, and rigor). Our applied research methodology is presented in Figure 1. In contrast to behavioral science, the design science approach systematically seeks to create “new and innovative artifacts” (Hevner et al., 2004). This means it is the most suitable approach for creating, specifying, and evaluating a carsharing model, addressing both its relevance and its rigor. Regarding relevance cycle, our work is motivated by the increasing demand for alternative transportation modes, electric mobility, \( \text{CO}_2 \) emission reduction, and the associated decision making requirements. Our current research project focusing on electric mobility, provides further information and ensures the recent relevance and importance of the problem. The review of existing knowledge in the rigor cycle represents a second essential part of the research process (Peffers et al., 2007). We conducted a comprehensive literature review within the whole carsharing domain and presented important articles focusing on tactical optimization. The design cycle is an iterative process that
uses several build-and-evaluate loops, and revises the design artifacts until they are ready for a real world application. The built-and-evaluate activities were already tested and confirmed by March and Smith (1995) to be an important dimension for research on information technology. We conducted several cycles to ensure that environmental requirements, scientific methods, and existing expertise were all taken into account. The emerged tactical optimization model as final artifact provides decision support for CSOs and is therefore classified as nascent design theory in the field of Green IS (Gregor and Hevner, 2013). We tested the optimization model extensively and present an application example as instantiation of the artifact to enable proper documentation and publication of research results.

Figure 1. Applied research methodology based on Hevner (2007).

4 Optimization Model

4.1 Assumptions

The objective of the introduced model is to maximize the monthly net profit of a CSO. It takes into consideration a station-based two-way carsharing system. Following assumptions form the foundation of the tactical model for fleet size and composition optimization:

- The number and the locations of the established carsharing stations cannot be changed by the tactical planning process, because they are determined in advance by the strategic planning. Therefore, the monthly leasing costs represent the fixed strategic cost fraction of the monthly operating costs of a CSO.
- One demand represents one trip. The demand does not need to be satisfied completely. For each unsatisfied demand of a trip, penalty costs incur and increase squarely.
- Time frames are used to illustrate peak and off-peak times in the course of a day and a month. For simplification reasons one month is considered to have 28 days. Each day is separated in four time frames, which results in 112 time frames in total. The vehicles are available again after one time frame. Therefore, a trip has to be started and finished within one time frame and cannot be extended to the next.
- Since different propulsion methods are possible to implement, fast charging infrastructures to recharge potential electric and hybrid vehicles are considered. The charging process with a conventional power outlet would require a few hours and hence, the availability of an electric vehicle could not be ensured in each time frame.
- For charging infrastructures, vehicles, and parking lots monthly leasing costs are assumed.
- The possibility of renting parking lots, charging infrastructure and vehicles for a CSO exists at the beginning of each month. Thereby, it is possible to react to monthly fluctuations in demand.
A maximum limit of parking lots is defined for each established station, and hence, the number of vehicles is also limited.

Existing stations must be equipped with at least one vehicle to avoid customers’ disappointment.

Each demand for a vehicle class at each demand location is assigned to one or more established stations and a defined maximum distance between these two must not be exceeded.

A maximum average amount of CO\textsubscript{2} emissions in g/km of the total fleet must not be exceeded due to meeting local emission prerequisites.

The revenue for renting a vehicle is charged on a time and distance basis and is differentiated by the vehicle class.

### 4.2 Notation and Mathematical Formulation

We used several input data (see Table 1) for our mathematical optimization model, which can be distinguished between sets, parameters and decision variables.

