A Decision Support System for the Optimization of Electric Car Sharing Stations

Completed Research Paper

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Abstract

Electric car sharing is a mobility alternative addressing the world's growing need for sustainability and allowing to reduce pollution, traffic congestion, and shortage of parking in cities. The positioning and sizing of car sharing stations are critical success factors for reaching many potential users. This represents a multi-dimensional challenge that requires decision makers to address the conflicting goals of fulfilling demands and maximizing profit. To provide decision support in anticipating optimal locations and to further achieve profitability, an optimization model in accordance to design science research principles is developed. The integration of the model into a decision support system (DSS) enables easy operability by providing a graphical user interface that helps the user import, edit, export, and visualize data. Solutions are illustrated, discussed, and evaluated using San Francisco as an application example. Results demonstrate the applicability of the DSS and indicate that profitable operation of electric car sharing is possible.

Keywords*: Electric car sharing, decision support system, optimization model, design science research.*

Introduction and Motivation

Over the last several decades, rising energy and vehicle ownership costs, sensitivity to environmental sustainability, and social responsibility have caused people to take advantage of transportation alternatives (Dedrick, 2010; Katzev, 2003). Car sharing is one alternative that can satisfy the mobility needs of the modern urban population. Besides the possible monetary savings that a car sharer can achieve, a change of the society toward access-based consumption instead of ownership is a decisive factor that positively affects the demand for car sharing (Shaheen and Cohen, 2013; Bardhi and Eckhardt, 2012). The environmental advantages of car sharing include a decrease in the shortage of parking, a reduction in the number and age of private vehicles, and a decrease in mileage per person (Alfian et al., 2014; Burkhardt and Millard-Ball, 2006). Since electric vehicles cut down emissions and reduce noise as compared to conventionally powered vehicles, they are perfectly suitable for a car sharing concept and further enhance ecological sustainability (Shaheen et al., 2013; Lee et al., 2012). However, state-of-the-art electric vehicles are still associated with high acquisition costs, require a charging infrastructure, and have a limited range compared to conventionally powered vehicles. Theoretically these points work well with car sharing, yet only station-based approaches can appropriately accommodate charging infrastructures and suitably account for range limitations and charging cycles.

For car sharing organizations, the most critical success factor is the challenging task of positioning and sizing car sharing stations to reach the largest possible amount of potential users (Costain et al., 2012). The accessibility and the distance to users' homes as well as to public transport stations play an important role in attracting potential users (Celsor and Millard-Ball, 2007). Moreover, different demographic and geographic characteristics such as high population density, shortage of parking, mix of public transportation uses, and the ability to live without a vehicle affect car sharing usage and need to be considered (Celsor and Millard-Ball, 2007; Cohen et al., 2008; Stillwater et al., 2009). These factors have to be addressed by decision makers when setting up a car sharing network. While trying to allocate the optimal number of stations and vehicles, the organizational objective of profit maximization must be kept in mind. Best practice so far appears to be a trial-and-error concept: stations are randomly opened and then monitored. If not frequently used, they are closed after a trial period. Otherwise they remain unchanged or the number of vehicles is increased. We suggest supporting the planning process with a web-based application that takes several important parameters into account. This tool enables decision makers to execute different scenarios and eventually find the optimal network for their specific application. In addition to its supportive function in implementing car sharing in an economically successful way, our approach helps achieve direct and indirect conservation of resources, and thus leads to increased sustainability. At the same time, it is part of the Green IS concept, as it applies an interaction of information technology (IT) and people to enable the optimization of processes and products and to raise resource efficiency (Watson et al., 2010; Butler, 2011).

Our suggested decision support system (DSS) and the underlying optimization model are based on the model from Rickenberg, Gebhardt, and Breitner (2013). We modified and expanded their model to accurately forecast the expected demand and to maximize the profit of car sharing organizations. The graphical user interface (GUI) of the DSS helps decision makers import and edit data, set parameters, trigger numerical solving of the underlying model, and visualize optimization results. This enables instant validation, comparison, and assessment of results and scenarios. This is exemplarily demonstrated by means of a major city in the US and includes the creation of a specific dataset based on census data and local conditions. The described challenges lead to our research question:

> *RQ: How can decision makers be supported in finding an optimal car sharing network of electric vehicles?*

To answer this question, the remainder of this paper is structured as follows: first the research background is described, covering our research design and related work about car sharing. In the next section, the optimization model is explained and formally noted. Subsequently, the DSS, which employs the underlying model, is presented. The applicability of the model is checked, benchmarks are performed, and the results are shown together with corresponding sensitivities. The next section discusses the presented model, DSS, and corresponding results, followed by the limitations and recommendations of our research. We complete our article with a conclusion and outlook regarding this field of research.

Research Background

Research Design

Methodologically our research is based on design science research (DSR) principles as proposed by Hevner et al. 2004. 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 most suitable for the tasks needed to be accomplished when creating, specifying, and evaluating a car sharing model, addressing both its relevance and its rigor.

Regarding relevance, our work is motivated by the increasing demand for alternative transportation methods, e-mobility, and the associated decision making requirements. A current research project focusing on e-mobility provides further information and ensures the actual 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 car sharing domain, including optimization models, demand estimations, and electric vehicles. Furthermore, we carried out a targeted review of the DSS and DSR domains. The design cycle is an iterative process that uses several build-and-evaluate loops, and revises the design artifacts until a feasible level is reached. We conducted several cycles to ensure that environmental requirements, scientific methods, and existing expertise were all taken into account. As final artifacts, a further enhanced optimization model and the DSS "OptECarShare 1.5" emerged. We tested the DSS and the underlying optimization model extensively to enable proper documentation and publication of research results. The application of DSR in the context of our research as described in the above is visualized in Figure 1:

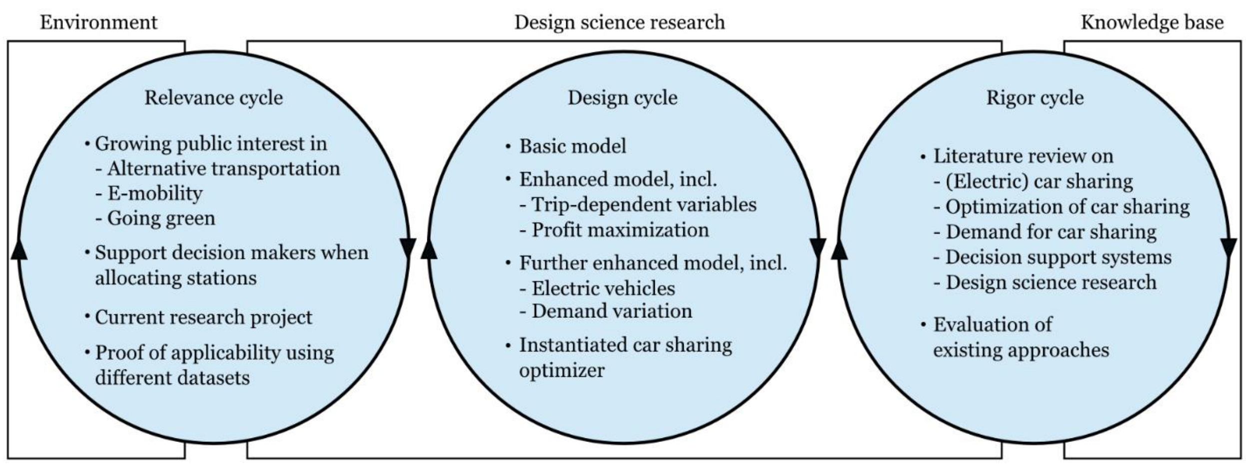

Figure 1. Design science research as applied in our approach based on Hevner (2007)