<table>
<thead>
<tr>
<th>Sets</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(c = {1, \ldots, C}) &amp; vehicle class</td>
<td>(f = {1, \ldots, F}) &amp; time frame</td>
<td></td>
</tr>
<tr>
<td>(i = {1, \ldots, I}) &amp; location of station</td>
<td>(j = {1, \ldots, J}) &amp; demand location</td>
<td></td>
</tr>
<tr>
<td>(t = {1, \ldots, T}) &amp; vehicle type (in terms of propulsion mode)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decision Variables</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(s_{cif} \geq 0) &amp; number of satisfied demand</td>
<td>(u_{cif} \geq 0) &amp; number of unsatisfied demand</td>
<td></td>
</tr>
<tr>
<td>(v_{cfit} \geq 0) &amp; number of vehicles</td>
<td>(z_{cji} \in {0, 1}) &amp; 1, if demand is assigned to a station; else: 0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameters</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_{o}c_{t}) &amp; CO\textsubscript{2} emissions of a vehicle (g/km)</td>
<td>(d_{urf}) &amp; duration of a time frame</td>
<td></td>
</tr>
<tr>
<td>(d_{cif}) &amp; Poisson distributed demand (# trips/time frame)</td>
<td>(g_{f}) &amp; factor of time frame</td>
<td></td>
</tr>
<tr>
<td>(d_{max}) &amp; max. distance between demand location and assigned station (km)</td>
<td>(comax) &amp; max. average admissible emission of CO\textsubscript{2} (g/km)</td>
<td></td>
</tr>
<tr>
<td>(d_{si}) &amp; distance between demand location and station (km)</td>
<td>(l_{fit}) &amp; leasing cost of charging infrastructure (US$/month)</td>
<td></td>
</tr>
<tr>
<td>(lp) &amp; leasing cost of a parking lot (US$/month)</td>
<td>(l_{si}) &amp; fixed cost of a station (US$/month)</td>
<td></td>
</tr>
<tr>
<td>(lv_{ct}) &amp; leasing cost of vehicle (US$/month)</td>
<td>(m_{axpi}) &amp; max. number of parking lots at a station (#)</td>
<td></td>
</tr>
<tr>
<td>(n_{t}) &amp; number of possible trips of a vehicle type (#)</td>
<td>(min) &amp; normal distribution of duration of a trip (min)</td>
<td></td>
</tr>
<tr>
<td>(dd) &amp; normal distributed distance driven per trip (km)</td>
<td>(p_{cij}) &amp; Poisson distributed demand (#)</td>
<td></td>
</tr>
<tr>
<td>(ep_{t}) &amp; average price for energy (US$/l or US$/kWh)</td>
<td>(ec_{at}) &amp; average energy consumption (l/km or kwh/km)</td>
<td></td>
</tr>
<tr>
<td>(revn_{c}) &amp; revenue for renting a vehicle (US$/min)</td>
<td>(revd_{c}) &amp; revenue for renting a vehicle (US$/km)</td>
<td></td>
</tr>
<tr>
<td>(ed) &amp; average duration of a trip (min)</td>
<td>(sd) &amp; standard deviation of duration of a trip (min)</td>
<td></td>
</tr>
<tr>
<td>(ek) &amp; distance of a trip (km)</td>
<td>(sd_{k}) &amp; standard deviation of distance of a trip (km)</td>
<td></td>
</tr>
</tbody>
</table>

Table 1. Used sets, decision variables, and parameters.

The assumptions and the above mentioned sets, decision variables, and parameters serve as a basis for our optimization model, which is formulated in the following. The objective function (1) maximizes the monthly net profit of a CSO. The first term contains the monthly revenues. For each satisfied trip, the charges for the customers are calculated per minute and distance travelled. The second term represents the variable monthly costs depending on the distances driven, the average energy consumption, and the energy price summed up for every satisfied trip. The third term contains the amount of penalty costs. For every time frame at all established stations each trip that will not be satisfied is squarely penalized. The fourth term is composed of the monthly leasing costs of built vehicles, parking lots, and charging infrastructures, if required. While the terms mentioned so far represent the tactical fraction of the monthly net profit, the last term depicts the strategic fraction. Since the stations are determined in advance by the strategic planning process, the leasing costs exist in every tactical decision level, no matter how many vehicles are included in the fleet or how much demand is satisfied or unsatisfied.
\[\begin{align*}
\text{Max} & \quad Z(s, u, v) \\
& = \sum_{c=1}^{m} \sum_{i=1}^{n} \sum_{f=1}^{o} s_{cift} \cdot (\text{min} \cdot \text{revm} + dd \cdot \text{revd}) \\
& \quad - \sum_{c=1}^{m} \sum_{i=1}^{n} \sum_{f=1}^{o} s_{cift} \cdot (dd \cdot ec_{ct} + ep_t) \\
& \quad - \sum_{c=1}^{m} \sum_{i=1}^{n} \sum_{f=1}^{o} u_{cift}^2 - \sum_{c=1}^{m} \sum_{i=1}^{n} \sum_{f=1}^{o} (v_{ct} + l_{f} + l_{p}) \cdot v_{cti} - \sum_{i=1}^{m} l_{si}
\end{align*}\]