Car Sharing and Related Work

Car sharing is a transportation strategy that offers the usage of vehicles in an organized manner by paying variable trip-dependent fees. After registration at a car sharing organization (CSO), users can utilize any available vehicle of the fleet as long and as often as required to satisfy their mobility needs. The payment structure differs between organizations, and is usually regulated via varying minute-by-minute fees. Some organizations charge additional fees for mileage or minimal monthly basic fees. In any case, car sharing users pay only for trips they actually take and have no unexpected costs such as maintenance, repairs, or continuous costs such as taxes.

Car sharing organizations offer their services in three main variations. The free-floating system enables the user to pick up and drop off a vehicles anywhere within a determined area (Weikl and Bogenberger, 2012; Firnkorn and Müller, 2011). Station-based car sharing services either require the users to do round-trips and return the vehicle to the same station it was picked up at (two-way car sharing), or allow for one-way trips between different stations. To ensure that there is no imbalance, relocation techniques are needed in this case (Jorge and Correia, 2013; Shaheen and Cohen, 2013). As our work considers electric vehicles with a specific charging infrastructure, station-based car sharing in a two-way mode is the most suitable concept and represents the basis of our model.

Research on car sharing related topics and the number of respective publications increased over the past few years. Many of these address the history and the development of car sharing organizations. A few also analyze locations, typical users and their habits, or the environmental and social benefits of car sharing. While a broader overview on related literature can be found in the article from Degirmenci and Breitner (2014), we focused our review on optimization approaches for car sharing, electric car sharing, estimation of demand, and DSS. The following section succinctly outlines the most applicable articles, to provide a state-of-the-art view on the topic of car sharing.

Publications on optimization of car sharing networks are manifold, yet they emphasize different aspects. Within our literature review we therefore categorize all relevant articles based on their main focus into one or more of six categories (Table 1). The first category, "location optimization", refers to the allocation of stations into a car sharing network and typically represents a strategic approach. The "vehicle optimization" category designates the tactical decision level with corresponding approaches that assess the optimal number of vehicles at each station. In addition to these long-term perspectives, articles also review operational business with goals such as optimizing the service or relocating vehicles. These are consolidated into the "operative optimization" category. Articles concerning the demand for car sharing, at times including profiles of typical car sharing users, fall into the "demand" category. The "DSS" category includes articles introducing decision support systems regarding various aspects of car sharing. "Electric car sharing" is considered separately from traditional car sharing approaches because both charging infrastructures and charging cycles have to be taken into account.

A representative example for the first category is Awasthi et al. (2007), who present a three-stage approach to the selection of car sharing stations. They identify potential stations, assign allotted weights for each station, and then select the final stations. Musso et al. (2012) introduce a similar approach to extending an existing car sharing network by assigning three success factors to different regions and installing new stations and vehicles in the highest-rated regions. De Almeida Correia and Antunes (2012) consider one-way car sharing and combine the strategic perspective of planning locations and size of car sharing stations with the operative aspect of profit maximization per period for different relocation procedures. The model from Boyaci et al. (2015) has a similar focus. It explores the best location, fleet size, and relocation techniques in a one-way car sharing application with the aim of maximizing profit. Cepolina and Farina (2012) provide a cost minimization model for the distribution of personal intelligent city accessible vehicles (PICAVs) within the city of Genoa (Italy), including a fully user-based relocation strategy. Many operative models introduced in the literature fully focus on daily service. One example is Fan et al. (2008), who develop a multistage stochastic linear model to maximize the daily profit by means of a dynamic daily allocation of vehicles. The model calculates a relocation scheme by means of fixed reservations for the next day. Kek et al. (2009) present an optimization model and DSS to reduce the cost for the relocation of one-way car sharing services by considering operational costs. Compared to approaches regarding conventional car sharing, research and applications in the "electric car sharing" category are still relatively limited. Khanna and Ventors (2013) provide a prototype concept to integrate electric car sharing into the public transport system and state that information and communication technology innovation is a key component to success. A field study presented by Steininger and Bachner (2014) investigates the provision of electric vehicles by a rail company and indicates that the service can succeed. Potential demand for electric car sharing is reviewed in a survey by Shaheen et al. (2013), who report that 66% of all participants of the population in San Francisco are interested or at least maybe interested in electric car sharing. Literature also suggests that critical success factors exist to reach those potential car sharing users. Andrew and Douma (2006) identified population density, age, residents commuting, household type, and parking situation as critical success factors. Results of a study from Costain et al. (2012) show that car sharing is preferably used during the weekend, with a rising trend throughout the week. An overview of demand estimation and defined operations is provided by Jorge and Correia et al. (2013). Due to the criticality of the success factors and the related demand, decision support appears to be reasonable and can be found in several approaches. An example for the "DSS" category is represented by an article of El Fassi et al. (2012), who developed a DSS based on a discrete event simulation, which determines the best expansion strategy for the desired investigation area. Possible strategies, for instance, consist of the establishment of new stations, the expansion of existing stations, and the merging and demerging of stations.