The following restrictions (2) to (12) limit the optimization process:

\[\begin{align*}
\sum_{i=1}^{m} z_{cij} &= 1 \quad \forall c, j \\
\sum_{c=1}^{k} \sum_{j=1}^{n} z_{cji} &\geq 1, \quad \forall i \\
\sum_{c=1}^{k} \sum_{j=1}^{n} v_{cti} &\geq 1, \quad \forall i \\
\sum_{c=1}^{k} \sum_{i=1}^{n} v_{cti} &\leq \text{maxp}_i, \quad \forall i \\
d_{ij} \cdot z_{cji} &\leq \text{dismax}, \quad \forall c, j, i \\
\sum_{j=1}^{n} d_{cij} \cdot z_{cji} &= \sum_{t=1}^{o} s_{cift} + u_{cift} \quad \forall c, i, f \\
d_{cij} &= g_f \cdot p_{cj} \quad \forall c, j, f \\
s_{cift} &\leq v_{cti} \cdot n_t \quad \forall c, i, f, t \\
\sum_{c=1}^{k} \sum_{i=1}^{n} \sum_{t=1}^{o} v_{cti} \cdot co_{ct} / \sum_{c=1}^{k} \sum_{i=1}^{n} \sum_{t=1}^{o} v_{cti} &\leq \text{comax} \\
s_{cift}, u_{cift}, v_{cti} &\geq 0 \quad \forall c, i, f, t \\
z_{cji} &\in \{0, 1\} \quad \forall c, j, i
\end{align*}\]

Constraint (2) ensures that every demand value for each vehicle class \(c\) at a demand location \(j\) is assigned to exactly one established station \(i\). Thus, we sum up the binary variable \(z_{cji}\), which must be equal to one. Corresponding to our assumptions, at least one demand location has to be assigned to each established station, with one as the minimum number of vehicles \(v_{cti}\) per station. This is considered by constraints (3) and (4). The following constraint (5) denotes a maximum number of parking lots \(\text{maxp}_i\) at each established station and, correspondingly, a maximum number of vehicles that must not be exceeded. Likewise, for (6), a defined maximum distance \(\text{dismax}\) between a demand location and an assigned established station must not be exceeded. Constraint (7) indicates that the satisfied demand \(s_{cift}\) and the unsatisfied demand \(u_{cift}\) for a vehicle class in one time frame \(f\) at an established station (right side of the equation) has to be equal to all the assigned demand values for this vehicle class in this time frame.
(left side of the equation). Equation (8) expresses the expected demand $d_{clf}$ which is defined through a specific time frame factor $g_f$ (summed up to 100%) multiplied by the Poisson distributed demand $p_{clf}$. The time frame factor varies for each time frame to consider peak and off-peak times during the course of a day as well as of a month. In addition, the satisfied demand cannot be higher than all possible trips $n_t$ offered by the vehicles included in the fleet, which is shown by constraint (9). The number of possible trips in each time frame considers the average travel time and the subsequent charging time for electric vehicles before the vehicle is available for the next customer. To ensure that a maximum average amount of CO$_2$ emissions $comax$ of the total fleet will not be exceeded, constraint (10) is included in the model. Equation (11) and (12) constitute the specific value range of the decision binary variable.

5 Application Example San Francisco

5.1 Initial Context and Benchmarks

We chose the city of San Francisco as an example for the application of the tactical optimization model we developed. The city meets geographic preconditions for a successful carsharing business, such as a high population density, parking pressure, and mix of transportation modes (Celsor and Millard-Ball, 2007; Cohen et al., 2008; Stillwater et al., 2009). For our investigation, we set the demand locations analogous to the subdivision of blocks according to the U.S. Census Bureau, which sums up to 573 demand points for the entire city. The center of each block represents our specific location indicated by geographical coordinates. Our demand estimation is based on exemplary characteristics of carsharing users. The five most frequently mentioned social-demographics are presented in Table 2.