Table 1. Car sharing related literature categorized by focus

Author	Year	Focus on:						Content
		Location optimization	Vehicle optimization	Operative optimization	Electric car sharing	Demand	DSS	
Alfian et al.	2014			x				Simulation tool to evaluate the service model in car sharing systems
Andrew and Douma	2006					x		Study of car sharing market in US. Success factors are: density, age, residents commuting, household type, parking situation
Awasthi et al.	2007	x	x					Optimization of car sharing location based on a case example in France
Bardhi and Eckhardt	2012					x		Analysis of access-based consumption in the context of car sharing
Boyaci et al.	2015	x	x	x	x			Generic model for supporting the strategy (station location and size) and tactical decisions of one-way car sharing systems
Burkhardt and Millard-Ball	2006					x		Analysis of car sharing users
Celsor and Millard-Ball	2007	x				x		Tool to identify neighborhoods that can support car sharing in the US
Cepolina and Farina	2012		x		x			Optimization of distribution of electric vehicles (PICAVs) in Genoa
Cervero	2003					x		Analysis of car sharing users in the first year of a CSO in San Francisco
Cervero and Tsai	2004					x		Analysis of car sharing users in the second year of a CSO in San Francisco and positive developments within the city
Costain et al.	2012					x		Analysis of user behavior: case example Toronto
de Almeida Correia and Antunes	2012	x		x				Maximize daily profit by an optimization approach to depot location in one-way car sharing services
Di Febbraro et al.	2012			x				Simulation and optimization of the relocation problem of one-way car sharing: case example Turin
El Fassi et al.	2012		x	x			x	Optimization of car sharing stations and vehicles within existing CSO (operative planning)
Fan et al.	2008			x				Multistage stochastic linear model to maximize the daily profit by relocating the vehicles
Habib et al.	2012					x		Development and validation of an econometric model for behavior of car sharing users to provide support for car sharing planners
Jorge and Correia	2013					x		Literature review of demand estimation of car sharing systems
Jorge et al.	2014			x				Mathematical model to optimize relocation operations to maximize the profit and a simulation tool to study different real-time relocation policies
Kek et al.	2009			x			x	Optimization model and DSS to determine a set of near-optimal manpower and operating parameters for the vehicle relocation problem
Kek et al.	2006			x				Simulation model on operator-based relocation techniques
Khanna and Venters	2013				x			Case study in Berlin to integrate electric car sharing into the public transport system
Millard-Ball et al.	2005					x		Analysis of the market, barriers, impacts, and critical success factors
Morency et al.	2011					x		Analysis over three years of car sharing members in Montreal
Musso et al.	2012	x	x					Expansion plan of car sharing services in new districts in Rome
Nobis	2006					x		Survey of the awareness and market potential of car sharing service in Germany
Rodier and Shaheen	2003					x		Scenario analysis using an advanced travel demand model in the Sacramento region
Schaefers	2012					x		Analysis of motives of car sharing usage in the US
Shaheen and Cohen	2008					x		International comparison of car sharing
Shaheen and Martin	2010					x		Explorative study of demand for car sharing systems in Beijing
Shaheen et al.	2013				x			Study of electric vehicle car sharing in San Francisco
Steininger and Bachner	2014				x			Evaluating costs, market potential and environmental merits of implementation of car sharing in Austria
Stillwater et al.	2009					x		IS-based study of influencing factors of car sharing demand
Ter Schure et al.	2012					x		Impacts of parking situation and car sharing demand
Wagner et al.	2014		x				x	Decision support of points of interest in free-floating car sharing system
Wang et al.	2012					x		Survey of profile of car sharing members in Shanghai

However, none of these articles provide support for strategic optimization of location, number, and size of stations. Neither considers electric vehicles in their optimization approaches. However, many publications emphasize the importance of a well-planned network that optimally addresses the demand. They further indicate the suitability of electric vehicles for car sharing. We therefore consolidated many of the above ideas in our approach. We developed a mathematical model that optimizes an electric car sharing network and maximizes the organization's profit as objective function. Critical conditions discussed in many of the articles are combined in the constraints of this model. We also gave a lot of critical thought to our dataset and diligently implemented the existing background knowledge into our supply and demand datasets. We implemented this model to provide valuable insight for real-life decision makers.

Optimization Model

The presented optimization model is based on the basic model from Rickenberg, Gebhardt, and Breitner (2013) and maximizes the annual profit of a car sharing organization. The following assumptions form the basis of the optimization model:

- The object in consideration is the classic two-way car sharing scheme. Every vehicle has its designated parking lot, meaning vehicles have to be picked up and returned to the same location.
- The objective of the optimization model explicitly concerns strategic planning of a car sharing network; operational aspects are not considered.
- Stochastic and normal distributed demand points for car sharing exist.
- The demand points are allocated within the investigation area and are provided on a punctual basis by geographic coordinates.
- The demand has to be fulfilled completely to reach the maximum customer satisfaction.
- Possible supply points in the form of car sharing stations are spread over the specific investigation area to satisfy the demand. These points are also characterized by exact geographic coordinates.
- For each of the potential stations, a maximum limit of parking lots is defined to reflect local land-use conditions in the surroundings of the respective station.
- Annual leasing costs for vehicles, parking lots, and stations are introduced. These contain all incidental expenses, and explicitly not only the initial costs.
- Subject matter is electric vehicles, which are completely battery powered and require trip-dependent charging cycles.
- Two different options of the charging process can be simulated for the otherwise homogenous fleet. Firstly, regular charging can be used through the conventional local grid-connection. As an alternative, more efficient fast chargers via special 50 kW DC charging elements can be chosen. Depending on the option, different charging times and adjusted leasing costs are being considered.
- The implementation of electric vehicles into the car sharing fleet requires additional parameters. Charging condition and influencing elements such as range, average speed, and power consumption are therefore considered. The power consumption depends on the duration of a trip and the distance driven. Hence, these are integrated as trip-dependent parameters and modelled stochastically by a normal distribution.
- A maximum number of possible trips per day results from the choice of trip-dependent parameters and the corresponding fast or regular charging times.
- The charging time is linearly correlated to the travel time. This means that one hour of travel time is always associated with a fixed time to recharge the battery.
- Variations in demand typically do not represent a part of a strategic, i.e., long-term problem. To grant decision makers a certain degree of variation, the suggested model allows the demand to be varied throughout the week by determining peak and off-peak weekdays. An additional variation of the demand (e.g., throughout the day or year) is not expected to add further value to the strategic allocation of stations and vehicles and should rather be included in operative approaches.

Table 2. Parameters used

Sets:	
$i = (1, \ldots m)$: *potential station location*	$j = (1, \ldots, n)$: *demand location*
Parameters:	
d_j: *normal distributed demand* [$rents/week$]	min: *expected duration of a rent* [min]
rev: *revenue for renting* [$USD\ p.a.$]	$trip$: *expected distance driven* [km]
$energy$: *average energy consumption* [kwh/km]	$price$: *price* [USD/kwh]
cv: *leasing cost of a vehicle* [$USD\ p.a.$]	cp: *leasing cost of a parking lot* [$USD\ p.a.$]
cc^{reg}: *leasing cost of regular charger* [$USD\ p.a.$]	cc^{fast}: *leasing cost of fast charger* [$USD\ p.a.$]
cs: *leasing cost of a station* [$USD\ p.a.$]	
x^{reg}: *possible trips regular* [$units$]	x^{fast}: *possible trips fast* [$units$]
$dmax$: *demand of busiest interval* [$rents/day$]	
$maxl_i$: *max. lots at station i* (#)	$maxlfast$: *max. lots with fast charger* (#)
$dist_{ij}$: *distance betw. station i and demand point j* [km]	$maxdist$: *max. distance betw. i and j* [km]
Decision variables:	
v_i^{reg}: *number of vehicles regular charged at station i*	y_i: 1, *if station is built*, 0 *else*
v_i^{fast}: *number of vehicles fast charged at station i*	z_{ij}: 1, *if demand location j is served by station i*, 0 *else*

$$\boldsymbol{Max.\,F}\left(\boldsymbol{v^{reg}}, \boldsymbol{v^{fast}}, \boldsymbol{y}\right) = \overbrace{\sum_{j=1}^{n} d_j * (min * rev)}^{revenue} - \overbrace{\sum_{j=1}^{n} d_j * (trip * energy * price)}^{variable\ costs} \tag{1}$$
$$- \overbrace{\sum_{i=1}^{m} \left(v_i^{reg} * (cv + cp + cc^{reg}) + v_i^{fast} * (cv + cp + cc^{fast}) + y_i * cs\right)}^{leasing\ costs}$$