<table>
<thead>
<tr>
<th>Typical user characteristics</th>
<th>References</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age between 22 and 44 years</td>
<td>Andrew and Douma, 2006; Burkhardt and Millard-Ball, 2006; Firnkorn and Müller, 2012; Morency et al., 2011</td>
</tr>
<tr>
<td>Above-average education</td>
<td>Andrew and Douma, 2006; Burkhardt and Millard-Ball, 2006</td>
</tr>
<tr>
<td>Single non-family household</td>
<td>Burkhardt and Millard-Ball 2006; Habib et al., 2012; Stillwater et al., 2009</td>
</tr>
<tr>
<td>Availability of cars per household one or less</td>
<td>Andrew and Douma, 2006; Habib et al., 2012</td>
</tr>
<tr>
<td>Lives in housing unit with more than five apartments</td>
<td>Andrew and Douma, 2006; Burkhardt and Millard-Ball, 2006; Firnkorn and Müller, 2012</td>
</tr>
</tbody>
</table>

Table 2. User characteristics of the typical carsharer.

We used the latest forecasted data published by the U.S. Census Bureau, available on their homepage. Based on that data we first determined for each block the percentages of individuals who meet all of the five mentioned aspects and multiplied them with the number of inhabitants of this block. We assume an average trip frequency of three trips per user per month, in accordance with Burkhardt and Millard-Ball (2006), Habib et al. (2012), and MoreNCY et al. (2011). As not every potential user who meets the five aspects, actually participates in carsharing, the absolute number of car sharers is lower. In addition, different months can have different demands for carsharing, and therefore, we consider two different demand scenarios (2.5% and 7.5% of potential users, who meet the five aspects) in our calculations. The following calculation summarizes the demand estimation for each block:

\[
demand \text{ per block} = \frac{\text{number of inhabitants} \times \text{percentages of all five aspects} \times 3 \text{ trips per months}}{\text{percentage of demand scenario}}
\]

The estimation for the demand results in less demand points for the whole city, since many demand points do not cover all five aspects and therefore no demand for carsharing exists. The demand points are spread throughout the city. To illustrate adequately the fluctuating demand in the course of the month and the day, it must be subdivided into time frames. An appropriate solution is chosen based on the duration of six hours for each time frame. Thus, a day is subdivided into four time frames and the whole month is considered to have 112 time frames in accordance to our assumption that one month has only 28 days. To consider peak and off-peak times, the demand is multiplied with a specific factor in accordance to real booking data of our nation-wide project partner CSO operating in two-way mode. During
the night the demand is usually very low, hence, we set the demand in the first time frame of a day as the lowest. Later in the day, the demand increases slightly. The peak can be expected in the afternoon, where the value is the highest of the considered day. In the evening the demand usually decreases again (Millard-Ball et al., 2005). To simulate changing conditions throughout the month, potentially caused by vacation periods, weather conditions, or special events such as trade fairs, we assume that every week has a different demand level. As visible in Table 3, the first week has the highest demand level, the following two weeks have an average demand level, while the last week is considered as off-peak.

<table>
<thead>
<tr>
<th>Week 1</th>
<th>Week 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>0-6 a.m.</td>
<td>0-6 a.m.</td>
</tr>
<tr>
<td>Monday</td>
<td>0.0056</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.0007</td>
</tr>
<tr>
<td>Wednesday</td>
<td>0.0007</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.00084</td>
</tr>
<tr>
<td>Friday</td>
<td>0.00105</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.00175</td>
</tr>
<tr>
<td>Sunday</td>
<td>0.0014</td>
</tr>
</tbody>
</table>

Table 3. Demand multiplier per time frame to consider peaks and off-peaks.

Furthermore, several input data must be chosen for the mathematical model, which is presented in the following Table 4. To ensure heterogeneity of the fleet we consider three vehicles types: gas, hybrid, and electric. We distinguish the demand by two vehicles classes in order to meet customer preferences with 70% for small and 30% for medium size vehicles to allow for varying trip purposes as for example, in San Francisco a carsharing trip is commuted with around 1.59 persons (Cervero and Tsai, 2004). The demand follows the Poisson distribution, since it is appropriate for the modeling of the frequency of an event over a certain period. We use the following differently powered vehicles: Honda FIT (gas, small), Honda Civic Sedan (gas, medium), Toyota Yaris (hybrid, small), Toyota Prius (hybrid, medium), Mitsubishi EV (electric, small) and Nissan Leaf (electric, medium).

<table>
<thead>
<tr>
<th>Vehicle</th>
<th>Initial input values for the tactical optimization.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Honda FIT [US$ p.m.]</td>
<td>200 Av. CO₂ emission Honda FIT [g/km] 120</td>
</tr>
<tr>
<td>Honda Civic Sedan [US$ p.m.]</td>
<td>230 Av. CO₂ emission Honda Civic Sedan [g/km] 148</td>
</tr>
<tr>
<td>Toyota Yaris [US$ p.m.]</td>
<td>250 Av. CO₂ emission Toyota Yaris [g/km] 75</td>
</tr>
<tr>
<td>Toyota Prius [US$ p.m.]</td>
<td>300 Av. CO₂ emission Toyota Prius (medium) [g/km] 90</td>
</tr>
<tr>
<td>Mitsubishi EV [US$ p.m.]</td>
<td>300 Av. CO₂ emission Mitsubishi EV (small) [g/km] 0</td>
</tr>
<tr>
<td>Nissan Leaf [US$ p.m.]</td>
<td>360 Av. CO₂ emission Nissan Leaf (medium) [g/km] 0</td>
</tr>
<tr>
<td>Fixed cost station [US$ p.m.]</td>
<td>50 Average trip length [min] 90</td>
</tr>
<tr>
<td>Charging infrastructure [US$ p.m.]</td>
<td>400 Standard deviation trip [min] 43</td>
</tr>
<tr>
<td>Parking lot [US$ p.m.]</td>
<td>200 Average trip distance [km] 25</td>
</tr>
<tr>
<td>Energy price per liter gas [US$]</td>
<td>0.30 Standard deviation distance [km] 15</td>
</tr>
<tr>
<td>Energy price per kWh [US$]</td>
<td>0.126 Revenue per minute (small) [US$] 0.15</td>
</tr>
<tr>
<td>Maximum distance [km]</td>
<td>0.75 Revenue per minute (medium) [US$] 0.20</td>
</tr>
<tr>
<td>Maximum average CO₂ emissions [g/km]</td>
<td>75 Revenue per km (small) [US$] 0.23</td>
</tr>
</tbody>
</table>

Table 4. Initial input values for the tactical optimization.

The costs for the vehicles are assumed as monthly leasing rates and are determined by the recent leasing costs. They consist of initial and running costs for purchase, battery, insurance, taxes, maintenance, cleaning, administration, and depreciation. The monthly costs for parking lots, stations establishment, and charging infrastructures cover the entire running cost such as maintenance and cleaning, as well as parking signage. The revenues are charged on a time and distance driven basis and are distinguished between the two vehicle classes. Trip durations and trip distances are normal distributed. The mean
values are chosen based on the findings of recent articles. The distance driven per trip varies between 20 and 60 kilometers (Duncan, 2011; Morency et al. 2011). The whole duration of a trip varies between half an hour and four hours (Alfian et al., 2014). The average CO₂ emission values are chosen in compliance with manufacturers’ information for each vehicle type and class explicit not taking into account the incidental emissions for production. The prices for the energy are based on mean values over the last year.

Since we optimize the fleet size and composition of an already existing carsharing business, we assume a basic scenario for established carsharing stations using the strategical optimization model of Sonneberg et al. (2015). We assume 55 carsharing stations in total, and use their geographical coordinates for our tactical optimization model. The distribution of stations is visualized in Figure 2. The stations are located in the inner districts of San Francisco (except for one), as only worthwhile stations are considered. The demand in the other areas either drop to zero or are too small for a CSO to implement a station in this area. All of our considered demand points can be served by at least one station with a maximum distance of 0.75km.

![Figure 2. Distribution of stations as basic scenario for tactical optimization of San Francisco.](image)

Our example of application uses the mentioned parameters from Table 4. Calculations are conducted on a standard laptop (Intel Core i5, 2.5 GHz CPU, 16 GB RAM) using GAMS 24.5.6 with the solver IBM ILOG CPLEX and a set optimization gap of 3%. The results of the benchmarks are presented in table form, which contains of CSO profit, number of each vehicle type t (1=gas; 2=hybrid; 3=electric) and class (small; medium), total number of vehicles, average CO₂ emission, percentages of satisfied trips of small and medium classes and percentage of total demand satisfaction. For our benchmarks (Table 5), we varied the maximum average CO₂ emissions of 0g/km, 75g/km, and 150g/km in two possible demand scenarios (low and high) to demonstrate its impact on fleet composition as well as on profits of CSOs.