$$\sum_{i=1}^{m} z_{ij} \geq 1 \quad \forall\, j \tag{2}$$

$$y_i \geq z_{ij} \quad \forall\, i \text{ and } j \tag{3}$$

$$v_i^{reg} * x^{reg} + v_i^{fast} * x^{fast} \geq \sum_{j=1}^{n} (dmax_j * z_{ij}) \quad \forall\, i \tag{4}$$

$$v_i^{reg} + v_i^{fast} \leq maxl_i \quad \forall\, i \tag{5}$$

$$v_i^{fast} \leq maxlfast \quad \forall\, i \tag{6}$$

$$dist_{ij} * z_{ij} \leq maxdist \quad \forall\, i \text{ and } j \tag{7}$$

$$y_i \in \{0, 1\} \quad \forall\, i \tag{8}$$

$$z_{ij} \in \{0, 1\} \quad \forall\, i \text{ and } j \tag{9}$$

$$v_i^{reg}, v_i^{fast} \geq 0 \quad \forall\, i \tag{10}$$

Figure 2. Underlying mathematical model

The objective function (1) maximizes the profit of a car sharing organization by calculating the revenue and subtracting the resulting variable and the annual leasing costs. Demand points can be served by one or more stations to split the expected demand (2). Constraint (3) ensures that every demand point can only be assigned to a station that is actually built. The existing demand has to be satisfied completely in compliance with corresponding charging times (4). The factors x^{reg} and x^{fast} are used to calculate the possible number of trips per day, taking into account the average speed, trip duration, and corresponding charging times. Every station has a limited number of parking spaces for vehicles (5) to consider local parking conditions at that station. To prevent a grid overload, constraint (6) sets a maximum amount of fast charging infrastructures at all stations. Constraint (7) ensures that a maximum distance between a demand point and an associated station is not exceeded. Equations (8), (9), and (10) set the specific value range of the decision variables of the model.

DSS

In addition to the developed mathematical model that optimizes the network of car sharing stations, a decision support system (DSS) is constructed. The developed DSS is a Java-based web application that enables decision support for the optimal placement and size of car sharing stations. It integrates the optimization model and additional applications into one system. As principles of usability and comprehensible visual appearance are applied, it enables decision makers to easily run their own case studies. After the desired datasets are developed and imported and after parameters are selected, the DSS solves the equations of the underlying model and displays the appropriate results in an illustrative way. As a result it contributes to less pollution and a more sustainable environment in accordance with the Green IS/DSS concept. The basic requirement for the optimization is the software GAMS, a modeling system for mathematical programming. Further software used to develop the DSS is Eclipse Luna with the actual Java Development Kit and Notepad++. The resulting system architecture and data flow is shown in Figure 3.

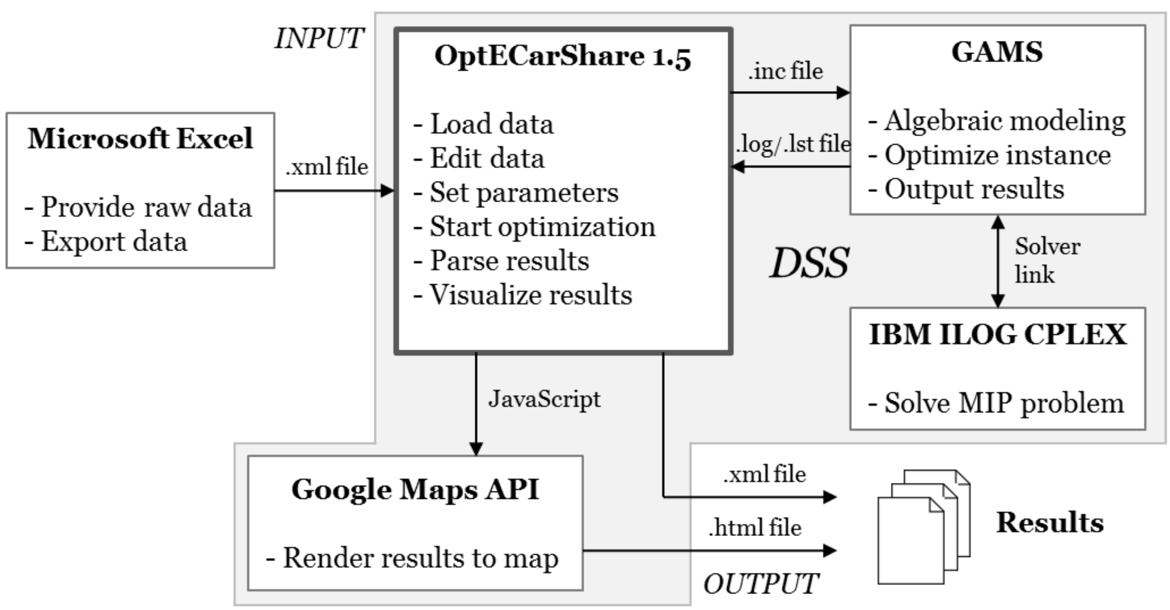

Figure 3. Dataflow of the decision support system

As illustrated above, a dataset for the respective investigation area needs to be developed by decision makers as external input in the form of an .xml file. The DSS provides the option to both load and edit data, such as potential car sharing stations. Furthermore, parameters of the mathematical model can be set and varied by the user to simulate different scenarios. When starting the optimization, an .inc file that contains the input data including the values of parameters is written. GAMS and the connected solver IBM ILOG CPLEX then calculate the optimal solution of the mathematical model. GAMS automatically generates a .log and a .lst file which are used to display the optimization process and the results. For an additional graphical visualization, the resulting car sharing network can be exported to an .html file via Google Maps API.