<table>
<thead>
<tr>
<th>CO₂ emission limit</th>
<th>Profit in US$</th>
<th>Small</th>
<th>Medium</th>
<th># total vehicles</th>
<th>Av. CO₂ in g/km</th>
<th>Demand satisfaction in %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td># t₁</td>
<td># t₂</td>
<td># t₃</td>
<td># t₁</td>
<td># t₂</td>
</tr>
<tr>
<td>Demand scenario 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(low: 2.5%)</td>
<td>-39,952</td>
<td>0</td>
<td>0</td>
<td>52</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0g/km</td>
<td>-16,026</td>
<td>1</td>
<td>51</td>
<td>0</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>150g/km</td>
<td>-13,063</td>
<td>52</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Demand scenario 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(high: 7.5%)</td>
<td>25,096</td>
<td>0</td>
<td>0</td>
<td>49</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0g/km</td>
<td>49,738</td>
<td>2</td>
<td>51</td>
<td>3</td>
<td>0</td>
<td>14</td>
</tr>
<tr>
<td>150g/km</td>
<td>52,423</td>
<td>55</td>
<td>3</td>
<td>0</td>
<td>8</td>
<td>9</td>
</tr>
</tbody>
</table>

Table 5. Benchmarks: Variation of CO₂ emission limit and demand profiles.
5.2 Discussion of Results

Regarding the presented benchmarks for demand scenario 1 in the previous section, it is notable that the profit is negative for all three considered limits of CO\(_2\) emissions, though the loss decreases the higher the CO\(_2\) emission limit. This can be explained by looking at the vehicle composition. For all three levels, the total number of vehicles remains the same, but due to the strict limit of 0g/km of CO\(_2\) emissions, only electric vehicles can be used, which are more expensive in comparison to hybrid and gas. These vehicles need charging infrastructure, which the CSO has to pay for, and adds to the already slightly higher monthly leasing costs for the electric vehicles. Considering the limit of 75g/km the majority of vehicles are hybrids due to their efficient consumption in combination with low average CO\(_2\) emissions. They fulfil the need to not exceed the set limit. Setting the emission limit higher than the average of all considered vehicles, it does not influence the composition and only worthwhile vehicles are deployed, which leads to a homogeneous fleet of only gas vehicles. The average limit of CO\(_2\) emissions is calculated by the number of vehicles and their average CO\(_2\) emissions. Our benchmarks reveal that the limit is followed exactly, since for CSOs it is more profitable to use gas or hybrid vehicles instead of CO\(_2\) neutral electric ones. Furthermore, the satisfaction of demand is striking as it does not change for the three considered CO\(_2\) limits. The CSO satisfies most of the demand to achieve as little loss as possible from unsatisfied trips, since with every unsatisfied demand the penalty costs increase. This means that in the low demand scenario it is not worthwhile to run a carsharing business, but since following months may have higher demands, customer needs are satisfied instead of cancelling the whole business.

For the assumed higher demand in scenario 2 the CSO will reach a positive net profit irrespective of the maximum CO\(_2\) limit. Even with a limit of 0g/km and a homogeneous fleet consisting of only electric vehicles, the monthly net profit can be about $25,000. The higher the CO\(_2\) limit, the more profit for the CSO, since gas and hybrid vehicles are again cheaper than electrics. Considering the 75g/km limit, the majority of vehicles are hybrid, and yet electric and gas vehicles are still included to fulfil customer needs on the one hand and meet the CO\(_2\) limit on the other hand. A limit of 150g/km allows an unconditional composition and thus the fleet composing consists of a lot of gas and a few hybrid vehicles. As the number of total vehicles and therefore also the demand satisfaction percentage increases, the higher the limit for the CO\(_2\) emissions. When gas and hybrid vehicles are allowed to be used, the result is lower costs which leads to higher demand satisfaction. The satisfaction of one demand (or trip) becomes profitable earlier for a CSO and hence it will satisfy more demand with higher emission limits. This means that for an electric vehicle the utilization must be higher than for gas and hybrid vehicles before becoming profitable. Hence, for the low emission level it is more profitable to not satisfy the demand instead of providing more electric vehicles.