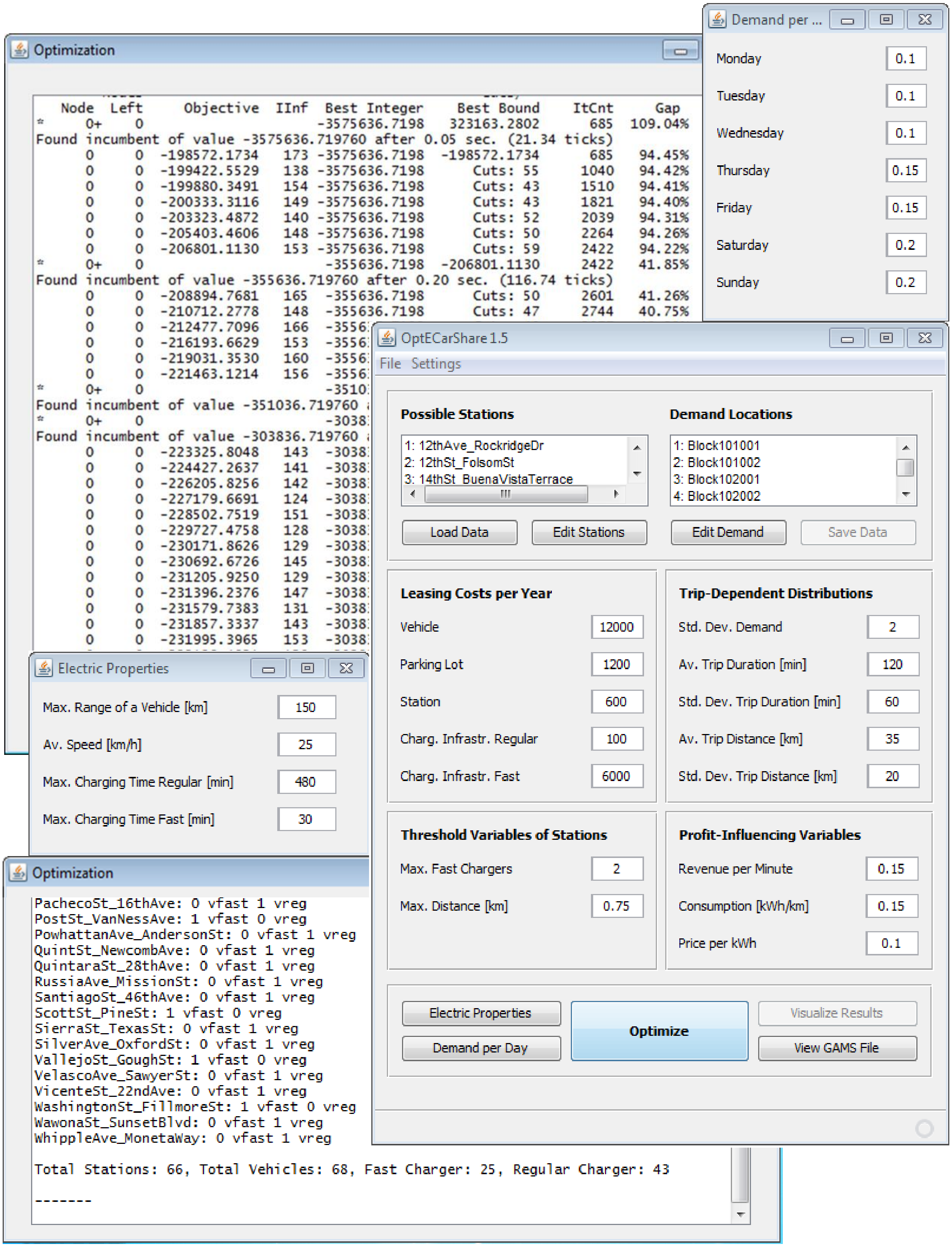

Figure 4. Design and functionality of the decision support system

Figure 4 provides an overview on the respective windows of the GUI. The main GUI "OptECarShare 1.5" is grouped into six graphically separated sections and a menu bar. In the menu bar, users can define the GAMS path and the working directory, as well as optimization accuracy, which is preset to five percent. The first section enables loading and modification of a dataset. The two vertical scrollbars can be used to quickly review the stations and demand points, which are displayed in numerical order. The stations and demand locations, as well as their specific properties, can be viewed in detail and easily edited via the "Edit Stations" and "Edit Demand" buttons. The next four sections contain the basic parameters. The first section contains different incidental costs that are described as leasing costs per year. This includes the leasing cost for a vehicle, parking lot, and station, as well as costs for the regular and the fast charging infrastructures. The second section of the main GUI contains different trip-dependent distributions. The dataset assigns mean values to every demand location that are normal distributed with an adjustable standard deviation. In addition, the normal distributed trip duration and the trip distance with their corresponding deviations can be set. In the third section, the threshold variables for the maximum number of fast charging infrastructures and the maximum distance between supply and demand locations can be adjusted. The fourth section includes the variables that directly affect profit, including revenue per minute, consumption per kilometer, and energy price. The last section at the bottom of the application contains six buttons. The "Set Electric Properties" and "Demand per Day" buttons are used to modify preset values, as shown in Figure 4. The "Optimize" button starts the optimization through the linkage to GAMS, as explained before. The "Optimization" window illustrated above displays the running process. As GAMS and CPLEX work with the branch and cut algorithm, every line shows one single branch with information about the related objective, best integer, best bound, and the gap to the optimal solution. Only those branches are displayed that are better than the solution found before. At the end of the optimization process, the results are displayed in the Optimization window. The "Visualize Results" button activates the linkage between the DSS and Google Maps. The resulting network of car sharing stations is shown in Figure 5. The "View GAMS File" button opens the corresponding mathematical model. The DSS further includes error messages that prevent the start of the optimization when input is incorrect or missing, e.g., if the overall weekly demand exceeds 100 percent. They quickly take decision makers to the error so that it can be fixed quickly. The final "OptECarShare 1.5" web application, the optimization model, and sample data sets are available at 130.75.63.115/OptECarShare.

Dataset Creation, Applicability, and Benchmarks of San Francisco

In order to evaluate the developed DSS, we provide an application example together with benchmarks. An additional application example supporting our results is available at 130.75.63.115/OptECarShare to show transferability. The success of a car sharing organization depends on different demographic and geographic characteristics such as high population density, parking pressures, mix of transportation means, and the ability to live without a vehicle (Celsor and Millard-Ball, 2007; Cohen et al., 2008; Stillwater et al., 2009). For this purpose, we chose the city of San Francisco, which satisfies all required characteristics and already successfully accommodates car sharing networks. San Francisco has an appropriate population of more than 825,000 inhabitants within an approximately quadratic urban area with an edge length of about eleven kilometers. With the resulting population density of more than 7,000 people per square kilometer, San Francisco is one of the most populated cities in the US, leading to a lack of parking space. Within the mostly rectangular oriented streets, a well-developed public transport system covers the complete city. In addition to train and bus connections to the adjoining San Francisco Bay Area, there are networks of light rails, cable cars, historic streetcars, trolley coaches, and buses. With only one operating company supervising all of these means of public transportation and with co-resident expansion plans in place, the ability to live without a vehicle continues to improve. After choosing an operation area, the positioning of demand and supply points is the most crucial factor for a car sharing organization (Costain et al., 2012). For our validation, we set the demand locations analogous to the subdivision of blocks according to the U.S. Census Bureau. With the exception of five sparsely populated blocks (e.g., the Golden Gate Park) which are not considered, San Francisco is divided into 573 blocks. Each block is characterized by a particular demand location in its center of settlement indicated by geographical coordinates. A total of 1,448 potential supply points is distributed consistently over the whole investigation area and, likewise with precise geographical positions. Due to the proven correlation between public transport and car sharing, possible stations are set close to access points of public transportation (Celsor and Millard-Ball, 2007).

The estimation of demand levels for car sharing is summarized in a literature review published by Jorge and Correia (2013). As stated in recent studies and investigations, some generalizations about car sharing participants are feasible. Correspondingly, we base our demand estimation on several population characteristics. The by far highest share of people conducting car sharing are those between 22 and 39 years old (Andrew and Douma, 2006; Burkhardt and Millard-Ball, 2006; Firnkorn and Müller, 2012; Morency et al., 2011). A typical car sharer is above-average educated (at least to bachelor degree level) and often lives in small non-family households with a maximum of two people (Andrew and Douma, 2006; Burkhardt and Millard-Ball, 2006; Habib et al., 2012; Stillwater et al., 2009). Equipped with less than one vehicle per household, a car sharer generally lives in an apartment building with more than five housing units (Andrew and Douma, 2006; Burkhardt and Millard-Ball 2006; Firnkorn and Müller, 2012; Habib et al., 2012). Several other criteria such as typical income levels are not considered due to ambiguous information. Based on these findings, we determined a group of potential car sharing users for each block that complies with all of these requirements. We used the latest forecasted data published by the U.S. Census Bureau for 2013 based on Census 2010, available on their homepage. Based on that data, we calculated the weekly demand per block as input for the mathematical model as follows.

First, we determined five population characteristics for each block, by assigning typical age, education, housing unit, available vehicles, and household type. We then allocated the number of potential car sharing users per block in accordance with these characteristics. Depending on the respective characteristics, the number of potential users may drop to zero, for example in blocks with family households or elderly people who are not typical car sharing users. As not every potential users actually participates in car sharing, the absolute number of car sharers is much lower. Different surveys suggest inconsistent values, therefore we vary the percentage between 1% and 10% in the benchmark section. In accordance with Burkhardt and Millard-Ball (2006), Habib et al. (2012), and Morency et al. (2011), we assume an average trip frequency of three trips per user per month. Hence, we calculated the demand per week for each block as follows:

$$\frac{number\ of\ potential\ users * percentage\ of\ focus\ group * 3\ trips\ per\ months}{30\ days\ per\ month} * 7\ days\ a\ week \qquad (11)$$

The potential station locations within the optimization model are characterized by a particular limit of parking lots. These numbers result from local conditions such as bilateral parking, parallel or transverse parking, on-street, or off-street parking. Table 3 summarizes the initial values used for the required parameters to execute the DSS. We chose the distinct values based on the following explanations. The first values refer to the various annual leasing costs. The leasing costs for one vehicle include initial and running costs for purchase, battery, insurance, taxes, maintenance, cleaning, administration, depreciation, and amortization over the year. Leasing costs for parking lots correspond to rental charges of the ground. Cost for maintenance and cleaning of a parking lot as well as parking signage are incurred within the costs for a station. The leasing costs for a regular charging infrastructure unit contain the establishment and maintenance of a power line to the grid of the infrastructure. The annual leasing cost for a unit of fast charging infrastructures consider the installation, connection, and maintenance of high voltage power lines to the power mains.

Table 3. Applied values for parameters

Parameter	Value	Parameter	Value
Vehicle [USD p.a.]	12,000	Max. number of fast chargers per station	2
Parking lot [USD p.a.]	1,200	Max. distance [km]	0.75
Station [USD p.a.]	600		
Regular charging infrastructure [USD p.a.]	100	Max. range of a vehicle [km]	150
Fast charging infrastructure [USD p.a.]	6,000	Average speed [km/h]	25
		Charging time regular [min]	480
Std. dev. of demand	2	Charging time fast [min]	30
Average trip duration [min]	120		
Std. dev. trip duration [min]	60	Monday	0.1
Average trip distance [km]	35	Tuesday	0.1
Std. dev. trip distance [km]	20	Wednesday	0.1
		Thursday	0.15
Revenue per minute [USD]	0.15	Friday	0.15
Consumption [kWh/km]	0.15	Saturday	0.2
Price per kWh [USD]	0.1	Sunday	0.2

The discussed demand levels per block serve as mean value within a normal distribution. Likewise, the trip duration and the trip distance are normal distributed. The mean values are chosen based on findings of recent studies. The distance driven per trip varies between 20 and 60 kilometers (Cervero and Tsai, 2004; Duncan, 2011; Morency et al. 2011). The whole duration of a trip, including driving and parking times, varies between half an hour and four hours (Alfian et al., 2014). To limit the solution, thresholds are considered. The threshold of a maximum number of fast charging infrastructures restricts the solution regarding the capital expenditure and the securing of network coverage. One of the strongest factors of influence on the solution is the maximum distance between demand and station location. Various surveys and observations deviate between 250 meters and two kilometers, others state a maximum walking distance of 10.75 minutes (Morency et al., 2008; Costain et al., 2012; Celsor and Millard-Ball, 2007). The revenue per minute includes both driving and parking times. The energy consumption per kilowatt hour of the vehicle is computed per kilometer. Besides these adjustments, some additional parameters related to the charging cycles were chosen. The maximum range of the vehicle is set to a typical range of the average electric vehicle. The average speed is set to a typical city locomotion of 25 km/h in accordance to Kriston et al. (2010). Recharging of an empty battery with a regular charging infrastructure via a standard outlet such as a charging station connected to the grid takes about eight hours. The 50 kW DC high voltage fast charging infrastructure significantly increases the process. We chose a value of 30 minutes to recharge a battery based on the specifications of different manufacturers. Literature states that the demand level varies between weekdays and weekends, which is adjustable via a corresponding button (Millard-Ball et al., 2005). Values are chosen to simulate that the usage of car sharing rises slightly but constantly throughout the week and achieves its maximum at the weekend (Costain et al., 2012; Cervero, 2003; Alfian et al. 2014).

The application example uses the above parameters from Table 3. Calculations were conducted on a standard laptop (Intel Core i7 2.5 GHz CPU with 16 GB RAM) using GAMS 24.1.3 with CPLEX 12.5.1 and a set optimization gap of 10% or a maximum computing time of 6,000 seconds. Figure 5 visualizes the resulting station network for the city of San Francisco in Google Maps. When users of the DSS click the markers, the properties of the respective station are shown, i.e., the specific number of regular and fast chargers. In order to avoid an information overload in the illustration, markers for the demand are not directly shown. However, when users click on an area close to a station marker, the demand locations and their respective properties are displayed.