Comparing both demand scenarios, the profit is remarkable, which also stands in line with the findings of Jorge et al. (2012) who conclude that a reduction in the demand leads to a reduction of the profit. With lower expected demand, the CSO is not able to achieve positive profits, since the utilization of vehicles seems not to be high enough for a successful carsharing business. However, some months might have less demand and the CSO can have better months with higher expected demands, where the profit is positive. Comparing the 0g/km CO\(_2\) limits, there must be in sum more months with a high demand level to cover the loss in the lower demand months, as otherwise the business would not be worthwhile. The total number of vehicles is higher in the demand scenario 2, since more demand exists, although the demand percentage is even lower. The lower percentage of demand satisfaction is caused by the greater assumed demand. The CSO can obtain more revenues and hence less profitable demand is not weighted as high as in scenario 1, where the demand and thus the revenues are much lower. For both scenarios it can be observed that the percentage of demand satisfaction is always higher for the small size vehicles. The overall demand for medium size vehicles is lower, and hence especially in off-peaks the demand may drop to zero whereas for small size vehicles even in off-peaks there is at least a low demand level.

To conclude, the applicability check demonstrate the functionality of the artifact. In general, lower CO\(_2\) limits lead to higher costs and consequently to a decrease of the CSOs’ profit caused by higher number of electric and hybrid vehicles. Thus, from a business perspective, it is not advisable to include electric
vehicles in the carsharing fleet, since they are not profitable yet. Electric vehicles and partly also hybrids are solely necessary for image and prestige reasons or to fulfill law requirements regarding CO\textsubscript{2} emission limits.

6 Limitations and Recommendations

We created, refined, and evaluated research artifacts in order to provide decision support for the optimization of composition and size of a carsharing fleet. We followed the structure of Gregor and Hevner (2013) by the development of a nascent design theory that contributes to the IS research domain. With the instantiation by means of an applicability check, we could identify the influence of the variation of crucial input values to the results. As advised for DSR, deeper empirical evaluation in the field forms a major part of the relevance cycle and will increase practicality, rigor, and generalizability of our approach. As in 86.5% of the decision support related DSR artifacts, no complete field trial has been realized here (Arnott and Pervan, 2012). As opposed to an application based on our model, we recommend a further cooperation with existing carsharing companies though in order to validate and evaluate our approach.

Our research is positioned within the Green IS domain and addresses issues of eco-friendly transportation allowing for improved sustainability through easy and self-explanatory usage of monthly tactical optimization for carsharing services. We developed a solution-oriented artifact that reacts to the lack of design and impact oriented research (Malhotra et al., 2013; Gholami et al., 2016). While increasing their profits, CSOs can use the developed model to counteract ecological issues through optimizing the composition and size of a heterogeneous carsharing fleet for a greener operating business. As carsharing and especially carsharing with heterogeneous fleets including electric and hybrid vehicles, focuses on a clean environment with state-of-the-art technology, the introduced model contributes to enhanced ecological sustainability. The model serves as decision support for managers, planners, and decision-makers. Characteristics of a city, for example the city of San Francisco, can be easily integrated as input values to help planners solve the complex problem of determining the composition and size of the carsharing fleet. Theoretically, the applicability of the model is not limited, that means it can be used for any established carsharing organization worldwide operating in a station-based mode. The evaluation of the model and its applicability, however, has so far only been carried out for San Francisco. Further test for different cities are required. The model should also be applied on other exemplary cities to ensure transferability and generalizability.