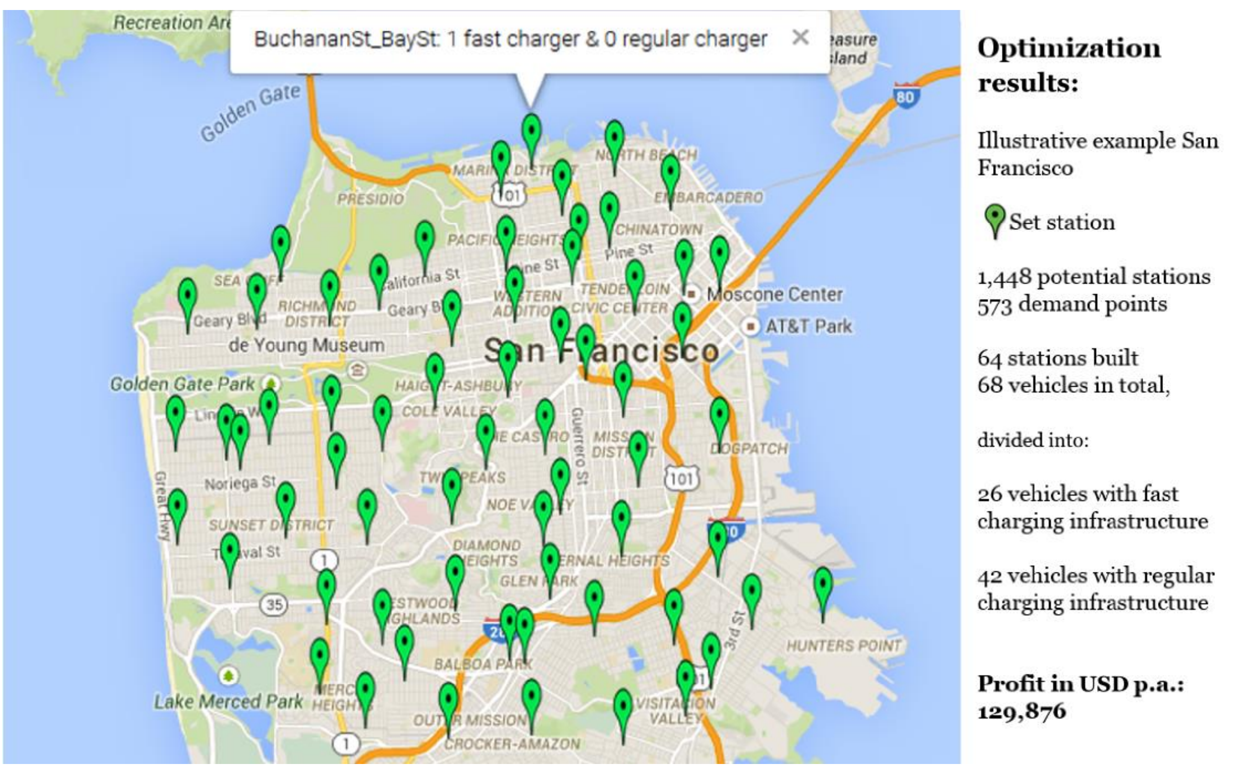

Figure 5. Optimization results

The results indicate that a car sharing organization can gain a profit of USD 129,876 when reaching 5% of the potential users in the identified focus group. In this example, a total of 64 stations are built. The number of required vehicles to satisfy the existing demand is 68, including 26 vehicles with fast and 42 with regular charging infrastructure. In general, the optimal values to maximize profit depend on the settings and parameters used. Different alternatives can be calculated and visualized to allow decision support for the process of finding the solution that best meets the actual budgetary or strategic goals of the car sharing organization.

With the applicability of the model demonstrated in the above example, the section below varies certain parameters and provides corresponding benchmarks. Table 4 is divided into three parts, with 0.5 km, 0.75 km, and 1 km as maximum distance between each demand point and the next car sharing station. Each part illustrates the respective annual profit and provides the indicated number of stations and vehicles (as the sum of regular and fast charging infrastructures). With a higher maximum distance, fewer vehicles and stations are necessary to satisfy the demand. This also means that the average utilization per vehicle is higher and the profit increases. It should be noted though that the overall demand might decrease if potential users do not have a car sharing opportunity nearby. We tested the model with five different demand profiles (1%, 3%, 5%, 7.5%, and 10% usage of the identified focus group). The results show the necessary minimum number of car sharing users to establish profitable electric car sharing. In combination with an additional market analysis, decision makers therefore get a good idea of their business case. As expected, with a higher percentage of users, the car sharing organization needs more stations and vehicles, but also generates a higher profit or reaches its break-even point. Moreover, the number of vehicles with fast charging infrastructure increases with more users to satisfy the additional demand. We also considered two different average trip durations, which presumably depend on local conditions and thus differ between cities. With longer trip durations, the profit of the car sharing organization increases markedly although more vehicles are required. In many cases the profit more than doubles when comparing the 3-hour trip duration to the 2-hour duration. This again shows the decision makers the importance of knowing the specific demand of their respective investigation area and urges them to cautiously examine their business case. Results also show that the number of vehicles with fast charging infrastructure usually increases with a higher trip duration to ensure quick availability of the vehicle for the next user. The number of vehicles with a regular charging infrastructure consequently declines since vehicles with fast chargers can serve more users. In summary our benchmarks validate DSS and model. They also highlight the importance of knowing the potential users, as the tool is only as good as the data used for the calculations. Especially the demand is one of these critical success factors. The tool supports decision makers in evaluating their business case and points out the fine line between success and failure.

Table 4. Benchmarks

Average trip duration of 2 hours	Max. dist. = 0.5 km				Max. dist. = 0.75 km				Max. dist. = 1 km			
	profit (USD)	stations (#)	vfast (#)	vreg (#)	profit (USD)	stations (#)	vfast (#)	vreg (#)	profit (USD)	stations (#)	vfast (#)	vreg (#)
1% of focus group	-1,263,348	123	1	122	-425,148	61	5	56	-156,848	40	9	31
3% of focus group	-909,476	121	9	112	-208,175	68	15	53	83,824	42	20	25
5% of focus group	-527,120	117	17	102	134,579	66	25	43	279,580	51	29	27
7.5% of focus group	-94,709	115	29	90	403,191	71	37	43	588,091	56	41	24
10% of focus group	272,686	121	41	84	758,186	73	47	41	872,186	58	54	23

Average trip duration of 3 hours	Max. dist. = 0.5 km				Max. dist. = 0.75 km				Max. dist. = 1 km			
	profit (USD)	stations (#)	vfast (#)	vreg (#)	profit (USD)	stations (#)	vfast (#)	vreg (#)	profit (USD)	stations (#)	vfast (#)	vreg (#)
1% of focus group	-1,001,207	125	5	120	-259,307	66	16	51	-84,907	44	27	23
3% of focus group	-348,149	115	25	90	133,250	69	36	40	333,250	51	40	20
5% of focus group	146,707	118	40	82	563,909	78	49	38	719,606	60	57	17
7.5% of focus group	687,456	124	58	79	621,456	86	65	45	1,147,856	86	74	23
10% of focus group	1,240,667	130	75	79	1,502,266	108	87	43	1,731,366	81	96	14

Discussion

We created, refined, and evaluated research artifacts in order to provide decision support for the optimization of the location and size of electric car sharing stations. We based our introduced optimization model on existing OR models and integrated it into a DSS. In doing so, we provide for additional usability by creating an intuitive interface for managers, planners, and decision-makers. We further explained the creation of the required dataset using the application example of San Francisco. Respective benchmarks completed our demonstration and show feasibility of model and DSS.

The developed decision support system “OptECarShare 1.5” answers our research question by providing a DSS that optimizes the allocation of electric car sharing stations while maximizing the profit. The model allows users to easily integrate the characteristics of a city to solve the complex problem of determining optimal locations and sizes of car sharing stations. It enables car sharing organizations to plan and implement car sharing within a new city in one big step to demonstrate extensive market presence from the beginning as compared to common trial-and-error concepts. Numerous parameters such as electric properties of vehicles or various leasing costs are included to help fine-tune the strategic optimization. This feature eases the inclusion of different scenarios and accounts for alternative vehicles, such as subcompact or mid-range electric vehicles, or the use of different charging infrastructures as is shown in our examples. It also enables decision makers to perform sensitivity analyses to evaluate the effects of different input parameters and thus helps to ascertain a profitable solution for their individual case. In order to achieve low computing times, a gap can be set, so that a result is found quickly. With additional computing time further improvements of the gap are possible. However, since the model addresses strategic planning as compared to operative control, for example, computing time does not represent a critical aspect. This also applies to other operative factors, such as demand variations throughout the day or year (e.g., peaks due to events), cleaning cycles, or vehicle inspection, which are not considered. The applicability and feasibility of the developed DSS were tested using the city of San Francisco as an example. The city fulfills the required prerequisites to theoretically allow for profitable car sharing and has a proven track record of successful car sharing implementation. The benchmarks suggest that the approach of electric car sharing can be profitably realized. As expected, in addition to the optimal allocation of stations and vehicles throughout the city, the demand plays an important role in our results and is the key to a successful implementation. An additional case example regarding the city of Portland further supports our results and is available at 130.75.63.115/OptECarShare. Overall results indicate that our DSS and the underlying optimization model can be applied beyond these two examples and can help decision makers to evaluate the profitability of their respective case. Results further emphasize the importance of accurate data, specifically regarding demographics, to ensure a sound dataset allowing for realistic demand estimations.

Since car sharing, and especially electric car sharing, aim for a clean environment with state-of-the-art technology, the introduced model also contributes to enhanced ecological, social, and economic sustainability. Moreover, the model and DSS allow car sharing organizations to plan their station arrangements in a time-saving, yet optimal manner. This makes the artifacts a part of the Green IS concept, as IT is utilized to achieve environmental enhancement. As the DSS provides the main user interface and incorporates the underlying model, it may also be called a Green DSS.

Limitations and Recommendations

Our model and DSS create a precise recommendation of station allocation throughout a city. However, certain limitations and possible enhancements need to be considered. Theoretically, the applicability of the model is not limited, i.e., it can be used for any city worldwide that fulfills the discussed conditions with regards to geographic and demographics characteristics. The evaluation of the model and its applicability was limited to the city of San Francisco in the course of this article. Additional benchmarks were carried out for the city of Portland, and are available online. Further tests for other cities with different structure or population are required to ensure transferability and generalizability.

Our model is based on many simplifications and assumptions. A realistic estimation of the demand is crucial to success. We consolidated a number of articles and created an image of the typical electric car sharing user. In combination with census data, a reasonable first demand estimation can be calculated without financial impact. However, the demand depends on many different variables, such as the price of car sharing, structure of the city, and public transport, but also on the competitive market situation.

Demographic data for the considered area allows for a first estimation of the demand. Additional criteria can help further refine the group of potential users. Our model does not explicitly consider competition, yet a variation in the percentage of the focus group can indirectly adjust the demand to lower values when competitors are present. To underline their business case we would still encourage decision makers to gain additional data, for example, from questionnaires or interviews in the corresponding areas.

Not only are further parameters such as average trip duration, speed, and distance related to the expected demand, they also strongly depend on individual characteristics of the respective city, including density of traffic and expansion of the local public transport. Although the model facilitates station allocation, it cannot replace a sound evaluation by decision makers. Also, we only considered deterministic data and not a stochastic distribution. In any case, the application example shows that the modelling of the demand is adequate by using literature to identify a potential user group and thereby distribute the potential demand. Further, the implementation of additional multi-mobility constraints, i.e., emphasizing the importance of stations near public transportation and especially the central station might improve the model. We only consider the demand of the habitual abode of potential users and not the demand around business areas or public transport stations due to a lack of data and research in this realm. In addition, only one average price for all car sharing users is assumed. In future amendments of the model, the price elasticity of demand should be considered as it has an influence on the demand and the profit of a car sharing organization. The model could also be expanded by creating timeframes throughout the day and the week and combining them with demand-related prices. These suggestions already considerably overlap with operational approaches and fine-tune our strategic model rather than significantly changing it. Since the demand for car sharing in a one-way and free-floating mode is increasing (Ciari et al., 2014), the two-way service suggested in our model is not optimal to reach the highest demand. Due to the requirement for charging infrastructures for electric vehicles, the free-floating service is not a suitable approach though. However, our model can be enhanced to include station-based one-way car sharing. A relocation algorithm has to be developed or adopted from an operative approach and constraints for the parking lots or charging infrastructures at each station would also have to be modified. At stations that are preferably used to return vehicles, more charging infrastructures and parking lots need to be provided. Even though possible, one-way trips generate significantly more costs by requiring additional charging infrastructures at each station and staff for the relocation. Thus the proposed two-way model represents an effective way of implementing electric car sharing strategically using today's technology.

Despite the applicability and performance of the introduced model and DSS, certain refinements may enhance the quality of the model. The most promising adjustments can be achieved in the context of demand. The constraint to satisfy demand completely forces the installation of a station even if that station is then used by only a few people. This means that the specific station is actually non-profitable. In contrast to this, demand can decrease due to dissatisfaction of potential users. The reputation of the car sharing organization can deteriorate and therefore less demand accrues, which means that profit decreases. To further optimize profit, assumptions can be made regarding the charging infrastructures by assigning two or more vehicles to one infrastructure. For these assumptions, a safety parameter should be included to cover the risks so that more vehicles are available in case one vehicle cannot be charged on time. Also, the demand as a constant parameter could be logically connected to the supply using a factor that depends on the distance between supply and demand: the closer the supply is to the demand, the higher the demand. Likewise, due to the constant demand, the model also assumes that the client would pay whatever the car sharing provider charges. This missing interconnection between price and demand is likely to cause issues when practically applying the model. Currently, the model will calculate a rising profit with increased prices, not taking into account that less people would use the service. Costs for stations and corresponding parking lots should be amended by choosing more realistic values for the respective location. This means that a parking lot next to the central station is more expensive than one farther away. However, the costs for a parking lot is only a minor part of the overall cost so that this differentiation would not have a significant influence on the profit, settings, and size of stations. The profit calculation in our model focuses on revenue and expenditure. No taxes or other country-specific duties are included.

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 DSS 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 cooperation with existing car sharing companies though in order to further validate and evaluate our approach.

Conclusions and Outlook

Increased environmental awareness and possible cost savings are making people reconsider their current modes of transportation and the need for personal vehicle ownership. Car sharing, and especially electric car sharing, represents an attractive alternative. To successfully implement car sharing within a city, station locations, their sizes, and an optimal number of vehicles to satisfy the demand have to be found.

In this article, we introduced a model to provide decision support for the complex task of planning the optimal locations and sizes of electric car sharing stations. The integration of the model into a DSS enhances the applicability and usability of our approach. The DSS provides a user-friendly interface, allows data import, and triggers the optimization and visualization of results. The DSS and the underlying model were evaluated and demonstrated using the example of the city of San Francisco. The benchmarks reveal that the identification of realistic demand levels can separate profitable from non-profitable car sharing. Although certain limitations have been identified, the applicability and usefulness of the optimization model and the DSS were evaluated and shown. Noticeable benefit could be drawn from deeper empirical evaluation in the field and a more profound quantitative analysis, which is suggested to be carried out in the context of the DSR relevance cycle. Especially when discussing the model, implications, and recommendations for additional research can be derived. The optimization model itself can and should be further refined by the scientific community to achieve constantly increasing sustainability through Green DSS. To conclude, we emphasize that the potential of electric car sharing is considerable, with regard to both sustainability and profitable installation. The developed model thereby supports the strategic planning phase by providing decision support. Along with further enhancements, our work can contribute to supporting society's path towards a low emission and noise-reduced environment.

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