Certainly, the model is based on various assumptions and simplifications. Especially the demand plays a crucial role. The time-depended demand with the chosen peaks and off-peaks, although partly based on data shared by an operating CSO is still an estimation. The Poisson distribution was a reasonable decision since this probability distribution is appropriate for the modelling of the frequency of an event over a certain time period. Nevertheless, queueing theory could be taken into account in future research with the focus on Markov chains. An arrival process at each established station instead of demand locations could improve the optimization results. However, the disadvantages that would come up are increasing computing time and the problem that in reality, carsharing customers would not wait at the station until the carsharing process can begin. A limitation of our model refers to the assumption that time frames cannot overlap each other. We presume that each vehicle is always available at the beginning of each time frame. Consequently, it is prescribed when the customer has to finish the trip at the latest which is not practicable in reality. If overlapping time frames are considered in future research, the chosen length of six hours can be reconsidered as well. The shorter the time frames, the more accurate is the modelling of the fluctuation in demand in the course of a day. An additional aspect that can be discussed as a limitation is that the model considers only station-based carsharing operating in two-way mode. Especially the electric vehicles cause challenges (e.g. implementation of charging infrastructure at any station) for the one-way mode. Besides additional charging infrastructure and additional parking lots, which have to be determined, relocation techniques have to be considered to address possible imbalances in the carsharing network. Also, free floating does not seem to be a reasonable and
profitable approach for electric vehicles. However, the proposed two-way model represents an effective way for the monthly tactical planning of heterogeneous carsharing fleets to maximize the profit of CSO while considering emission limits. In our example, only three types of vehicles in terms of propulsion mode are used. Nevertheless, it is feasible to integrate an infinite number of types to provide a heterogeneous carsharing fleet. Furthermore, we considered only two vehicle classes (small and medium). In the use of the optimization model, further classes can be regarded, for instance, large vehicles, which represents operational aspects. Further research could combine both, tactical with operation optimizations. With the developed optimization model, CSOs have the possibility to react to any month with different expected demand. At the same time, they are able to maximize their profit and accomplish the goal of conserving resources and environment in accordance to the Green IS concept by setting limits for the CO₂ emissions.

An aspect not yet mentioned is the potential value of the model for city planners or governments. They are supported in defining reasonable CO₂ emission thresholds to ensure CSOs are required to include alternative propulsion methods in their fleets. It also gives an indication of monetary disadvantages with decreasing emission levels and can help to define required subsidies to support environmental sustainability while ensuring profitable business of the CSO.

7 Conclusions and Outlook

Increased environmental awareness and a growing number of people living in cities induce the population to reconsider their current modes of transportation and their need for personal vehicle ownership. Carsharing serves as an attractive transportation alternative to conserve resources and the environment, especially when including electric or hybrid vehicles in the fleet; at the same time it represents an appealing economic option that relieves its users from any running vehicles expenses. This makes the carsharing concept an inclusive approach of Green IS, as it allows any person possessing a driver’s license to use a vehicle at moderate, trip-dependent costs. Taking the perspective of the CSO, the presented tactical optimization model allows them to provide a sustainable mobility concept without compromising profitability. It also allows city planners to contribute to a clean local environment by refining their CO₂ emission thresholds, while understanding and addressing potential profitability concerns of the CSO. These aspects further substantiate the Green IS concept applied in the introduced tactical carsharing optimization model. Our model, integrated in current software, enables an interaction of IT and humans and supports thereby the prime goal of conserving resources and the environment of Green IS. Much research on carsharing optimization consider strategical or operational planning. However, including also a tactical stage with CO₂ emission limits might help to optimize the stated objectives even further and completes the three necessary stages for an entire optimization of carsharing businesses (Boyaci et al., 2015). Hence, we contribute with our model to the Green IS research field by providing a solution approach at a tactical level from an optimization perspective by considering crucial CO₂ emission levels and different vehicles types to ensure customer satisfaction on the one hand but also profitability for CSO on the other hand.

The focus of our article was to provide decision support through the development and provision of a mathematical optimization model determining the composition and size of a heterogeneous carsharing fleet while considering emission limits with time-dependent demand. All of the input values can be adjusted for any city worldwide by having forecasted and experienced values for the demand. We support decision makers by providing the possibility to react to monthly demand fluctuations focusing on customer satisfaction and profitability. We chose the city of San Francisco as an example for the application of our tactical optimization model. Our benchmarks for two different demand scenarios reveal the strong influence of the set maximum level of CO₂ emissions with regards to fleet composition and monthly net profit. The optimization model itself can and should be further refined by the scientific community to achieve constantly increasing sustainability through Green IS. Along with further enhancements, our work contributes to supporting society’s path towards a low emission and noise-reduced environment in agglomerations where carsharing is feasible.
References


